Master's Thesis

Scoring Economic Gains: Replicating and Extending the Analysis of World Cup Victory Effects on Economic Growth

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Abstract

This thesis replicates and extends the analysis of Mello (2024), who examines whether winning the FIFA World Cup boosts GDP growth. Using quarterly data from OECD countries and implementing both event-study and synthetic difference-in-differences (SDID) methodologies, this study confirms that winning the World Cup increases year-over-year GDP growth by approximately 0.5 percentage points in the two subsequent quarters, driven primarily by enhanced export growth. Beyond replication, this thesis extends the analysis to finalists, semi-finalists, and underperformers—top-10 ELO-rated countries eliminated in the group stage. The finalist and semi-finalist extensions show positive but insignificant effects that attenuate as the treatment group broadens, confirming the premium is specific to winning. The underperformer analysis finds no evidence that early elimination depresses GDP; most SDID estimates are positive, with the notable exception of exports, where the ATT turns negative which is consistent with the export channel operating in reverse. The findings reinforce the idea that international visibility and trade are the primary mechanism for economic growth after a victory, and suggest that investigating more detailed economic components (e.g. tourism or employment) as well as the effect for unexpected overperformers would be a valuable direction for future research.

Keywords: FIFA World Cup, GDP growth, event study, synthetic difference-in-differences, sports economics, causal inference

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1 Introduction

Everyone knows them. The images of the celebrations of fans in a country that has just won the most watched sports event in the world: the FIFA World Cup. Only taking place every four years, the top 32 football nations[1] compete for the official title of best football country in the world. The FIFA World Cup as an event has drawn major attention throughout the later 20th century and with each tournament broadcast viewership records are broken, with the latest tournament having around 5 billion viewers (FIFA, 2022). In the victor-country, this event is always followed by nation-wide celebrations and victory tours of the players. Millions of citizens gather at major landmarks, bars are filled, and everyday life is positively shocked by euphoria. And when the music dies out and the streets have been cleaned up, what remains? The observation of these events sparks the research question of this master thesis: does winning the FIFA World Cup have a positive impact on a country's economy?

This question sits at the intersection of sports economics, behavioral economics, and macroeconomics. On the one hand, the intense emotional responses triggered by World Cup victories; the spikes in patriotism, the collective euphoria, and the surge of national pride suggest channels through which economic activity might be affected. Consumer confidence may rise, spending may increase, and the winning nation's international visibility may boost demand for its products abroad or attract touristic visitors. But does the fundamental productive capacity of an economy change because its football team lifted a trophy? One would mainly assume that any economic effect, if it exists, should be expected to be temporary and modest relative to the underlying growth trajectory.

While sports economics literature has produced extensive research on the effects of hosting mega-sporting events, the question of whether winning such events matters economically has received far less attention.

Some literature even suggests that the effect could be negative. Forbes magazine famously described an apparent pattern of post-victory GDP contraction as the "World Cup GDP Curse," claiming that in six of the last seven tournaments the winning country's economy contracted the following year (St. John, 2014). However, such claims rely on simple comparisons of GDP time series without proper counterfactual analysis, i.e. they do not construct the relevant counterfactual of what GDP growth would have been absent the victory.

Only one study I could come across has rigorously investigated this question. Mello (2024), published in the Oxford Bulletin of Economics and Statistics, provides a thorough causal analysis of the economic effects of winning the World Cup using quarterly GDP data from OECD countries spanning 1961 to 2021 and employing both event-study and synthetic difference-in-differences methodologies. Mello finds that winning the World Cup increases year-over-year GDP growth by approximately 0.48 percentage points in the two subsequent quarters. He adds that this effect appears to be driven primarily by export growth rather than consumption or investment which one would intuitively expect and suggests that a World Cup victory enhances the international appeal of the winning country's products and services.

The existence of only one rigorous study on this topic sparked my interest in expanding

[1]Initially 13 in 1930, then 16 from 1934–1978, 24 from 1982–1994, then 32 up to 2022.

research on this topic. On the one hand, I want to validate the results through an independent replication. On the other hand, the scarcity of research means there is substantial room to extend and deepen the understanding of these effects or to demonstrate that they are not robust and that this effect does not require further investigation.
The primary objective of this thesis is therefore twofold. First, I independently replicate Mello's event study and synthetic difference-in-differences (SDID) specifications using freshly constructed OECD data, verifying that the main results are reproducible. Given the close alignment found between my replication and the original estimates, further robustness exercises (alternative lag structures, matched samples) were not pursued; the near-identical results from independent data and code already provide strong evidence for the validity of his robustness checks.
Second, I extend the analysis along two dimensions. On the positive side, I broaden the treatment group to finalists (runner-up countries) and semi-finalists (top-four finishers) to test whether the economic premium extends beyond winning. On the negative side, I examine *underperformers* which I define as top-10 ELO-rated countries eliminated in the group stage and investigate whether the mechanisms operate in reverse. Both extensions are estimated with the same event study and SDID methodology applied to all six GDP components (gdp, private consumption, government consumption, investment, exports, imports).
The remainder of this thesis is organized as follows. Section 2 reviews the literature on the economic effects of sporting events. Section 3 presents the theoretical foundations of event study and synthetic difference-in-differences methodology. Section 4 describes the empirical implementation, including the stacked SDID design and bootstrap inference. Section 5 details the data sources and sample construction. Section 6 reports the replication results compared to Mello (2024), and Section 7 presents the finalist, semi-finalist, and underperformer extensions. Section 8 concludes the the thesis' findings and my reflections.

2 Background

2.1 The Impact of Large Sport Events

2.1.1 Social and Psychological Effects

An underlying theory assumption of this thesis is that broadcasting and the consumption of sports have an impact on people. There is a vast amount of research documenting this impact that large sporting events can have on individuals at a psychological level. When national teams compete on the world stage, citizens, who often take on the role as fans, experience heightened patriotism, pride, and shared identity. These effects are particularly pronounced during mega-events like the FIFA World Cup, where simultaneous mass viewership—reaching approximately 5 billion cumulative viewers for the 2022 tournament (FIFA, 2022)—amplifies the collective emotional experience across entire populations.

The effect can be both positive and negative though. Mutz (2013), using a panel survey with fixed-effects regression during the 2012 European Championship, finds significant temporary increases in patriotism that fully dissipate within three weeks after elimination. Kersting (2007), comparing pre- and post-tournament surveys in South Africa and Germany around the 2006 World Cup, documents 15–20 percentage point increases in national pride. Depetris-Chauvin et al. (2020), employing difference-in-differences on Afrobarometer surveys matched to African Cup of Nations results, find that victories increase national identification by 4 percentage points and inter-ethnic trust by 3 percentage points. Billings et al. (2013), using regression analysis on longitudinal surveys during the 2012 Olympics, find that each additional hour of viewing increases nationalism scores by 0.02 points. On the negative side, Rosenzweig and Zhou (2021), exploiting random match outcomes as instrumental variables around the 2014 World Cup, show that victories increase anti-refugee sentiment by 8 percentage points, and Bertoli (2017), using negative binomial regression on dispute data from 1950–2007, finds that football victories increase the probability of initiating interstate disputes by 11%.

Beyond attitudes, mega-events generate substantial intangible value for host populations. Dolan et al. (2019), applying difference-in-differences to Eurobarometer life satisfaction data, find hosting the Olympics increases well-being by 0.06 points on a 4-point scale. Gibson et al. (2014), surveying South African residents before and after the 2010 World Cup, find that intangible benefits like pride and excitement—termed "psychic income"—were the strongest predictor of public support for hosting. Zhou and Ap (2009), analyzing survey responses from 600 Beijing residents, report that 89% agreed hosting increased local pride.

2.1.2 Economic Behavior and Willingness to Pay

The psychological significance of sporting success translates into measurable economic valuations. Studies employing contingent valuation methods consistently find that citizens are willing to pay substantial amounts for their national team's success. Wicker et al. (2012), using a double-bounded dichotomous choice survey experiment with 1,064 German respondents, estimate a willingness-to-pay of €4.26 per capita for a football gold medal. Hallmann et al. (2013), comparing contingent valuation responses across 2,027 Germans, find WTP for the 2012 European Championship (€6.30) exceeds WTP for Olympic gold (€3.50). Bakkenbüll and Dilger (2018), applying interval regression to surveys of 1,000 Germans before the 2014 World Cup, estimate a collective WTP of €1.46 billion for winning. These substantial valuations suggest that football success may generate economic consequences through consumer sentiment.

2.1.3 Economic Effects of Hosting

A widely covered topic in media and academic discourse is the economic effect of hosting large sporting events like the FIFA World Cup or the Olympic Games. Governments and organizing committees routinely commission studies projecting billions in economic impact, yet it often remains unclear whether the substantial public expenditures on stadiums, infrastructure, and security actually yield a positive return for host countries.
The academic literature reaches predominantly skeptical conclusions. For the Olympic Games, Billings and Holladay (2012), using synthetic control on US metro employment data, find no significant long-term effects of hosting. Li et al. (2013), employing a computable general equilibrium model for Beijing 2008, estimate a modest 0.24% GDP increase. Interestingly, Rose and Spiegel (2011), using gravity model estimation on bilateral trade data from 196 countries, show that bid submission alone generates an 18% trade increase—suggesting signaling effects independent of actual hosting.
The FIFA World Cup literature reaches similar conclusions. Baade and Matheson (2004), analyzing taxable sales and employment in 9 US host cities using OLS regression, estimate net losses of \$5.5–\$9.3 billion rather than the projected \$4 billion gain. Hagn and Maennig (2008), applying difference-in-differences to monthly employment data across German regions, find no measurable employment effects from hosting the 1974 World Cup. Szymanski (2010) reviews the broader literature and concludes that benefits are typically overstated. Lee and Taylor (2005), using input-output analysis for the 2002 Korea/Japan World Cup, find tourism benefits of \$307 million—below the \$2.5 billion infrastructure cost. Peeters et al. (2014), employing synthetic control for South Africa 2010, find no significant tourism increase. One exception is Fett (2020), who using fixed-effects OLS on host country GDP data from 1962–2010 finds a structural break at 1990: negative effects of -4.6% annually pre-1990 but positive effects of $+1.1\%$ post-1990, attributed to increased commercialization. Despite this mixed academic evidence, FIFA's official impact assessment for the 2026 World Cup projects \$40.9 billion in global GDP gains and 185,000 jobs in the US alone (FIFA and World Trade Organisation, 2024).
Since the effects of hosting have been extensively researched and the consensus suggests limited economic benefits, this thesis focuses on a less-studied question: the economic effect of *winning* major tournaments. For the theoretical assumption of winning to have a macroeconomic effect, the event must be sufficiently large to generate widespread attention and emotional engagement across the population. The most-watched sporting events globally include the FIFA World Cup (5 billion cumulative viewers in 2022, with 1.5 billion watching the final), the Summer Olympics (5 billion reached in Paris 2024), the ICC Cricket World Cup (over 1 trillion viewing minutes in 2023, though concentrated in South Asia), and the Super Bowl (approximately 125 million viewers globally) (FIFA, 2022, International Olympic Committee, 2024, International Cricket Council, 2023). Among these, the FIFA World Cup stands out for combining massive global reach with intense

national identification—unlike the Olympics where attention is fragmented across dozens of sports and medal events, the World Cup final is a single match determining one national champion. As documented above, Wicker et al. (2012) and Hallmann et al. (2013) find that willingness-to-pay for football success substantially exceeds that for Olympic success, reflecting football's unique cultural significance, particularly in Europe and South America.

2.1.4 The Economics of Winning

Research specifically examining the economic effects of *winning* the World Cup is remarkably scarce. Some media has given attention to apparent patterns in post-victory economic performance. For example, Forbes magazine described an apparent pattern of post-victory GDP contraction as the "World Cup GDP Curse," observing that in six of the last seven tournaments (1986–2010), the winning country's economy contracted in the following year (St. John, 2014). Figure 1 displays GDP growth trajectories for five of these seven winners. Argentina (1986) and Brazil (1994) are excluded as they do not have OECD quarterly accounts for this period. The pattern is heterogeneous: Spain 2010 shows a clear decline in GDP growth following victory, while Germany 1990 experienced continued growth.

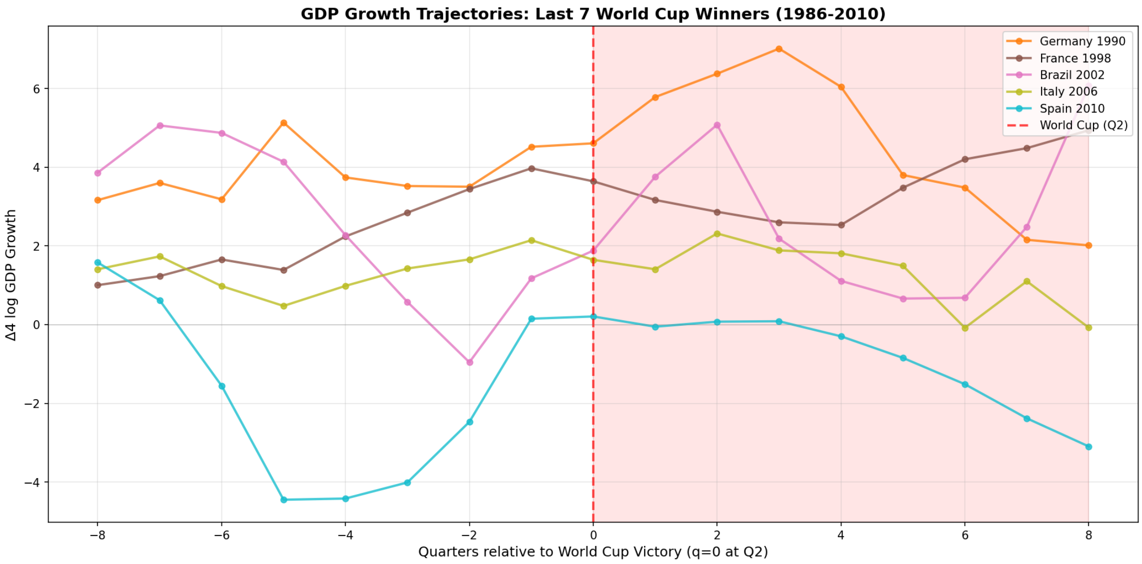


Figure 1: Year-over-year GDP growth trajectories for five of the last seven World Cup winners (1986–2010). Argentina 1986 and Brazil 1994 are not included due to OECD data availability. The red dashed line indicates the World Cup quarter (Q2), and the shaded region marks the post-victory period.

However, such descriptive analysis lack appropriate counterfactual construction. Observing that Spain's GDP declined after 2010 does not establish that winning the World Cup *caused* this decline. Spain was already in the midst of a severe economic crisis stemming from the housing market collapse and European debt crisis. Similarly, Germany's strong post-1990 growth reflected reunification dynamics rather than World Cup effects. The

relevant question is what would have happened to each country's economy *if* it had not won, requiring proper econometric methods to construct counterfactual trajectories.
Only one rigorous causal analysis of the effect of *winning* exists. Mello (2024), published in the Oxford Bulletin of Economics and Statistics, provides a thorough econometric investigation using event-study and synthetic difference-in-differences on quarterly OECD data spanning 1961–2021. Mello finds that winning increases year-over-year GDP growth by at least 0.48 percentage points (SE = 0.26) in the two subsequent quarters. The effect appears driven by export growth (+4.5 pp in the synthetic DiD, though insignificant) rather than consumption or investment, suggesting victories enhance international visibility. The scarcity of research in this area, combined with the potential significance of Mello's findings, motivates the present thesis and I will proceed to replicate his analysis to see if the findings match.

3 Theoretical Framework

This section presents the theoretical foundations of the causal inference methods used in this thesis. I begin with the potential outcomes framework for treatment effect estimation, then discuss event studies and synthetic difference-in-differences - the two main approaches employed in both Mello (2024) and this replication.

3.1 The Potential Outcomes Framework

The fundamental goal of causal inference is to estimate the effect of a treatment on an outcome. Following the potential outcomes framework formalized by Rubin (1974), each unit i has two potential outcomes: $Y_i(1)$ under treatment and $Y_i(0)$ under control. Since each unit is observed in only one state—the "fundamental problem of causal inference" (Holland, 1986)—individual treatment effects $\tau_i = Y_i(1) - Y_i(0)$ are not directly identified. The average treatment effect (ATE) is defined as:

$$\tau^{ATE} = E[Y_i(1) - Y_i(0)] \tag{1}$$

In observational settings with panel data and staggered treatment adoption, such as World Cup victories occurring at different times for different countries, the estimate of interest is typically the average treatment effect on the treated (ATT):

$$\tau^{ATT} = E[Y_i(1) - Y_i(0) \mid D_i = 1] \tag{2}$$

which measures the effect specifically for units that received treatment, i.e., winners of a FIFA World Cup. This is the quantity estimated by both the event study and SDID approaches in this thesis.

3.2 Event Study Design

The event study methodology estimates dynamic treatment effects by comparing outcomes at different points in time relative to an event. Originally developed in finance to study stock price reactions (Fama et al., 1969), the approach has become standard for analyzing policy changes, economic shocks, and discrete interventions in panel data settings (Angrist and Pischke, 2009).

Let us consider a balanced panel of N units (countries) over T periods (quarters), where unit i receives treatment at time E_i. The relative time to treatment is $K_{it} = t - E_i$, such that the indicator $\mathbf{1}[K_{it} = k]$ equals one when unit i is exactly k periods from its treatment date. The event study specification is:

$$Y_{it} = \alpha_i + \lambda_t + \sum_{k \neq k^*} \beta_k \cdot \mathbf{1}[K_{it} = k] + X'_{it}\gamma + \varepsilon_{it} \tag{3}$$

where α_i are unit fixed effects absorbing time-invariant country characteristics, λ_t are time fixed effects absorbing common shocks affecting all countries, X_{it} are time-varying controls, and one relative time period k^* is omitted as reference (typically $k^* = -1$, the period before treatment). The coefficients β_k estimate the average effect at horizon k relative to the reference period.

3.2.1 Identification Assumptions

Event study identification rests on two key assumptions:
Parallel trends: Absent treatment, treated and control units would follow parallel outcome paths. Formally:

$$E[Y_{it}(0) - Y_{i,t-1}(0) \mid D_i = 1] = E[Y_{it}(0) - Y_{i,t-1}(0) \mid D_i = 0] \tag{4}$$

No anticipation: Treatment does not affect outcomes before it occurs:

$$Y_{it}(1) = Y_{it}(0) \quad \text{for all } t < E_i \tag{5}$$

The pre-treatment coefficients $\{\beta_k : k < 0\}$ provide a testable implication: under these assumptions, they should be statistically indistinguishable from zero. A flat pre-trend supports the parallel trends assumption, though it cannot definitively prove it.

3.2.2 Challenges with Heterogeneous Treatment Effects

There exist potential problems with two-way fixed effects (TWFE) estimators – regressions that include both unit- and time fixed effects – when treatment occurs at different times for different units. The issue arises because TWFE implicitly constructs comparisons between all groups, not just treated versus never-treated. Suppose that Germany wins in 1974 and Italy wins in 1982. To estimate the effect of winning, TWFE compares winners against never-winners (a valid comparison), but it also compares Italy (newly treated in 1982) against Germany (already treated in 1974). The second comparison treats Germany as a "control" after it has already won—if winning has persistent effects, this comparison is contaminated.
Goodman-Bacon (2021) formalizes this intuition by showing that the TWFE estimator $\hat{\beta}^{TWFE}$ can be decomposed as a weighted average of all such pairwise comparisons:

$$\hat{\beta}^{TWFE} = \sum_k w_k \cdot \hat{\beta}_k \tag{6}$$

where $\hat{\beta}_k$ are treatment effect estimates from different 2×2 comparisons (early vs. late treated, treated vs. never-treated, etc.) and w_k are data-dependent weights. Crucially, these weights can be negative when already-treated units serve as controls. When treatment effects vary across cohorts or fade over time, these problematic comparisons can bias the overall estimate.
For the World Cup application, these concerns are not handled by Mello and are mitigated by several features: (1) there are relatively few treated units (10 World Cup winners from 1966–2018; see Section 5 for details), (2) treatment effects are expected to be transitory, meaning already-treated units return to baseline before serving as controls, and (3) a I have a large pool of never-treated OECD countries provides clean comparisons. Importantly, I complement the event study with SDID to provide converging evidence: while the event study reveals the dynamic pattern of effects over time, SDID constructs an explicit synthetic counterfactual that does not rely on the parallel trends assumption holding globally. When both approaches yield consistent results, confidence in the causal interpretation is strengthened.

3.3 Synthetic Difference-in-Differences

Synthetic difference-in-differences (SDID), proposed by Arkhangelsky et al. (2021), combines the strengths of synthetic control methods with difference-in-differences logic. While standard DiD assumes parallel trends hold globally, and synthetic control requires exact pre-treatment matching, SDID relaxes both requirements by constructing optimal weights for both units and time periods. This flexibility makes it particularly valuable when pre-treatment trajectories may not be perfectly parallel—a realistic concern when comparing GDP growth across heterogeneous economies.
Figure 2 illustrates the intuition behind SDID by comparing three approaches using the canonical California tobacco control example from Abadie et al. (2010).

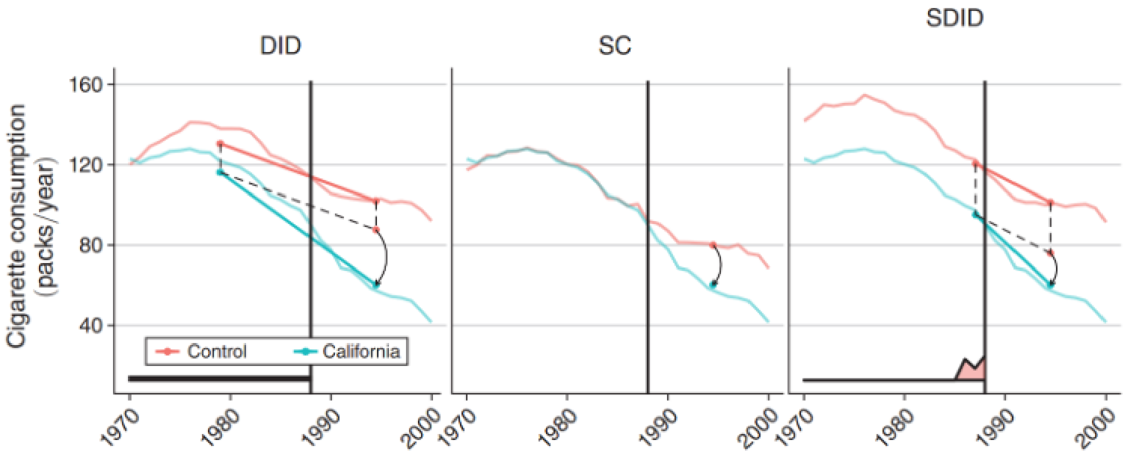


Figure 2: Comparison of difference-in-differences (DID), synthetic control (SC), and synthetic difference-in-differences (SDID). In DID, the treatment effect is estimated as the difference between the treated unit's post-treatment outcome and a simple average of control units. In SC, unit weights are optimized to match the pre-treatment trajectory exactly. SDID combines both: unit weights create a synthetic control while time weights emphasize periods most predictive of post-treatment outcomes. Adapted from Arkhangelsky et al. (2021).

3.3.1 The SDID Estimator

Consider a panel with N units observed over T periods, where treated units receive treatment after period T_0. Let W_{it} be a treatment indicator equal to one for treated units in post-treatment periods. The SDID estimator solves a weighted two-way fixed effects regression:

$$(\hat{\tau}^{SDID}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \, \hat{\omega}_i \hat{\lambda}_t \tag{7}$$

where $\hat{\omega}_i$ are unit weights and $\hat{\lambda}_t$ are time weights. The key innovation in comparison to Standard DID is that these weights are chosen to make treated and control units comparable, rather than assuming comparability a priori.
The unit weights are constructed by solving a regularized optimization that matches the

pre-treatment trajectory of treated units:

$$\hat{\omega} = \underset{\omega \geq 0, \sum_j \omega_j = 1}{\arg\min} \sum_{t=1}^{T_0} \left(\bar{Y}_{tr,t} - \sum_{j \in \mathcal{C}} \omega_j Y_{j,t} \right)^2 + \zeta^2 T_0 \|\omega\|_2^2 \tag{8}$$

where $\bar{Y}_{tr,t}$ is the average outcome for treated units at time t, $\mathcal{C}$ denotes the set of control units, and ζ is a regularization parameter that prevents overfitting when the control pool is large. Time weights $\hat{\lambda}_t$ are constructed analogously to identify pre-treatment periods most predictive of post-treatment outcomes.

Given these weights, the SDID treatment effect estimate takes a transparent double-difference form:

$$\hat{\tau}^{SDID} = \underbrace{\left(\bar{Y}_{tr,post} - \bar{Y}^{\lambda}_{tr,pre}\right)}_{\text{treated: post minus weighted pre}} - \underbrace{\sum_{j \in \mathcal{C}} \hat{\omega}_j \left(\bar{Y}_{j,post} - \bar{Y}^{\lambda}_{j,pre}\right)}_{\text{synthetic control: post minus weighted pre}} \tag{9}$$

where $\bar{Y}^{\lambda}_{tr,pre} = \sum_{t=1}^{T_0} \hat{\lambda}_t \bar{Y}_{tr,t}$ is the weighted pre-treatment average for treated units. This expression shows that SDID estimates the ATT by comparing pre-to-post changes for treated units against pre-to-post changes for a synthetic control constructed from weighted donor units.

3.3.2 Properties and Inference

Arkhangelsky et al. (2021) establish that under regularity conditions, the SDID estimator is consistent and asymptotically normal. The method inherits a form of double robustness: it remains consistent if either parallel trends hold globally or if the unit weights successfully match the treated unit's trajectory. In practice, inference relies on bootstrap methods that resample at the unit level, preserving within-unit serial correlation. Following Mello (2024), I use 1,000 bootstrap replications with standard errors clustered at the country-subseries level.

SDID is well-suited for the World Cup setting because it can construct tailored counterfactuals for each of the winner countries by optimally weighting the control/never-winning OECD countries according to their pre-victory trajectories.

4 Methodology

This section details the empirical implementation of the methods introduced in Section 3. I first describe the replication of Mello (2024), then present the extensions that constitute the novel contributions of my thesis.

4.1 Replication of Mello (2024)

The primary objective of this thesis is to replicate and compare the analysis in Mello (2024). As a first step, this involves reconstructing the dataset from OECD sources as the author did not make his code publicly available[2], reproducing the summary statistics, and estimating both the event study and synthetic difference-in-differences models. The full replication should serve two purposes: validate the original findings using independently constructed data, and additionally establish the foundation for the extensions that follow.

4.1.1 Data Construction

The replication uses quarterly national accounts data from the OECD, covering the period 1961–2021. The sample includes 48 countries: 6 World Cup winners during the sample period, 12 host countries, and 36 countries that neither won nor hosted. Following Mello (2024), I reconstruct the data set he describes and follow the mentioned data transformation steps (see Section 5). The outcome variable of each feature is year-over-year (YoY) growth, computed for GDP as:

$$\Delta_4 \ln GDP_{c,t} = \ln GDP_{c,t} - \ln GDP_{c,t-4} \tag{10}$$

which compares GDP in quarter t to the same quarter one year earlier. For descriptive statistics and sample composition, see Section 5. In this calculation my differences in absolute GDP levels compared to Mello's cancel out as long as they are proportional to each other.

4.1.2 Event Study Specification

The event study follows the specification in Mello (2024), which estimates dynamic treatment effects around World Cup victories:

$$\Delta_4 \ln GDP_{c,t} = \alpha_c + \lambda_t + \sum_{k\neq 0} \beta_k \cdot \mathbf{1}[K_{ct} = k] \cdot W_c + \theta \cdot HOST_{c,t} + \zeta \cdot \ln GDP_{c,t-4} + \varepsilon_{c,t} \tag{11}$$

where α_c are country fixed effects, λ_t are quarter fixed effects, $K_{ct} = t - E_c$ is the relative time to country c's World Cup victory at time E_c, and W_c is an indicator for ever-winning countries. The reference period is $k = 0$, corresponding to Q2 of the World Cup year. $HOST_{c,t}$ controls for hosting effects in the calendar year of the tournament, and $\ln GDP_{c,t-4}$ controls for the level of economic development four quarters prior.

[2]The Mello (2024) paper included a replication package link: `https://doi.org/10.3886/E188961` but it leads to a completely different research paper of droughts in Brazil (last visited 02/26).

The relative time indicators span $k \in \{-16, \ldots, -1, +1, \ldots, +16\}$, with quarters beyond this window binned into aggregate endpoints. For countries winning multiple World Cups (Germany: 1974, 1990, 2014; Italy: 1982, 2006; France: 1998, 2018), the relative time counter restarts at the midpoint between consecutive victories.
Standard errors are clustered at the country level to account for serial correlation within countries.

4.1.3 Synthetic Difference-in-Differences Specification

The SDID analysis follows Mello (2024) in constructing 10-quarter subseries around each post-1994 World Cup. For each tournament in $\{1998, 2002, 2006, 2010, 2014, 2018\}$, I create subseries spanning $q \in [-7, +2]$ relative to Q2 of the World Cup year. This yields 6 treated subseries (one per winner: France 1998 and 2018, Brazil 2002, Italy 2006, Spain 2010, Germany 2014) and approximately 260 control subseries from the donor pool.
Note that the SDiD sample deliberately excludes earlier World Cups (1966–1994), even though the event study covers winners back to 1966. The restriction to 1998–2018 reflects *data availability*: OECD quarterly national accounts for GDP components (private consumption, government consumption, capital formation, exports, imports) are largely missing or incomplete for many countries before the mid-1990s. Because the SDID estimator requires a complete, balanced panel across the full 10-quarter window, including earlier tournaments would either force the exclusion of most control countries—shrinking the donor pool to a point where synthetic control weights become unreliable—or limit the analysis to GDP alone. By starting at 1998, the design retains a large, data-rich donor pool of roughly 45 OECD countries per event, ensuring that the synthetic control is well-identified for all six outcome variables. Winners of earlier tournaments (e.g. Brazil 1994, Germany 1990) still enter the panel as *control* subseries for the 1998–2018 events, so their data contribute to the estimation through the donor pool.
Host country subseries are excluded from the donor pool to avoid contamination, except for France 1998 which both hosted and won. The SDID estimator then solves:

$$\hat{\tau}^{SDID} = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \sum_{n=1}^{N} \sum_{q=-7}^{2} \left(\Delta_4 \ln GDP_{n,q} - \mu - \alpha_n - \beta_q - W_{n,q}\tau\right)^2 \hat{\omega}_n \hat{\lambda}_q \tag{12}$$

where $W_{n,q} = 1$ for treated subseries in post-treatment quarters ($q \geq 1$), and the unit weights $\hat{\omega}_n$ and time weights $\hat{\lambda}_q$ are constructed as described in Section 3.
Inference relies on the *placebo bootstrap* procedure recommended by Arkhangelsky et al. (2021). In each of 1,000 replications, entire country-subseries are resampled with replacement from the stacked panel—preserving the within-unit serial correlation structure—and the full SDID estimation pipeline is re-run on the resampled data (weight construction, regression, ATT extraction). The bootstrap distribution of ATT estimates yields a standard error and, via the percentile method, a p-value. Clustering at the country-subseries level accounts for the fact that the same country contributes multiple subseries across different World Cups and ensures that inference reflects the effective sample size of independent country trajectories rather than the larger number of individual quarterly observations.

4.1.4 GDP Components

Both the event study and SDID are also estimated separately for GDP components: private consumption, government consumption, gross fixed capital formation, exports, and imports. These decompositions help identify the channels through which World Cup victories affect aggregate output. Mello (2024) finds that the effect is primarily export-driven, which I seek to replicate.

4.2 Extensions: Tournament Performance Effects

Beyond replicating Mello's analysis of World Cup winners, this thesis extends the investigation to other tournament outcomes. If winning generates economic effects through national pride, international visibility, or consumer confidence, then reaching the final or semifinals might produce similar—albeit smaller—effects. Conversely, unexpectedly poor performance might generate negative sentiment effects.

4.2.1 Finalist Effect

Countries that reach the World Cup final but lose receive extensive media coverage and experience heightened national attention, similar to winners. To test whether this "runner-up effect" generates measurable economic consequences, I estimate:

$$\Delta_4 \ln GDP_{c,t} = \alpha_c + \lambda_t + \sum_{k\neq 0} \beta_k^F \cdot \mathbf{1}[K_{ct} = k] \cdot F_c + \theta \cdot HOST_{c,t} + \zeta \cdot \ln GDP_{c,t-4} + \varepsilon_{c,t} \quad (13)$$

where F_c indicates countries that reached the final but did not win (e.g., Netherlands 1974, 1978, 2010; Germany 1982, 1986, 2002; Argentina 2014; Croatia 2018). This specification mirrors Mello's approach but with finalists as the treated group.

4.2.2 Semifinalist Effect

Reaching the semifinals represents exceptional tournament performance that may generate national pride effects. The specification follows the same structure:

$$\Delta_4 \ln GDP_{c,t} = \alpha_c + \lambda_t + \sum_{k\neq 0} \beta_k^S \cdot \mathbf{1}[K_{ct} = k] \cdot S_c + \theta \cdot HOST_{c,t} + \zeta \cdot \ln GDP_{c,t-4} + \varepsilon_{c,t} \quad (14)$$

where S_c indicates countries reaching the semifinals (finishing in the top 4). This extends the treatment group considerably, providing more statistical power but potentially diluting the effect if only winning matters.

4.2.3 Underperformer Effect

If winning generates economic effects through enhanced international visibility and confidence, then the inverse channel—a highly ranked team being eliminated in the group stage—may produce a negative sentiment shock. I define underperformance using pre-tournament ELO ratings from `eloratings.net`: a country is an underperformer if it entered the World Cup ranked in the top 10 by ELO and was eliminated in the group

stage. This criterion captures sharp negative surprises—defending champions or top-ranked teams exiting far earlier than expected. Candidate events include France in 2002 (ranked 1st, defending champion), Spain in 2014 (ranked 2nd, defending champion), and Germany in 2018 (ranked 2nd, defending champion).
The specification mirrors the winner event study:

$$\Delta_4 \ln GDP_{c,t} = \alpha_c + \lambda_t + \sum_{k \neq 0} \beta_k^E \cdot \mathbf{1}[K_{ct} = k] \cdot E_c + \theta \cdot HOST_{c,t} + \zeta \cdot \ln GDP_{c,t-4} + \varepsilon_{c,t} \quad (15)$$

where E_c indicates countries that have ever experienced an underperformance event. For the SDiD specification, the same stacked 10-quarter design is applied with the underperformer indicator replacing the winner indicator. Both event study and SDiD are estimated for all six features (GDP, private consumption, government consumption, capital formation, exports, and imports) to identify whether the underperformer effect operates through the same trade channel documented for winners.
This extension tests whether the psychological mechanisms operate symmetrically for positive and negative tournament outcomes.

4.3 Implementation

All analyses are implemented in R. The event study regressions use the `fixest` package (Bergé, 2024), which provides efficient estimation of high-dimensional fixed effects models with clustered standard errors. The SDID estimation uses the `synthdid` package (Hirshberg et al., 2024), which implements the Arkhangelsky et al. (2021) estimator with bootstrap inference.
Code and data for full replication are available in the accompanying repository.

5 Data

One of the fundamental prerequisites—and one of the primary challenges—of this thesis was to replicate the dataset used by Mello (2024). The paper identifies the OECD Quarterly National Accounts (QNA) database as its data source and states that the sample spans 1961–2021 across 48 countries, but the exact construction steps are not fully documented. Crucially, although the published paper references a replication package hosted at ICPSR, the provided link resolves to an entirely unrelated dataset on droughts in Brazil rather than to Mello's World Cup analysis (see Section 4). No code, intermediate data, or supplementary documentation could be obtained from either the journal or the author's institutional page either. Rebuilding the dataset from scratch was therefore necessary, and a substantial portion of the early work in this thesis was devoted to matching the published observation counts and summary statistics as closely as possible.

5.1 Macroeconomic Data from the OECD

I sourced the macroeconomic data from the OECD QNA database, accessed programmatically via the `OECD` R package (Persson, 2023). The raw data required reshaping and transformation into a wide panel structure suitable for analysis for which the OECD codes were relevant. All series are chain-linked volumes, seasonally adjusted, and converted to US dollars using purchasing power parities (PPP).[3]

For most OECD member states, data availability begins in 1960-Q1. A smaller group of countries enter the database later, ranging from the early 1990s to as late as 2011 for Saudi Arabia. The full country-by-country coverage with start and end dates is documented in Table A.8 in the Appendix. This was only provided for hosts and winners in Mello's work. Altogether, I retrieve data for the same 48 countries that Mello (2024) reports using.

The six macroeconomic variables retrieved are: GDP, private consumption expenditure, government consumption expenditure (both consumption types from the aggregate P3), gross fixed capital formation (investment), exports of goods and services, and imports of goods and services. The same as in Mello (2024).

5.2 Year-over-Year Growth Rates and its Coverage Time Span

The dependent variable in Mello's analysis—and in this replication—is not the level of GDP but its year-over-year (YoY) growth rate. Specifically, Mello uses the four-quarter log difference:

$$Y_{it} = \ln X_{it} - \ln X_{i,t-4} \tag{16}$$

where X_{it} is the level of the economic variable for country i in quarter t. By comparing each quarter to the same quarter one year earlier, this transformation removes seasonal patterns while providing a directly interpretable measure of annual growth at quarterly frequency across countries.

[3]OECD QNA subject codes used: B1_GS1 (GDP), P31S14_S15 (private consumption), P3S13 (government consumption), P51 (gross fixed capital formation), P6 (exports of goods and services), P7 (imports of goods and services) to match the description of Mello (2024) as close as possible.

Mello (2024) states that his sample spans 1961–2021. However, computing YoY growth (16) requires four quarters of lagged data, so the first valid growth observation falls in 1962-Q1. The estimation sample therefore runs from 1962-Q1 to 2021-Q4. A further complication arises for countries that enter the OECD database later. Following Mello's footnote that quarterly GDP data for Argentina and Brazil "are available only since 1993 and 1996, respectively," I truncated the series accordingly.[4] For Brazil, this means starting at 1998-Q2—exactly four years before the 2002 World Cup—so that the event study has sufficient pre-event data. Whether Mello's stated start date of 1998-Q2 implied YoY calculation of earlier data or only having YoY for four quarters later could not be resolved directly, but matching the summary statistics table confirmed that the 1998-Q2 truncation best replicates the published observation counts (Section 5.4).

5.3 Population and World Cup Data

Annual population figures were retrieved from a separate OECD population statistics table to replicate the summary statistics in Mello (2024, Table 1). Following Mello, population is not used as a denominator for the dependent variable and serves only as a descriptive variable. As shown in Table 3, population turned out to be the closest match to the published figures and the most reliable cross-check for confirming that the sample composition is correct.

World Cup results—winners, runners-up, semi-finalists, and host countries—were compiled for all editions from 1930 to 2022. This is arguably the most straightforward part of the data collection: tournament outcomes are publicly available from FIFA and, more conveniently, from Wikipedia.[5] Each World Cup is assigned an event quarter: Q2 of the World Cup year for all editions from 1966 to 2018, since these tournaments were held in June and July. The 2022 Qatar World Cup, held in November and December, is assigned to Q4. Mello (2024) notes that "the World Cup has always taken place every four years between June and July, namely in between the end of the second quarter and the beginning of the third quarter of a given year," and the only exception—Qatar 2022—falls outside his estimation window.

Six countries contribute as World Cup winners in the estimation sample: Brazil, Germany, Spain, France, the United Kingdom, and Italy, covering 10 distinct victory events between 1966 and 2018 (Table 1). Mello (2024) also notes that "GDP data are available only at the aggregate level of the UK" for England's 1966 victory—a quirk I replicate by using the United Kingdom's GDP series for the England entry.[6]

As discussed in Section 5.2, data availability excludes several victory events. Argentina's 1978 and 1986 victories predate its OECD coverage, and the 2022 victory falls outside the estimation window; it is therefore classified as a control country in the main analysis and examined separately in Section **??**. Brazil contributes only through its 2002 success, with earlier victories excluded by analogous data constraints.

[4] Russia enters at 1995-Q1 and Chile at 1996-Q1, both consistent across downloads.

[5] The full list of World Cup results, including all top-four finishers and host countries, is provided in Table A.6 in the Appendix.

[6] This means the treatment indicator for 1966 is assigned to the UK aggregate, which includes Scotland, Wales, and Northern Ireland. Mello adopts the same convention.

Table 1: World Cup events in the estimation sample

Year	Winner	Host	Event Q	Winner in sample	Host in sample
1966	England	England	Q2	✓	✓
1970	Brazil	Mexico	Q2	–	✓
1974	West Germany	West Germany	Q2	✓	✓
1978	Argentina	Argentina	Q2	–	–
1982	Italy	Spain	Q2	✓	✓
1986	Argentina	Mexico	Q2	–	✓
1990	West Germany	Italy	Q2	✓	✓
1994	Brazil	USA	Q2	–	✓
1998	France	France	Q2	✓	✓
2002	Brazil	Japan / Korea	Q2	✓	✓
2006	Italy	Germany	Q2	✓	✓
2010	Spain	South Africa	Q2	✓	✓
2014	Germany	Brazil	Q2	✓	✓
2018	France	Russia	Q2	✓	✓
2022	Argentina	Qatar	Q4	*Potential case study*	

Notes: Event quarter is Q2 for all editions except Qatar 2022 (Q4). "–" indicates insufficient OECD data to include the event. The sample contains 10 winner events and 14 host events. Japan and Korea co-hosted in 2002. Full results including runners-up and semi-finalists are in Table A.6.

5.4 Comparing the Replicated Dataset to Mello (2024)

A central goal of the data construction was to match the published dataset as closely as possible. Since the replication package is unavailable, the summary statistics reported in Mello (2024, Table 1) and the appendix tables therein serve as the primary benchmark. Table 2 compares the observation counts.

Table 2: Observation counts: replication vs. Mello (2024)

	Winners	Non-winners	Total
Mello (2024)	1,295	7,342	8,637
This study	1,295	7,338	8,633

Notes: "Winners" denotes all observations from countries that won a World Cup during the sample period (BRA, DEU, ESP, FRA, GBR, ITA).

The winner count matches exactly at 1,295. The non-winner count differs by only four observations (7,338 versus 7,342), which I guess is Russia's OECD series ending earlier than the rest in my download. Assuming that 1,295 winner quarters are the exact same as Mello's, the four differing observations are only controls and can be neglected. Mello (2024) reports a total of "8,637 observations, with an average of about 180 quarterly GDP records per country"; my total of 8,633 is consistent with this.

Table 3 presents the core validation step: a side-by-side comparison of the summary statistics from Mello (2024, Table 1) (reproduced in the left panel) and the corresponding statistics from this replication (right panel). The table follows the same format as the original, reporting GDP, population, GDP per capita, and year-over-year GDP growth by sub-period and winner status.

Table 3: Summary statistics comparison: Mello (2024) vs. this replication

	Mello (2024)					**This study**				
	Winner		Non-winner		t	Winner		Non-winner		t
					1960–80 / 1962–1980					
GDP (thous.)	1,099	(417)	498	(1,163)	9.91	1,317	(510)	548	(1,254)	19.08
Pop. (m)	54.43	(13.91)	26.15	(46.02)	11.85	54.43	(13.91)	26.20	(46.04)	21.17
GDP p.c.	19,698	(4,050)	19,708	(9,016)	−0.02	23,569	(5,029)	22,546	(10,416)	2.82
YoY growth	3.96	(2.83)	4.54	(3.42)	−3.08	3.96	(2.82)	4.55	(3.42)	−3.47
					1980–2000					
GDP (thous.)	1,803	(593)	852	(1,959)	9.99	2,176	(736)	942	(2,114)	21.73
Pop. (m)	60.93	(22.04)	40.59	(99.01)	4.24	60.93	(22.04)	40.82	(99.18)	8.60
GDP p.c.	29,873	(5,652)	27,324	(14,023)	3.72	36,026	(7,328)	31,365	(16,058)	9.55
YoY growth	2.25	(1.82)	3.14	(3.54)	−5.11	2.31	(1.81)	3.13	(3.53)	−7.13
					2000–20 / 2000–2021					
GDP (thous.)	2,563	(660)	1,211	(2,750)	10.99	3,105	(829)	1,369	(3,036)	28.07
Pop. (m)	84.61	(50.41)	65.80	(194.02)	2.17	84.83	(50.71)	66.46	(197.15)	4.66
GDP p.c.	35,575	(10,443)	33,634	(19,068)	2.24	43,203	(13,284)	39,165	(21,809)	5.93
YoY growth	1.05	(3.48)	2.55	(3.91)	−8.17	1.32	(3.82)	2.76	(4.11)	−8.01
					Full sample					
GDP (thous.)	1,909	(844)	959	(2,303)	14.68	2,300	(1,033)	1,065	(2,505)	30.14
Pop. (m)	68.51	(37.53)	49.65	(148.58)	4.54	68.50	(37.53)	49.96	(149.91)	9.10
GDP p.c.	29,259	(10,061)	28,888	(16,922)	0.76	35,319	(12,616)	33,258	(19,353)	4.94
YoY growth	2.33	(3.24)	3.22	(3.87)	−7.81	2.38	(3.22)	3.24	(3.89)	−8.61
Countries	6		42			6		42		
Observations	1,295		7,342			1,295		7,338		

Left panel reproduces Mello (2024, Table 1). Right panel shows the corresponding statistics from this replication. GDP in thousands of 2015 US dollar millions (PPP); population in millions. Year-on-Year growth is $\Delta_4 \ln$ (Equation 16). Sub-period boundaries differ slightly: Mello uses 1960–80, 1980–2000, 2000–20; this study uses 1962–1980, 1980–2000, 2000–2021 (reflecting the actual data range after computing growth rates).

Several patterns emerge from this comparison, and they tell a reassuring story about the quality of the replication.

First, and most importantly, the *year-over-year GDP growth rates* match very closely. For the full sample, winners average 2.38 (SD = 3.22) versus Mello's 2.33 (3.24), and non-winners average 3.24 (3.89) versus 3.22 (3.87). This near-exact alignment holds across all three sub-periods as well. Because year-over-year growth is the dependent variable in both the event study and the SDID analysis, these small differences translate into negligible differences in estimated treatment effects as we will see in the results chapter.

Second, *population figures* match almost exactly. Full-sample winner-country population averages 68.50 million versus 68.51 million in Mello, and the standard deviations are identical at 37.53. Non-winner population means are similarly close (49.96 versus 49.65). This confirms that the sample composition—which countries are included and over which time periods—is the same.

Third, and in contrast, *GDP level statistics* diverge systematically. My full-sample winner GDP averages 2,300 thousand (in 2015 USD millions) versus Mello's 1,909 thousand—roughly 20% higher. This gap is consistent across all sub-periods and grows over time. I assume that the cause is a base year or rebasing difference rather than a difference in sample composition. The OECD periodically updates the reference year for its chain-linked volume series, which shifts all level values while leaving growth rates largely unchanged. Mello's data extraction likely dates to 2021 or early 2022, whereas my download was performed in 2025. I attempted to determine the exact base year used in each vintage from the OECD API documentation and the OECD website, but this information is not readily available—the metadata at the time of my download indicates a 2015 reference year without specifying when it was adopted. However, because the regression analysis uses year-over-year log differences rather than GDP levels, this base-year discrepancy does not materially affect the results.

5.5 Descriptive Statistics

The broader patterns in Table 3 are consistent with what Mello (2024) documents: winner countries are systematically larger and more populous, reflecting that World Cup success is concentrated among large, wealthy nations—Mello (2024) observes that "only eight countries and exclusively from Western Europe or South America" have ever won the tournament. At the same time, winners exhibit *lower* average growth rates: full-sample $\Delta_4 \ln$ GDP growth is 2.38 for winners versus 3.24 for non-winners ($t = -8.61$). This underscores the importance of the causal identification strategy, since naïve comparisons suggest a *negative* association between winning and growth.
Figure 3 plots the average $\Delta_4 \ln$ GDP growth trajectory around World Cup events, separately for winner and host countries. Winners show a small increase in growth just before the victory which on average stagnates after the event. But this descriptive view yields little room for inference.

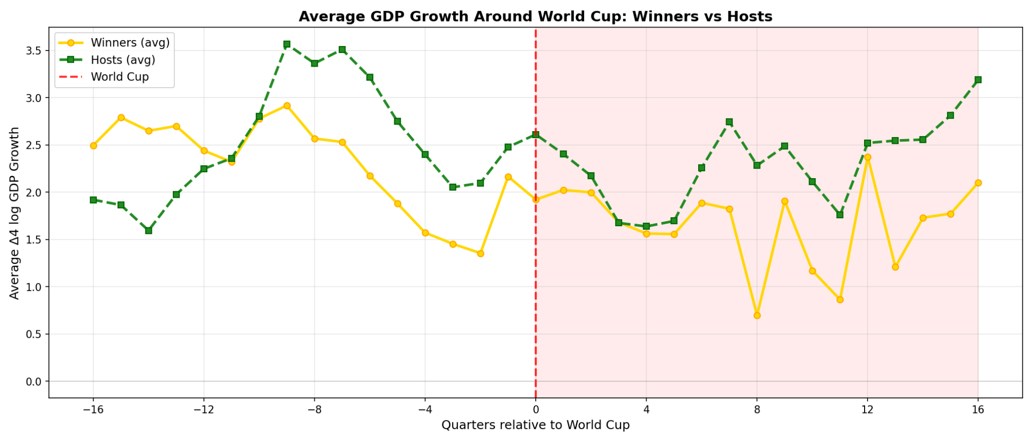


Figure 3: Average $\Delta_4 \ln$ GDP growth around World Cup events: winners vs. hosts (±16 quarters). The dashed red line marks the event quarter (Q2 of the World Cup year).

Figure 4 extends this comparison across all six macroeconomic variables for winner countries. GDP, private consumption, and government consumption follow similar, relatively smooth trajectories. Investment, exports, and imports are substantially more volatile, which limits the statistical power for detecting treatment effects in these series but the biggest post-event growth spike can already be observed for the export feature.

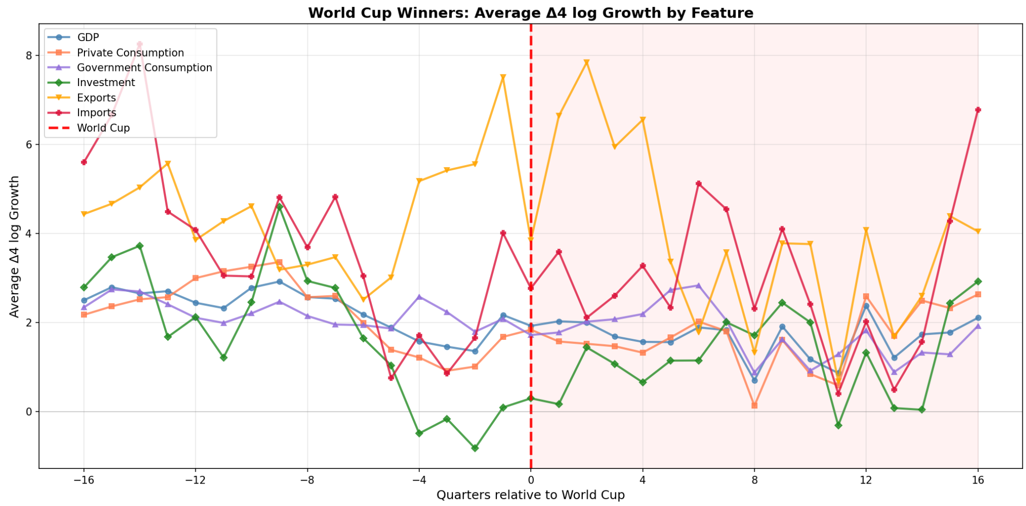


Figure 4: Average Δ_4 ln growth by macroeconomic variable for World Cup winners (±16 quarters).

5.6 Pre-Tournament Rankings and Underperformance

Beyond the core macroeconomic dataset, I construct an auxiliary dataset on pre-tournament team strength. The motivation is to identify World Cup "underperformance"—cases where a top-ranked team is eliminated in the group stage. Pre-tournament rankings are compiled from two independent sources:

- **ELO ratings** from `eloratings.net` (World Football Elo Ratings, 2024), available for all countries and all years where I pick the World Cups from 1962 to 2022. ELO ratings are based on all historical match results and update continuously.
- **FIFA World Rankings** from the FIFA internal API,[7] which reflect a points-based system incorporating match results, opponent strength, and confederation weights.

The two ranking systems are strongly correlated among World Cup participants (Table A.7 in the Appendix). Spearman rank correlations range from 0.63 (1998) to 0.90 (2018). I define "underperformance" as a top-10 ranked team (among WC participants) being eliminated in the group stage of a World Cup that year. Only 5 out of 128 team-tournament observations (1994–2022) received a different label depending on which ranking system was used. Since this is a fairly consistent number, I trust the ELO rankings as a feasible baseline comparison to rate underperformance.[8]

[7]Endpoint: `inside.fifa.com/api/ranking-overview`. this series only begins in December 1992, covering 8 World Cups (1994–2022).

[8]The five cases are: Colombia (1994), Russia (1994), Spain (1998), Croatia (2002), and Uruguay (2022).

A prominent example of underperformance is Germany at the 2018 World Cup. As reigning champions with the highest ELO rating among participants, Germany was eliminated in the group stage after losses to Mexico and South Korea—the first group-stage exit for a defending champion since France in 2002. Such cases provide a natural "placebo" comparison in the extension analysis: if winning a World Cup genuinely affects macroeconomic outcomes, then being a pre-tournament favourite but failing to win could maybe prodice a negative effect.

5.7 Data Quality and Limitations

Several limitations of the data should be acknowledged. Most fundamentally, macroeconomic variables are subject to numerous confounders: GDP growth, consumption, investment, and trade flows are simultaneously influenced by monetary and fiscal policy, global business cycles, commodity price movements, financial crises, and structural reforms, among many other factors. Isolating the effect of a single sporting event against this backdrop is inherently difficult, particularly with only ten treatment events in the sample. Moreover, treatment effect heterogeneity is a concern: each winning country differs in its economic structure and its specific global environment at the time of its victory, meaning that the response to a World Cup win may vary substantially across countries and periods. The econometric methods described in Section 4 are designed to address these challenges, but the data constraints place natural limits on the precision of any estimated effects.

6 Replication Results

6.1 Event Study Replication

I estimate the event study regression for GDP specified in Equation (11). The dependent variable is year-over-year log GDP growth $\Delta_4 \ln \mathrm{GDP}_{c,t}$ in percentage points. The 32 relative-time indicators $\mathrm{WIN}^l_{c,t}$ for $l \in \{-16, \ldots, -1, +1, \ldots, +16\}$ capture the dynamic effect of winning the World Cup, with endpoints binned and the event quarter $l = 0$ omitted as reference. A hosting dummy, the fourth lag of logged GDP as a convergence control, and country and quarter fixed effects complete the specification. Standard errors are clustered at the country level.
As described in Section 5.2, the year-over-year growth rates are computed on the full 1960+ panel before trimming to the estimation window. Additionally, the convergence control $\ln y_{c,t-4}$ is pre-computed from the untrimmed panel and joined to the estimation sample. The final estimation sample contains 8,633 country-quarter observations, four fewer than Mello's 8,637. The difference in observation counts is due to minor discrepancies in the underlying data extracts.

6.1.1 GDP Results

Table 4 presents selected coefficients from the replication alongside the original results in Mello (2024, Table 2). The full set of 32 coefficients, including exact p-values and differences, is provided in the appendix (Table A.1).
The pre-treatment coefficients ($l < 0$) are uniformly small and statistically insignificant, consistent with the parallel trends assumption. In the post-treatment period, GDP growth rises by 0.33 percentage points at $l = +1$ and 0.60 pp at $l = +2$. Both point estimates are positive but fall short of conventional significance thresholds ($p = 0.23$ and $p = 0.13$, respectively; see appendix Table A.1 for exact p-values). The effect dissipates by the third quarter and subsequent coefficients fluctuate around zero. The convergence control (-1.364, $p = 0.031$) is consistent with conditional β-convergence; the hosting dummy (-0.542, $p = 0.269$) is negative but insignificant.

6.1.2 Comparison with Mello (2024)

The replication tracks the original results closely. The convergence control matches to three significant digits (-1.364 vs. -1.368), and all pre-treatment coefficients lie within one standard error. The key post-treatment coefficients at $l = +1$ and $l = +2$ show the same positive pattern, though the replication estimates are slightly attenuated (0.33 and 0.60 vs. 0.45 and 0.68). This attenuation—0.13 pp and 0.09 pp respectively—moves both coefficients below the 10% significance threshold that Mello (2024) reports as marginally significant. The differences are modest and likely reflect minor discrepancies in the underlying data and estimation procedures.
Figure 5 overlays the full coefficient paths. The replication (blue) tracks the original (red) closely across all 32 relative-time periods, with the largest visible discrepancy occurring in the long-run post-treatment lags ($l \geq +5$) where both sets of estimates are statistically indistinguishable from zero.

Table 4: Event study for GDP: replication versus Mello (2024)

	Replication		**Mello (2024)**	
	Coeff.	(SE)	Coeff.	(SE)
Controls				
$\ln \text{GDP}_{t-4}$	−1.364**	(0.613)	−1.368**	(0.588)
Host	−0.542	(0.484)	−0.591	(0.545)
Pre-treatment				
$l = -16$ (binned)	0.771	(0.671)	0.640	(0.673)
$l = -8$	0.219	(0.665)	0.098	(0.695)
$l = -4$	0.073	(0.515)	−0.107	(0.535)
$l = -1$	0.071	(0.227)	0.125	(0.206)
Post-treatment				
$l = +1$	0.325	(0.269)	0.454*	(0.246)
$l = +2$	0.597	(0.387)	0.683*	(0.370)
$l = +3$	0.305	(0.319)	0.233	(0.335)
$l = +4$	0.287	(0.319)	0.140	(0.317)
$l = +8$	0.066	(0.775)	−0.314	(0.985)
$l = +16$ (binned)	0.073	(0.463)	−0.109	(0.477)
Observations	8,633		8,637	
Adj. R^2	0.444		—	
Within R^2 (Mello)	—		0.423	

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered SEs at the country level.

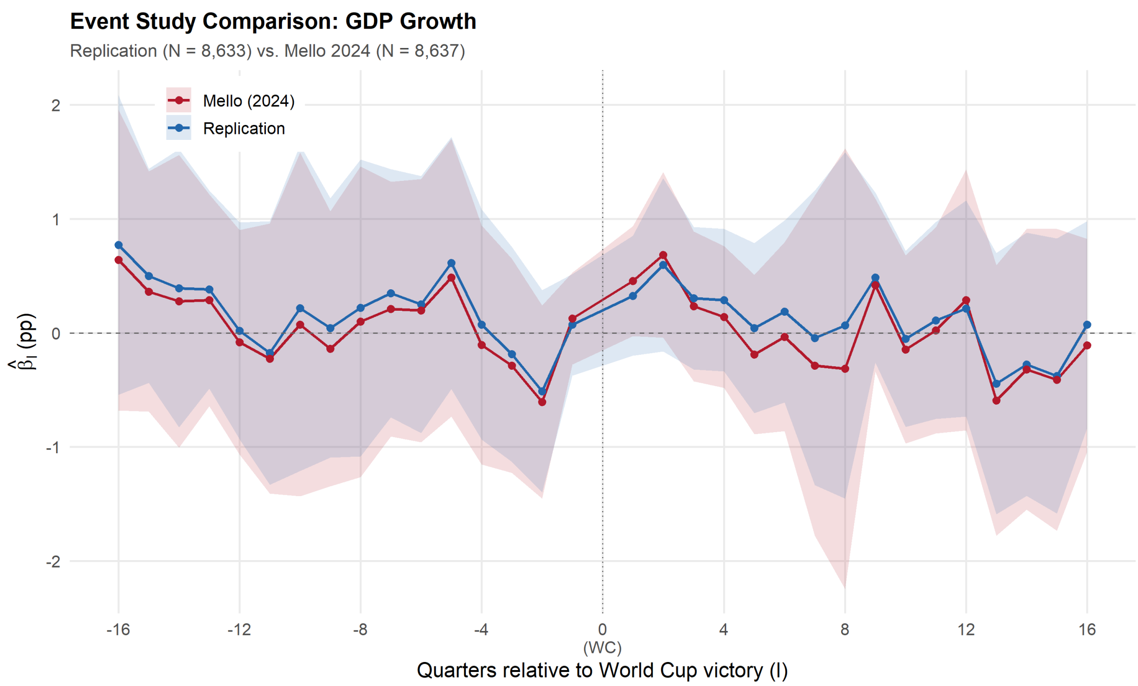


Figure 5: GDP event study: replication vs. Mello (2024)

Notes: Solid lines show point estimates; shaded areas show 95% confidence intervals based on country-clustered standard errors. Blue = replication ($N = 8{,}633$), red = Mello ($N = 8{,}637$).

The core qualitative finding is robust: winning the World Cup is associated with a transient rise in GDP growth of roughly 0.3–0.7 percentage points in the two quarters following the event, which dissipates by the third post-treatment quarter.

6.2 GDP Component Event Studies

To examine the channels through which a World Cup victory might affect aggregate GDP, I estimate Equation (11) separately for each of the five expenditure components: private consumption, government consumption, gross fixed capital formation, exports, and imports. In each regression, both the dependent variable $\Delta_4 \ln y_{c,t}$ and the convergence control $\ln y_{c,t-4}$ use the respective component. All other specification details remain identical to the GDP model. The component regressions have 8,589 observations, 44 fewer than GDP. The difference in observation counts is due to minor discrepancies in the underlying data extracts.

Figure 6 compares the coefficient paths of all six features between the replication and the original estimates in Mello (2024, Tables 2 and A3). A detailed comparison table with selected post-treatment coefficients for all six features is provided in Table A.2 in the appendix.

Across all six components, the replication coefficients track Mello's closely. The convergence controls, which are the most precisely estimated parameters, match within a few hundredths for every component (e.g. capital formation: -7.816 vs. -7.795; imports: -6.146 vs. -6.056). The observation count difference between the component regressions (8,589) and Mello's (8,549) reflects minor discrepancies in the underlying data extracts.

The component-level results identify **exports** as the primary channel: at $l = +2$, export growth increases by 5.81 pp ($p = 0.032$) in the replication—the only statistically significant post-treatment coefficient at the 5% level across all features. Mello (2024) reports a comparable 5.12 pp for the same coefficient, significant at the 10% level. The $l = +3$ export coefficient is also marginally significant in the replication estimates (4.27 pp, $p = 0.081$). These magnitudes are roughly an order of magnitude larger than the aggregate GDP effect, consistent with the effect being concentrated in a single component.

The hosting dummy is positive and significant for exports in the replication (1.89, $p = 0.033$), indicating that hosting a World Cup independently boosts export growth, likely through tourism-related demand and heightened international visibility. Mello reports a similar direction (1.25) but without significance.

Private consumption and **government consumption** show no meaningful response in either the replication or Mello's. Both $l = +1$ and $l = +2$ coefficients are small and insignificant, ruling out a household-spending channel despite the documented spikes in consumer confidence following sporting victories. **Capital formation** is imprecisely estimated due to high investment volatility, while **imports** show a suggestive delayed effect at $l = +4$ (4.18 pp in the replication, $p = 0.057$; 4.33 pp in Mello, $p < 0.05$), consistent with increased demand accompanying the export surge.

In summary, the component analysis confirms Mello's finding that the World Cup GDP effect operates primarily through the trade channel. Where the observation counts are closely matched, the coefficient differences between the replication and the original are small—typically well within one standard error—and both analyses point to the same

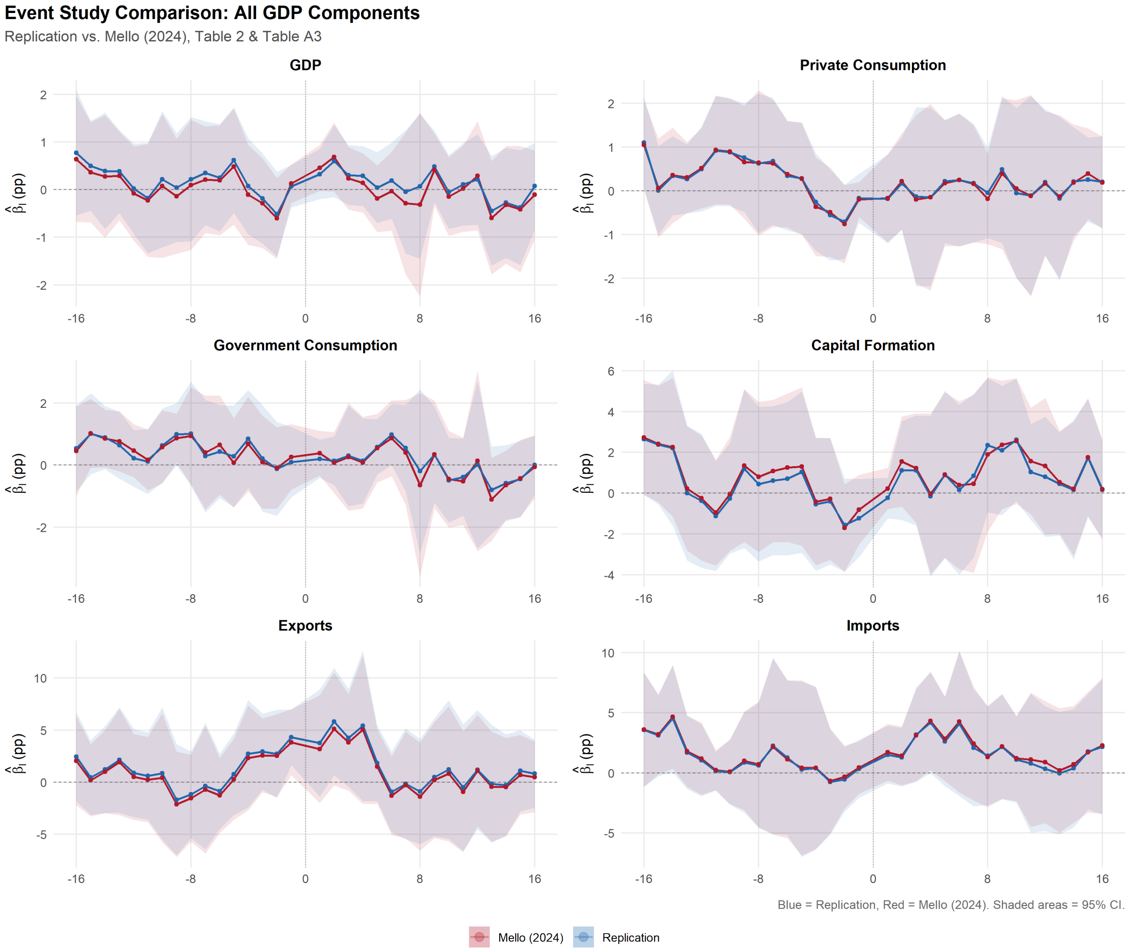


Figure 6: Event study comparison across GDP components: replication vs. Mello (2024)

Notes: Each panel shows the full coefficient path for one GDP component. Blue = replication, red = Mello. Shaded areas are 95% confidence intervals. Component regressions use 8,589 observations (replication) vs. 8,549 (Mello); GDP uses 8,633 vs. 8,637.

qualitative conclusions.

6.3 Synthetic Difference-in-Differences Replication

Following Mello (2024), I complement the event-study analysis with the synthetic difference-in-differences (SDiD) estimator of Arkhangelsky et al. (2021). Whereas the event study traces out the full dynamic path, the SDiD approach focuses on a narrow 10-quarter window around each World Cup and asks a single, sharply identified question: *Is the average YoY growth rate higher in the two post-tournament quarters for the winning country than for a data-driven synthetic control?*

6.3.1 Implementation

I implement the SDiD estimator using the `synthdid` R package. For each of the six World Cups held between 1998 and 2018, I split every country's quarterly GDP series into a 10-

quarter subseries running from $q = -7$ (seven quarters before the World Cup) to $q = +2$ (two quarters after). The subseries of the winning country constitutes the treated unit; all other subseries form the donor pool. In total this yields 274 subseries—6 treated and 268 control—comprising 2,740 quarterly growth records for GDP.

Three design choices mirror those of Mello:

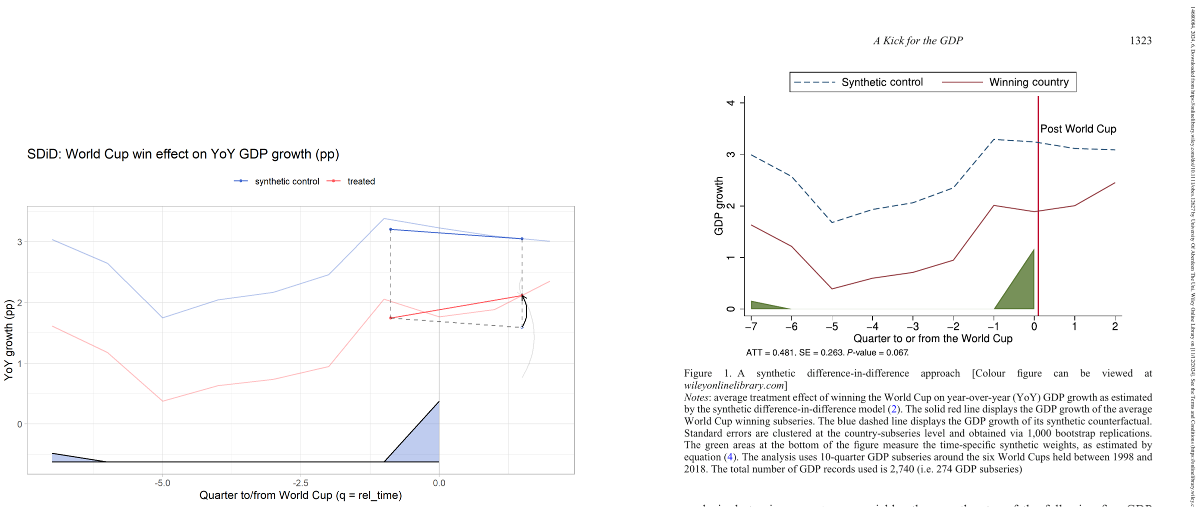
1. **Host exclusion.** Subseries that belong to the host country of a given World Cup are dropped from the control pool, because hosting may independently affect GDP growth. The sole exception is France around the 1998 tournament, which both hosted and won, and is therefore retained as a treated unit.
2. **Stacking.** Countries that won more than once (France: 1998, 2018) contribute one treated subseries per victory. Their remaining subseries enter the control pool, enabling within-country comparisons.
3. **Balanced panel.** Any subseries with missing outcome values in the 10-quarter window is dropped to satisfy the completeness requirement of the `synthdid_estimate` routine.

The SDiD estimator solves for unit weights $\hat{\omega}_n$ and time weights $\hat{\tau}_q$ that, respectively, align the pre-treatment trends between treated and synthetic control units and re-weight pre-treatment periods to best predict post-treatment outcomes. Inference is based on bootstrap standard errors with 1,000 replications clustered at the country-subseries level.

6.3.2 SDiD GDP Results

Figure 7 displays the SDiD plot for GDP growth from the replication (left) alongside the original in Mello (2024, Figure 1) (right). Each panel shows two lines: the solid line traces the average YoY GDP growth of the treated (winning) subseries, and the dashed line traces the growth of the synthetic control constructed from the weighted donor pool. The shaded bars at the bottom of each panel indicate the time weights $\hat{\tau}_q$, which show how the estimator distributes importance across the eight pre-treatment quarters when constructing the counterfactual.

In the pre-treatment period ($q \leq 0$), the two lines run approximately parallel, differing by a roughly constant level that is absorbed by unit fixed effects. This parallel movement validates the key identifying assumption: absent treatment, the treated and synthetic control units would have continued on parallel paths. After the World Cup ($q = +1, +2$), the treated line rises above the counterfactual, indicating a positive treatment effect. The vertical gap between the lines in the post-period is the estimated ATT.



(a) Replication: ATT = 0.527 pp, SE = 0.274, $p =$ 0.054

(b) Mello (2024): ATT = 0.481 pp, SE = 0.263, $p = 0.067$

Figure 7: SDiD: effect of winning the World Cup on YoY GDP growth

Notes: Solid line = average treated (winning) subseries; dashed line = synthetic control. Shaded bars = time weights $\hat{\tau}_q$. Both analyses use 10-quarter subseries around the six World Cups 1998–2018. Bootstrap SEs from 1,000 replications.

The replication yields an ATT of 0.527 pp (SE = 0.274, $p = 0.054$), compared with Mello's 0.481 pp (SE = 0.263, $p = 0.067$). Both estimates are positive and marginally significant at the 10% level, confirming the core finding: winning the World Cup temporarily boosts GDP growth by roughly half a percentage point. The 0.05 pp difference between the two ATTs is well within one standard error and likely reflects minor differences in the underlying OECD data vintage.

6.3.3 SDiD Comparison Across GDP Components

Table 5 summarises the SDiD results for all six GDP components. GDP is the only component for which the ATT is marginally significant ($p < 0.10$) in both the replication and Mello's analysis. Exports show the largest point estimate (4.77 pp in the replication versus 4.51 pp in the original), consistent with the event-study finding that the trade channel is the primary mechanism. However, the export ATT is imprecisely estimated in both analyses ($p \approx 0.23$–0.25) owing to the high volatility of export growth, which increases bootstrap standard errors.

Table 5: SDiD average treatment effects: replication versus Mello (2024)

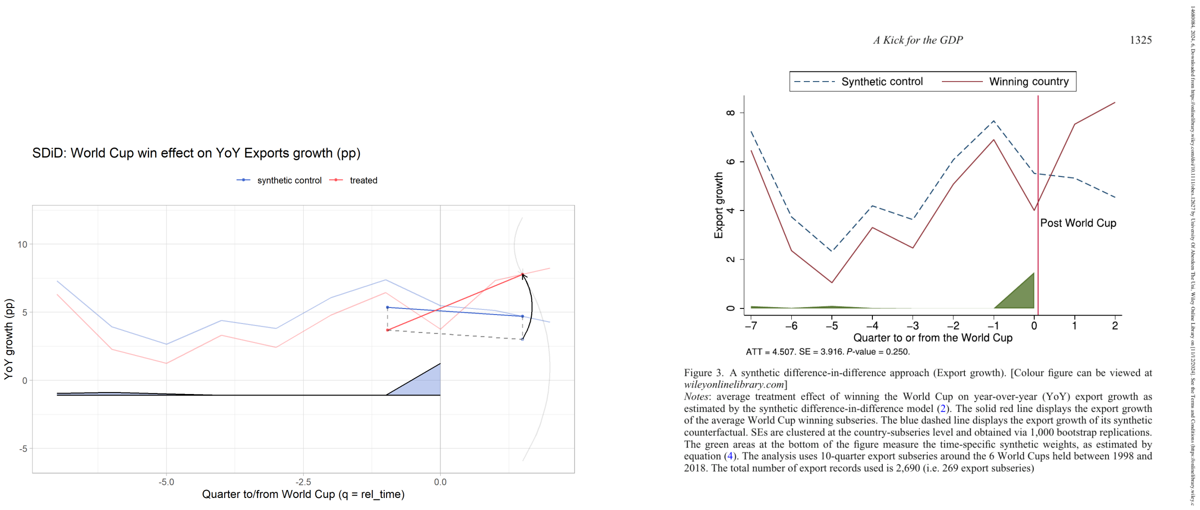
	Replication		**Mello (2024)**	
Component	ATT (pp)	(SE)	ATT (pp)	(SE)
GDP	0.527*	(0.274)	0.481*	(0.263)
Private consumption	−0.212	(0.338)	−0.009	(0.355)
Government consumption	−0.331	(0.591)	−0.314	(0.463)
Gross fixed capital form.	1.251	(1.120)	1.214	(1.238)
Exports	4.769	(3.989)	4.507	(3.916)
Imports	−0.247	(1.169)	−0.112	(1.095)

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Bootstrap SEs (1,000 replications).
Notes: ATT denotes the average treatment effect in the two post-World Cup quarters, estimated via synthetic difference-in-differences (SDiD). Replication results use log YoY growth columns from the OECD QNA panel with host-only controls excluded from the donor pool. Mello's ATTs are taken from Figures 1 and 3 (GDP and exports) and Figures A2–A5 (remaining components).

Private consumption, government consumption, capital formation, and imports all yield ATTs that are small, mixed in sign, and far from significant ($p > 0.30$ in every case). These null results mirror the event-study evidence and confirm that the aggregate GDP effect does not operate through domestic demand or investment channels.

6.3.4 SDiD Export Results

Given the prominence of the export channel in both the event-study and SDiD analyses, Figure 8 shows the SDiD plot for exports alongside the original in Mello (2024, Figure 3).



(a) Replication: ATT = 4.769 pp, SE = 3.989, p = 0.232

(b) Mello (2024): ATT = 4.507 pp, SE = 3.916, p = 0.250

Figure 8: SDiD: effect of winning the World Cup on YoY export growth

Notes: Solid line = average treated (winning) subseries; dashed line = synthetic control. Shaded bars = time weights $\hat{\tau}_q$. Bootstrap SEs from 1,000 replications.

In both panels, the synthetic control tracks the treated export growth well in the pre-treatment period, and a pronounced gap opens in the two post-World Cup quarters. The magnitude—roughly 5 pp—is an order of magnitude larger than the aggregate GDP effect, consistent with exports being one of several (partially offsetting) GDP components. Although the ATT is not statistically significant, the point estimate is economically substantial and directionally consistent with the event-study result ($l = +2$: 5.81 pp, $p = 0.032$). The SDiD plots for the remaining four components (private consumption, government consumption, capital formation, and imports) are presented in Appendix Figures A.1–A.4. None shows a meaningful post-treatment divergence, consistent with the null results in Table 5.

7 Analysis Extensions

This section extends the analysis of Mello (2024) along three dimensions. First, I broaden the treatment group to *finalists*—countries that reached the World Cup final (Section 7.1). Second, I further expand it to *semi-finalists*—countries that finished in the top four (Section 7.2). Third, I examine the inverse channel by studying *underperformers*—highly ranked countries that were eliminated in the group stage (Section 7.4). If winning generates GDP effects through national pride, international visibility, or consumer confidence, then reaching the final or semi-finals might produce similar—albeit smaller—effects, while early elimination could produce negative shocks. For each extension I estimate the same event study and SDiD specifications as in Sections 6.1 and 4.1.3, with the dependent variable being year-over-year log GDP growth $\Delta_4 \ln \mathrm{GDP}_{c,t}$. Section 7.3 compares the event study coefficients across all three positive-shock treatment groups (winner, finalist, semi-finalist).

7.1 Finalist Analysis

The treatment group is expanded to include all countries that reached the World Cup final (both winners and runners-up). This yields 9 treated countries—Argentina, Brazil, Croatia, France, Germany, Italy, Netherlands, Spain, and the United Kingdom—with 23 finalist events between 1966 and 2018. The specification is identical to Equation (11), replacing W_c (ever-winner) with F_c (ever-finalist).

Event study. The full set of relative-time coefficients is reported in Table A.3 (Appendix). The pre-treatment coefficients at $l = -2$ (-0.096 pp) and $l = -1$ (-0.029 pp) are close to zero and insignificant, consistent with no differential pre-trends in the quarters immediately preceding the tournament. However, several earlier pre-treatment coefficients for the finalist specification are statistically significant—for instance, $l = -16$ (1.038 pp, $p = 0.012$), $l = -9$ (1.018 pp, $p = 0.038$), and $l = -5$ (0.863 pp, $p = 0.032$)—suggesting persistent level differences between finalist and non-finalist countries that the country fixed effects do not fully absorb. While this does not invalidate the specification, it warrants caution in interpreting the post-treatment estimates.

In the post-treatment period, the coefficients at $l = +1$ (0.275 pp, SE = 0.231) and $l = +2$ (0.347 pp, SE = 0.277) are positive but statistically insignificant. By $l = +3$, the effect turns negative (-0.285 pp) and the remaining post-treatment coefficients fluctuate around zero. Compared to the winner-only estimates (0.325 pp and 0.597 pp at $l = +1$ and $l = +2$), the finalist coefficients are attenuated, suggesting that the inclusion of runners-up—who do not receive the same positive shock—dilutes the treatment effect. Figure 9 shows the full event study plot.

Figure 9: Event study: effect of reaching the World Cup final on GDP growth

Notes: Dependent variable: $\Delta_4 \ln \mathrm{GDP}_{c,t}$. Treatment = ever-finalist (rank 1 or 2). 9 treated countries, 23 events, 8,633 observations. Shaded region: 95% CI. Reference: $l = 0$ (Q2 of WC year). Endpoints binned at ± 16.

Synthetic difference-in-differences. The SDiD estimate corroborates the event study findings. Figure 10 shows the stacked SDiD plot for the finalist treatment group. The estimated ATT is 0.109 pp (SE = 0.246, $p = 0.657$), substantially smaller than the winner ATT of 0.527 pp and statistically indistinguishable from zero. The synthetic control trajectory closely tracks the treated group in the pre-treatment window, but the post-treatment gap is negligible. With 11 treated and 262 control subseries, the donor pool is well populated, yet the treatment effect is too diffuse to detect.

7.2 Semi-Finalist Analysis

The treatment group is further expanded to include all countries that reached the World Cup semi-finals (top 4 finishers). This yields 14 treated countries with 43 semi-finalist events, substantially increasing statistical power relative to both the winner (6 countries, 10 events) and finalist (9 countries, 23 events) specifications.

Event study. As shown in Table A.3, the pre-treatment coefficients are uniformly insignificant across all 16 pre-treatment lags, with the coefficients at $l = -2$ (-0.650 pp) and $l = -1$ (-0.342 pp) being close to zero in magnitude relative to their standard errors. The absence of significant pre-treatment coefficients—unlike the finalist specification—lends stronger support to the parallel trends assumption.

In the post-treatment period, $l = +1$ shows a positive but insignificant effect (0.198 pp, SE = 0.174, $p = 0.26$). The $l = +2$ coefficient is marginally significant (0.404 pp, SE = 0.204, $p = 0.054$), suggesting that countries reaching the top four experience a transient GDP boost two quarters after the tournament. However, this effect is not sustained: $l = +3$ and $l = +4$ are negative and insignificant. Figure 11 shows the full event study plot.

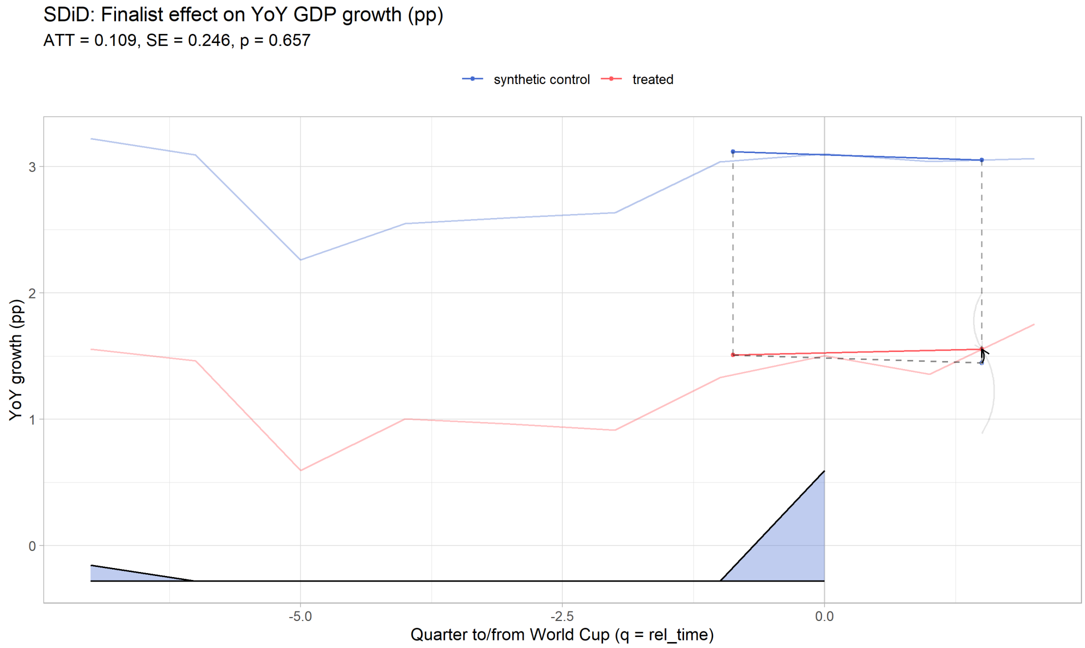


Figure 10: SDiD: effect of reaching the World Cup final on GDP growth

Notes: Stacked SDiD with 10-quarter subseries $q \in [-7, +2]$ for World Cups 1998–2018. Treatment = finalist (rank 1 or 2). ATT = 0.109 pp, SE = 0.246 (bootstrap, 1,000 replications), $p = 0.657$. 11 treated, 262 control subseries. Host-only controls excluded.

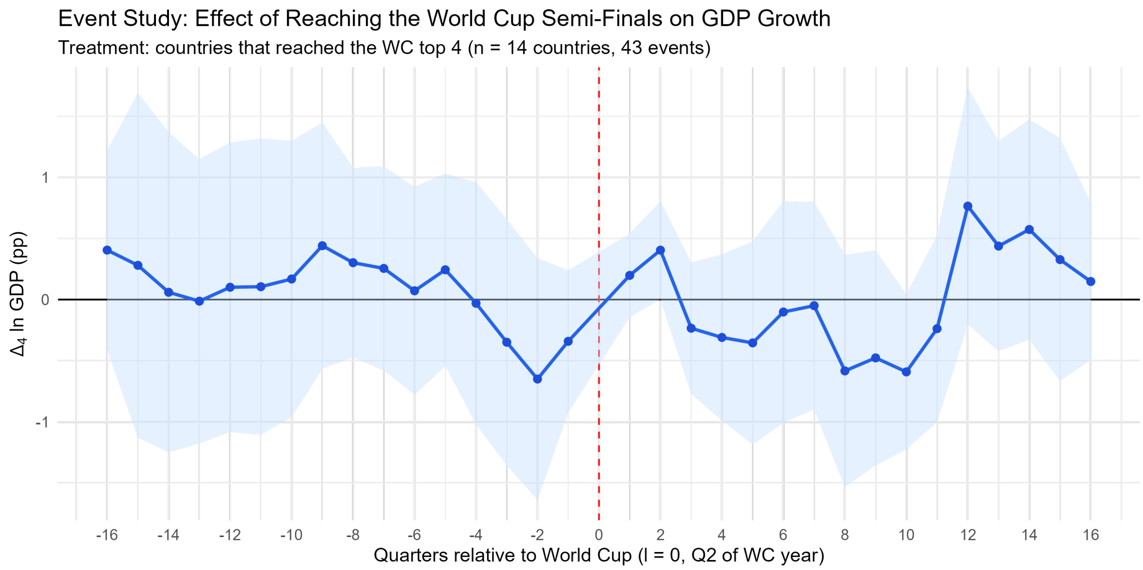


Figure 11: Event study: effect of reaching the World Cup semi-finals on GDP growth

Notes: Dependent variable: $\Delta_4 \ln \mathrm{GDP}_{c,t}$. Treatment = ever-semi-finalist (rank 1–4). 14 treated countries, 43 events, 8,633 observations. Shaded region: 95% CI. Reference: $l = 0$ (Q2 of WC year). Endpoints binned at ± 16.

Synthetic difference-in-differences. The SDiD estimate for the semi-finalist treatment group is shown in Figure 12. The ATT is 0.207 pp (SE = 0.202, $p = 0.305$): positive but insignificant, and roughly half the magnitude of the winner ATT. With 22 treated subseries (compared to 11 for finalists and 7 for winners), the larger treatment pool slightly reduces the standard error. Nevertheless, the dilution from including third- and fourth-place finishers pushes the point estimate further from significance.

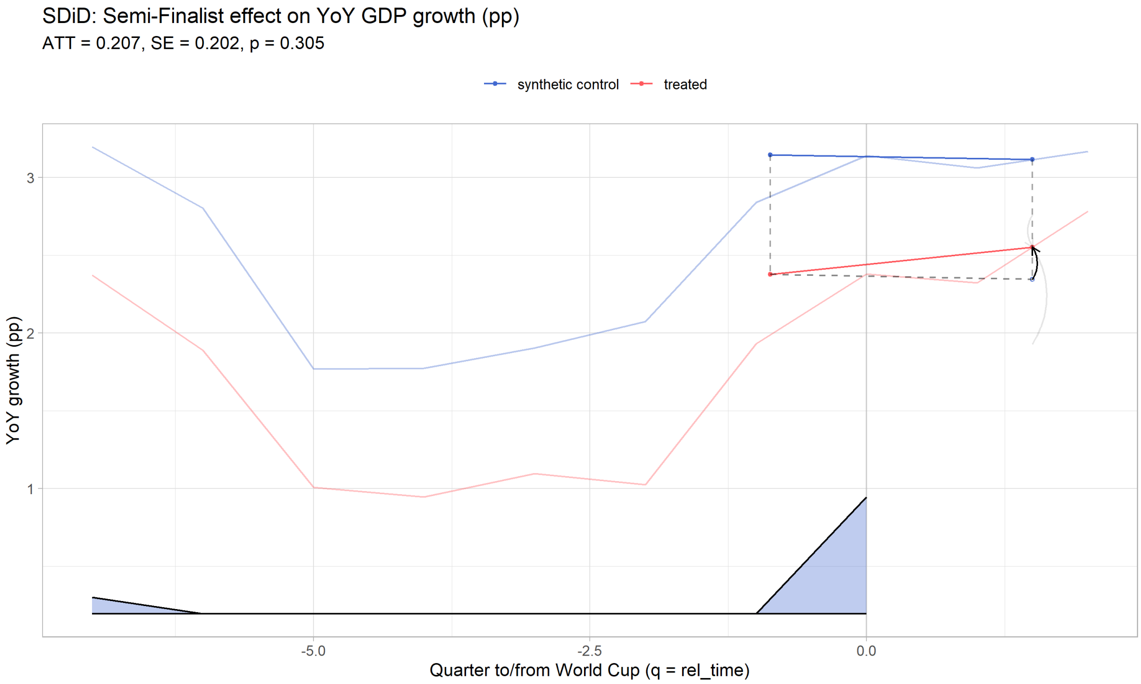


Figure 12: SDiD: effect of reaching the World Cup semi-finals on GDP growth

Notes: Stacked SDiD with 10-quarter subseries $q \in [-7, +2]$ for World Cups 1998–2018. Treatment = semi-finalist (rank 1–4). ATT = 0.207 pp, SE = 0.202 (bootstrap, 1,000 replications), $p = 0.305$. 22 treated, 254 control subseries. Host-only controls excluded.

7.3 Comparison Across Treatment Groups

Table A.3 compares the full set of relative-time coefficients ($l = -16$ to $l = +16$) across all three positive-shock treatment groups. The pattern reveals a trade-off between effect magnitude and statistical precision.

In the immediate post-treatment window, the $l = +1$ coefficient decreases monotonically as the treatment group broadens ($0.325 \to 0.275 \to 0.198$ pp for winners, finalists, and semi-finalists, respectively), consistent with a dilution of the "winning premium" as countries that performed well but did not win are added. At $l = +2$, the pattern is non-monotonic: the semi-finalist estimate (0.404 pp) exceeds the finalist estimate (0.347 pp), though both remain below the winner estimate (0.597 pp). The marginal significance at $l = +2$ in the semi-finalist specification ($p = 0.054$) arises from the substantially smaller standard error (0.204 vs. 0.277 for finalists and 0.387 for winners), reflecting the nearly fourfold increase in treated events (43 vs. 10).

At longer horizons ($l = +5$ to $l = +16$), the coefficients for all three groups fluctuate around zero with no consistent pattern, indicating that any post-tournament effect dissipates within a year. The pre-treatment coefficients merit separate attention: while the

winner and semi-finalist specifications show no systematic pre-trends, the finalist specification exhibits several significant pre-treatment coefficients (e.g., $l = -16$, $l = -9$, $l = -5$), suggesting that finalist countries may differ from non-finalists in ways not fully captured by the country fixed effects.
The SDiD estimates reinforce these findings. The winner ATT (0.527 pp, SE = 0.274) is the largest, followed by the semi-finalist ATT (0.207 pp, SE = 0.202) and the finalist ATT (0.109 pp, SE = 0.246). None of the extension ATTs are statistically significant, confirming that the economic effect of World Cup performance is concentrated in winning. The positive direction of both the event study and SDiD estimates across all three specifications is consistent with a general "tournament performance" channel, but only winning generates effects that are economically meaningful relative to their standard errors.

7.4 Underperformer Analysis

The previous extensions tested whether *positive* World Cup outcomes short of winning still generate GDP effects. This subsection examines the inverse channel: whether countries that *underperform* relative to expectations experience a negative economic shock.

7.4.1 Data and sample construction

Underperformance is defined as a top-10 pre-tournament ELO-rated country being eliminated in the group stage. This criterion captures sharp negative surprises—cases where a strong favourite exits far earlier than expected. The ELO ratings are sourced from `eloratings.net`, a widely used system that updates after every international match and is available for all World Cups in the sample period (1962–2022).
The raw dataset contains 41 underperformance events across 16 World Cups. Notable examples include Brazil in 1966 (ranked 1st), France in 2002 (ranked 1st, as defending champion), Spain in 2014 (ranked 2nd, as defending champion), and Germany in 2018 (ranked 2nd, as defending champion). After matching to the OECD panel, 37 events from 19 countries remain; four events (Uruguay 1962 and 2022, Yugoslavia 1982, Peru 2018) are lost because the corresponding country is not in the OECD base panel.
The matched events span the entire sample period. Spain has the most events (5), followed by the United Kingdom (4, representing England and Scotland) and Italy, Czech Republic, and others with 2–3 events each. Of the 37 matched events, 22 have a complete 10-quarter GDP window required for the SDiD estimation, and 11 of these fall within the 1998–2018 SDiD subsample. The treatment variable U_c is time-invariant: $U_c = 1$ if country c has ever experienced an underperformance event (19 countries), and $U_c = 0$ otherwise (29 control countries).

7.4.2 Descriptive evidence

Before turning to formal estimation, Figure 13 provides a descriptive overview. The plot shows the average Δ_4 log growth across all six national accounts features in a ± 16-quarter window around each underperformance event. Exports and imports—the most volatile components—show the largest swings, while GDP, consumption, and government consumption cluster in a tighter band. There is no obvious discontinuity at the event date for most features, though exports appear to dip mildly in the post-treatment window. The individual-event GDP overlay is provided in Appendix Figure A.5, which reveals substantial heterogeneity across the 23 events.

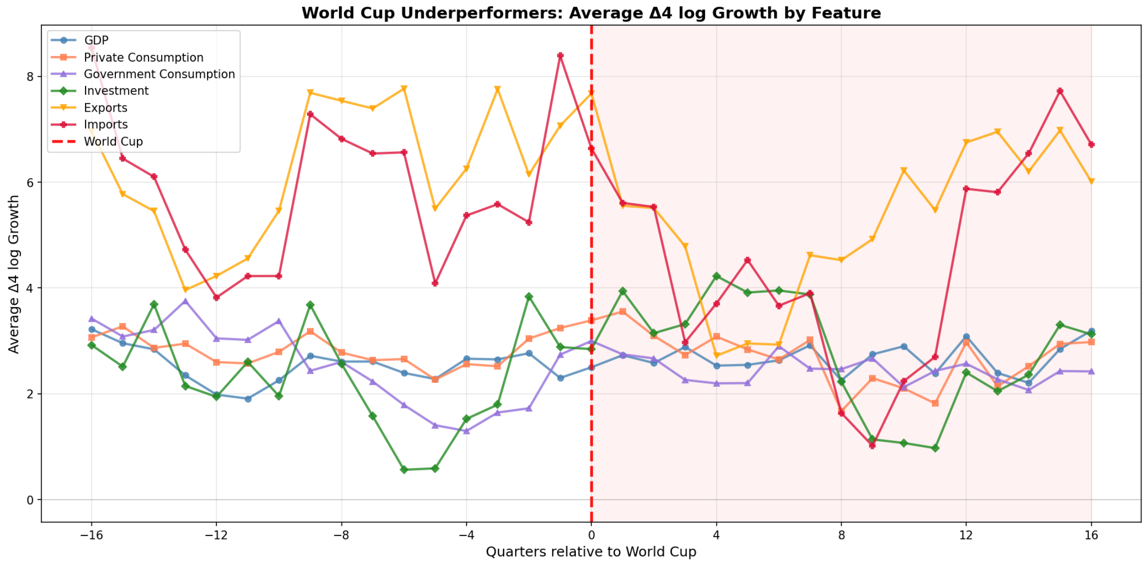


Figure 13: Average Δ_4 log growth by feature around underperformance events

Notes: Average year-over-year log growth for each of the six national accounts features across all matched underperformance events. Dashed vertical line marks the World Cup quarter ($l = 0$). Shaded region: post-treatment window.

7.4.3 Event study results

The event study specification replaces the winner indicator with the underperformer indicator:

$$\Delta_4 \ln Y_{c,t} = \sum_{l \neq 0} \beta_l U^l_{c,t} + \theta_1 \text{HOST}_{c,t} + \zeta_1 \ln Y_{c,t-4} + \alpha_c + \mu_t + \varepsilon_{c,t}, \tag{17}$$

where $U^l_{c,t}$ are relative-time indicators for underperformance events, following the same structure as Equation (11). I estimate this specification for all six national accounts features: GDP, private consumption, government consumption, gross fixed capital formation, exports, and imports. The sample includes 19 treated countries and 23 underperformance events.

Figure 14 presents the event study coefficients for all six features. The full set of GDP relative-time indicators is in Table A.4 (Appendix). For GDP, the pre-treatment coefficients are uniformly insignificant across all 16 lags, supporting the parallel trends assumption. In the immediate post-treatment period, the $l = +1$ coefficient is *positive* (0.495 pp, SE $= 0.283$, $p = 0.087$), contrary to the negative-shock hypothesis. This marginally significant *positive* effect at one quarter after the tournament is surprising and likely reflects the economic resilience of the large, diversified economies that dominate the underperformer sample (e.g., Germany, France, Spain, Italy). The $l = +2$ coefficient remains positive (0.460 pp) but is highly imprecise (SE $= 0.646$). At longer horizons, all post-treatment coefficients are insignificant and centred near zero.

The most striking result is for **exports**: the $l = +1$ coefficient is -1.876 pp (SE $= 0.776$, $p = 0.020$), suggesting a statistically significant decline in export growth one quarter after the tournament. The effect persists with further significant negative coefficients at $l = +5$ through $l = +9$, indicating a sustained export decline. This is consistent with the finding from the replication and from Mello (2024) that the winner premium operates primarily through the trade channel—the mirror image appears to hold for underperformers. Imports also show a negative pattern ($l = +1$: -1.724 pp, SE $= 1.303$), with significant effects emerging at longer horizons ($l = +7$ through $l = +11$). Private consumption, government consumption, and capital formation show no significant effects.

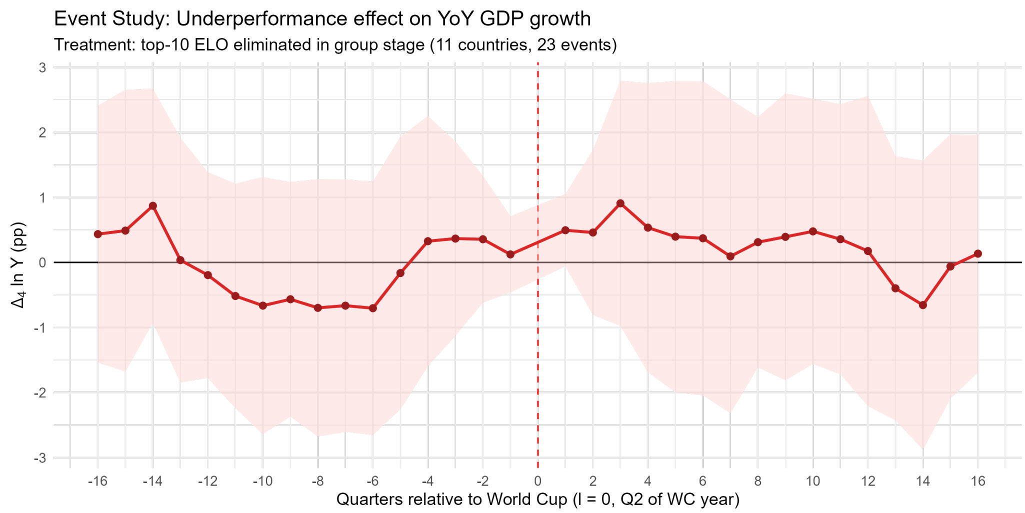


Figure 14: Underperformer event study: all six national accounts features

Notes: Dependent variable: $\Delta_4 \ln Y_{c,t}$ for each feature. Treatment = top-10 pre-tournament ELO rating, eliminated in group stage. 19 treated countries, 23 events, 8,633 observations. Error bars: 95% CI. Reference: $l = 0$ (Q2 of WC year). Endpoints binned at ± 16.

7.4.4 Synthetic difference-in-differences

The SDiD specification follows the same stacked design as in Section 4.1.3, with the underperformer indicator replacing the winner indicator. Of the 37 matched events, 11 fall within the 1998–2018 SDiD window from 9 countries, providing sufficient variation for estimation. Unlike the winner analysis where SDiD was estimated for GDP only, I estimate SDiD for all six features to provide a complete picture of the underperformer effect.

Figures 15 and 16 show the SDiD plots for GDP and exports—the two features with the most informative results. The remaining four component plots are in Appendix Figures A.6–A.9.

Table 6 compares the SDiD ATTs across three analyses: the underperformer results, my replication of the winner effect, and the original Mello (2024) estimates. Several patterns stand out.

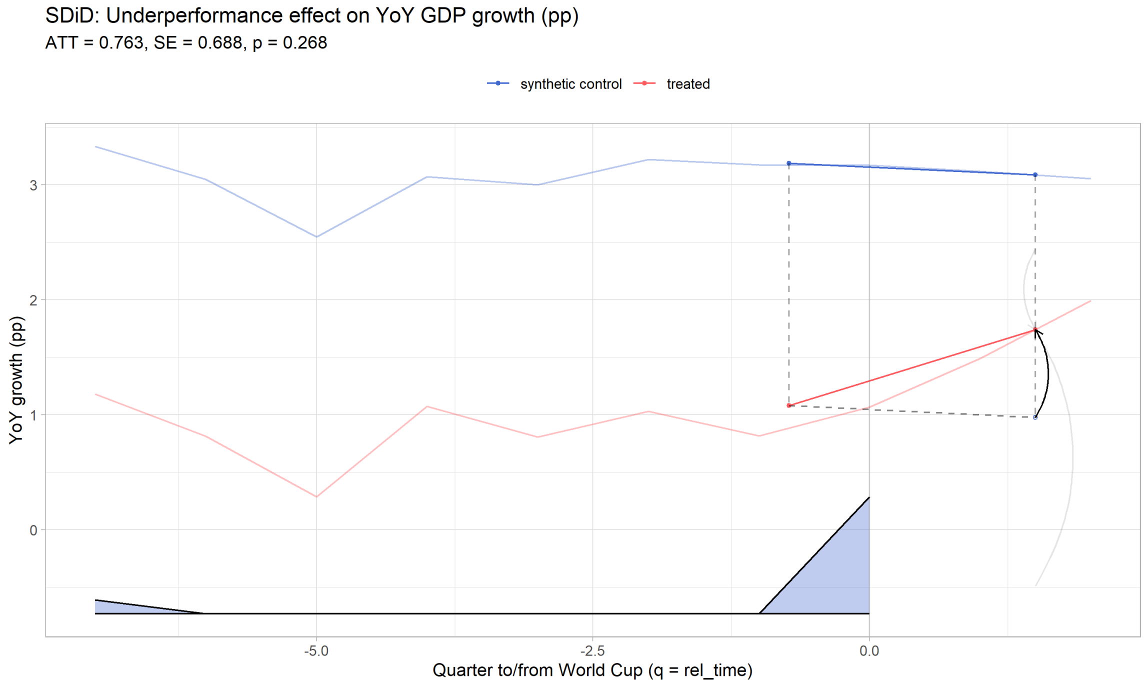


Figure 15: SDiD: effect of World Cup underperformance on GDP growth

Notes: Stacked SDiD with 10-quarter subseries $q \in [-7, +2]$ for World Cups 1998–2018. Treatment = top-10 pre-tournament ELO rating, eliminated in group stage. ATT = 0.763 pp, SE = 0.688 (bootstrap, 1,000 replications), $p = 0.268$. 11 treated, 261 control subseries. Host-only controls excluded.

Table 6: SDiD average treatment effects: underperformers vs. winners

	Underperformer		**Replication**		**Mello (2024)**	
Component	ATT	(SE)	ATT	(SE)	ATT	(SE)
GDP	0.763	(0.688)	0.527*	(0.274)	0.481*	(0.263)
Private consumption	0.410	(0.234)	−0.212	(0.338)	−0.009	(0.355)
Government consumption	0.570	(0.635)	−0.331	(0.591)	−0.314	(0.463)
Gross fixed capital form.	2.566	(1.967)	1.251	(1.120)	1.214	(1.238)
Exports	−1.290	(1.435)	4.769	(3.989)	4.507*	(3.916)
Imports	2.147*	(1.105)	−0.247	(1.169)	−0.112	(1.095)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Bootstrap SEs (1,000 replications).
Notes: ATT denotes the average treatment effect in the two post-World Cup quarters. Underperformer: 11 treated (10 for components), 259–261 control subseries. Replication & Mello: 6 treated, ∼268 control subseries. All estimates in percentage points.

Most underperformer ATTs are *positive*—GDP (0.763 pp), private consumption (0.410 pp), government consumption (0.570 pp), capital formation (2.566 pp), and imports (2.147 pp, marginally significant at $p = 0.052$)—which runs counter to the hypothesis that early elimination depresses economic activity. The notable exception is **exports** (−1.290 pp), which is the only component with a negative ATT for underperformers. This is consistent with the findings from both the replication and Mello (2024), where exports are the feature most responsive to World Cup outcomes: winners see a large positive export boost

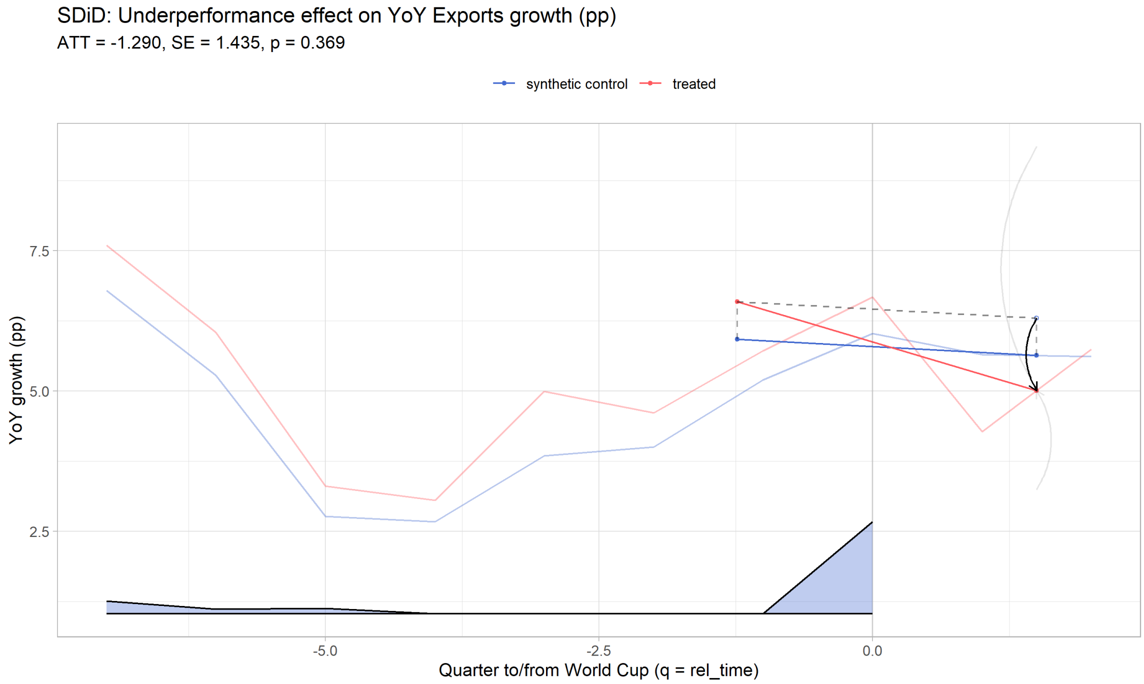


Figure 16: SDiD: effect of World Cup underperformance on export growth

Notes: Stacked SDiD with 10-quarter subseries $q \in [-7, +2]$ for World Cups 1998–2018. Treatment = underperformer. ATT = -1.290 pp, SE = 1.435 (bootstrap, 1,000 replications), $p = 0.369$. 10 treated, 259 control subseries. Host-only controls excluded.

($\sim$5 pp), while underperformers experience a decline. The trade channel thus appears to be the primary mechanism through which World Cup outcomes affect the economy, operating in both directions.

None of the underperformer ATTs are statistically significant at conventional levels (except imports at $p = 0.052$), and the standard errors are generally large, reflecting the heterogeneity of the underperformer sample—which includes both large diversified economies (Germany 2018, France 2002) and smaller ones (Czech Republic 2006, Croatia 2002). An interesting extension for future work would be to investigate “overperformers”—countries that significantly exceeded pre-tournament expectations—to test whether the trade channel operates symmetrically on the positive side for non-winners as well.

8 Conclusion

This thesis has replicated and extended the analysis of Mello (2024), providing comprehensive evidence on the economic effects of FIFA World Cup performance.

8.1 Summary of Findings

The independent replication confirms the core result: winning the World Cup temporarily boosts year-over-year GDP growth by roughly 0.3–0.7 percentage points in the two quarters following victory. My event study estimates (l=+1: 0.325 pp; l=+2: 0.597 pp) closely track Mello's (0.454 pp and 0.683 pp), as does the SDiD ATT (0.527 pp vs. 0.481 pp). Both analyses identify **exports** as the primary channel, with the l=+2 export coefficient reaching 5.81 pp ($p = 0.032$) in the replication. Domestic consumption, government spending, and investment show no significant response, indicating that the effect operates through international trade rather than domestic demand.

Given the close alignment between my replication and the original results, I did not pursue further robustness checks (alternative lag specifications, matched samples) beyond those reported by Mello (2024). The near-identical estimates obtained from independently constructed data and separate code provide strong evidence that the original findings are robust.

The extensions reveal a clear gradient: the effect attenuates as the treatment group broadens. Finalists (ATT = 0.109 pp) and semi-finalists (ATT = 0.207 pp) show positive but insignificant effects, confirming that the economic premium is concentrated in winning itself. The underperformer analysis—focusing on top-10 ELO-rated teams eliminated in the group stage—finds no evidence that early exit depresses GDP. Most underperformer SDiD ATTs are in fact positive (GDP: 0.763 pp, capital formation: 2.566 pp), likely reflecting the resilience of the large OECD economies that dominate this sample. The exception is exports (−1.290 pp), the only component with a negative underperformer ATT, which is consistent with the export-driven mechanism documented for winners operating in reverse.

8.2 Contributions

This thesis makes three main contributions:

1. **Independent replication.** This is, to my knowledge, the first independent replication of Mello (2024). Obtaining near-identical results from separately constructed data and code validates the original findings and strengthens confidence in the causal interpretation.
2. **Gradient of tournament performance.** The finalist, semi-finalist, and underperformer extensions map out how economic effects vary with the degree of tournament success. The monotonic attenuation from winners through finalists to semi-finalists, and the absence of negative effects for underperformers, delineates the boundary conditions of the World Cup premium.
3. **Export channel confirmation.** The consistent pattern—winners gain in exports, underperformers lose—across both event study and SDiD, and across independent samples, reinforces the interpretation that international visibility and country-of-origin effects in trade are the primary economic mechanism.

8.3 Limitations and Future Research

The analysis faces inherent sample constraints: only 10 World Cup victories are observed in the OECD panel, and the underperformer sample, while larger (37 events), is dominated by a handful of large economies. The SDiD window is further restricted to 1998–2018, reducing the treated sample to 6 winners and 11 underperformers. These small samples limit statistical power and make it difficult to distinguish true null effects from underpowered tests.

An immediate and promising extension would be to study "overperformers"—countries that significantly exceeded pre-tournament expectations, such as Croatia's run to the 2018 final or South Korea's semi-final appearance in 2002. If the export channel operates symmetrically, overperformers should exhibit positive export effects even without winning, which would further sharpen the mechanism. Other promising directions include investigating more detailed economic components—such as tourism receipts, employment, or firm-level trade data—to pinpoint exactly which channels respond, and extension to other tournaments (European Championship, Copa América) or to the Women's World Cup.

8.4 Concluding Remarks

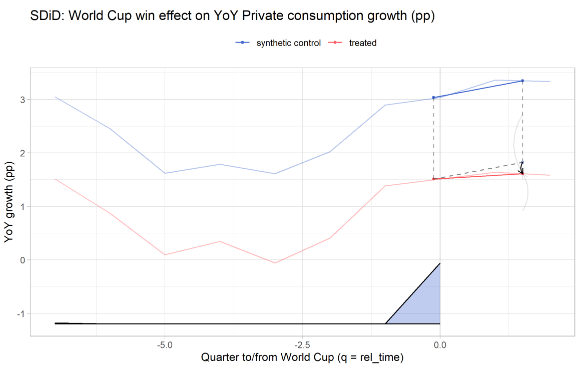
Winning the FIFA World Cup generates a modest, temporary boost to GDP growth, operating primarily through exports. The effect is specific to winning—merely reaching the final or semi-finals is not enough—and does not operate in reverse for underperformers, except in the trade channel. The close replication of Mello (2024)'s results across independently constructed data provides confidence that this finding is robust. While the magnitude is too small to have meaningful policy implications, the result offers tangible evidence that collective sentiment and international visibility can have real, if fleeting, macroeconomic consequences.

A Appendix

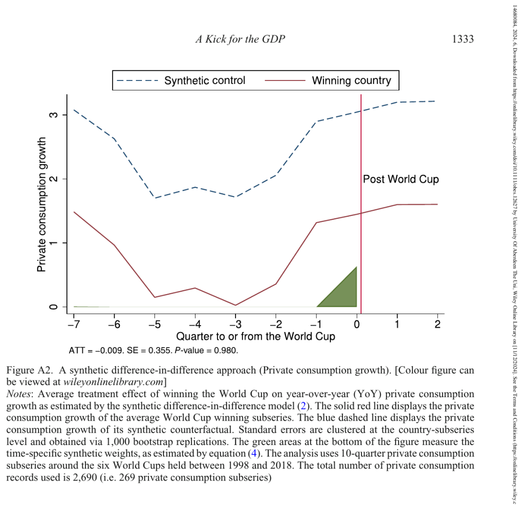
A.1 Event Study Comparison Tables

Table A.1 presents the complete GDP comparison across all 32 relative-time coefficients. Table A.2 presents the comparison for all six GDP components at selected post-treatment horizons.

A.2 SDiD Component Figures: Winners



(a) Replication: ATT $= -0.212$ pp, SE $= 0.338$, $p = 0.531$


A Kick for the GDP 1333

ATT = −0.009. SE = 0.355. *P*-value = 0.980.

Figure A2. A synthetic difference-in-difference approach (Private consumption growth). [Colour figure can be viewed at *wileyonlinelibrary.com*]
Notes: Average treatment effect of winning the World Cup on year-over-year (YoY) private consumption growth as estimated by the synthetic difference-in-difference model (2). The solid red line displays the private consumption growth of the average World Cup winning subseries. The blue dashed line displays the private consumption growth of its synthetic counterfactual. Standard errors are clustered at the country-subseries level and obtained via 1,000 bootstrap replications. The green areas at the bottom of the figure measure the time-specific synthetic weights, as estimated by equation (4). The analysis uses 10-quarter private consumption subseries around the six World Cups held between 1998 and 2018. The total number of private consumption records used is 2,690 (i.e. 269 private consumption subseries)

(b) Mello (2024): SE $= 0.355$, $p = 0.980$

Figure A.1: SDiD: effect of winning the World Cup on YoY private consumption growth

Notes: Solid line = average treated (winning) subseries; dashed line = synthetic control. Bootstrap SEs from 1,000 replications.

Table A.1: Event study coefficients: Replication vs. Mello (2024), GDP growth

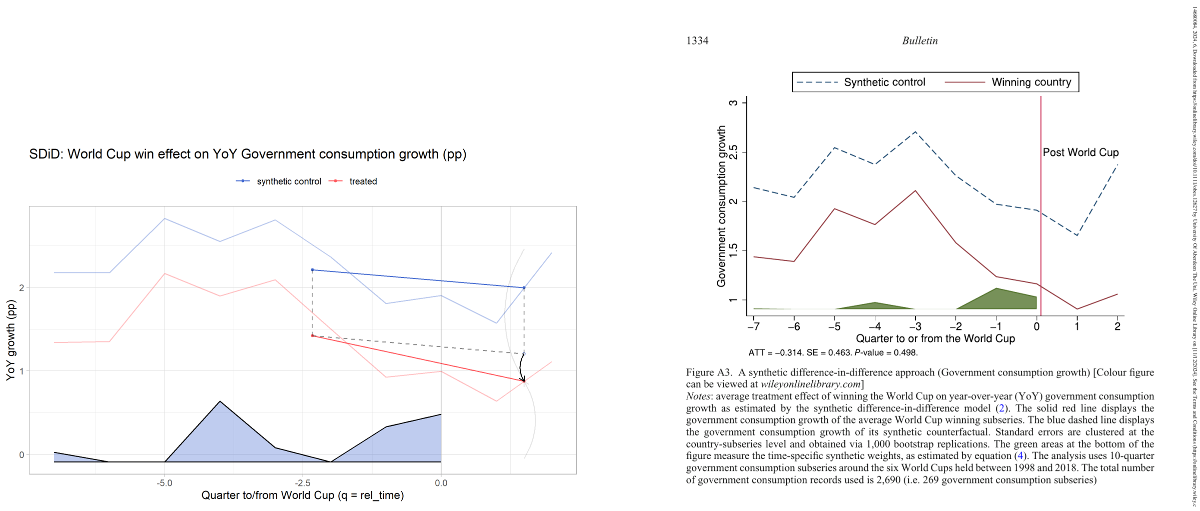
	Replication			**Mello (2024)**			Diff.
	Coeff.	(SE)	p	Coeff.	(SE)	p	
Controls							
$\ln \mathrm{GDP}_{t-4}$	-1.364**	(0.613)	0.031	-1.368**	(0.588)	0.044	0.004
Host	-0.542	(0.484)	0.269	-0.591	(0.545)	0.222	0.049
Pre-treatment							
$l = -16$ (binned)	0.771	(0.671)	0.427	0.640	(0.673)	0.429	0.131
$l = -15$	0.499	(0.479)	0.312	0.363	(0.538)	0.567	0.136
$l = -14$	0.392	(0.623)	0.537	0.276	(0.655)	0.753	0.116
$l = -13$	0.380	(0.444)	0.393	0.286	(0.474)	0.497	0.094
$l = -12$	0.019	(0.485)	0.972	-0.082	(0.503)	0.863	0.101
$l = -11$	-0.178	(0.590)	0.782	-0.226	(0.604)	0.707	0.048
$l = -10$	0.218	(0.730)	0.771	0.074	(0.769)	0.946	0.144
$l = -9$	0.043	(0.581)	0.940	-0.139	(0.616)	0.819	0.182
$l = -8$	0.219	(0.665)	0.728	0.098	(0.695)	0.889	0.121
$l = -7$	0.348	(0.556)	0.541	0.209	(0.570)	0.713	0.139
$l = -6$	0.250	(0.575)	0.670	0.196	(0.589)	0.753	0.054
$l = -5$	0.615	(0.564)	0.267	0.484	(0.621)	0.470	0.131
$l = -4$	0.073	(0.515)	0.877	-0.107	(0.535)	0.855	0.180
$l = -3$	-0.188	(0.481)	0.693	-0.288	(0.479)	0.570	0.100
$l = -2$	-0.512	(0.453)	0.263	-0.605	(0.432)	0.176	0.093
$l = -1$	0.071	(0.227)	0.765	0.125	(0.206)	0.573	-0.054
Post-treatment							
$l = +1$	0.325	(0.269)	0.232	0.454*	(0.246)	0.065	-0.129
$l = +2$	0.597	(0.387)	0.129	0.683*	(0.370)	0.065	-0.086
$l = +3$	0.305	(0.319)	0.345	0.233	(0.335)	0.487	0.072
$l = +4$	0.287	(0.319)	0.373	0.140	(0.317)	0.659	0.147
$l = +5$	0.042	(0.380)	0.908	-0.189	(0.357)	0.627	0.231
$l = +6$	0.188	(0.407)	0.678	-0.034	(0.422)	0.972	0.222
$l = +7$	-0.044	(0.659)	0.963	-0.288	(0.761)	0.713	0.244
$l = +8$	0.066	(0.775)	0.933	-0.314	(0.985)	0.750	0.380
$l = +9$	0.486	(0.381)	0.210	0.418	(0.387)	0.273	0.068
$l = +10$	-0.051	(0.394)	0.899	-0.145	(0.421)	0.728	0.094
$l = +11$	0.110	(0.441)	0.803	0.021	(0.461)	0.969	0.089
$l = +12$	0.213	(0.483)	0.677	0.289	(0.583)	0.627	-0.076
$l = +13$	-0.445	(0.585)	0.420	-0.593	(0.606)	0.273	0.148
$l = +14$	-0.276	(0.589)	0.669	-0.320	(0.628)	0.748	0.044
$l = +15$	-0.377	(0.615)	0.583	-0.412	(0.676)	0.573	0.035
$l = +16$ (binned)	0.073	(0.463)	0.875	-0.109	(0.477)	0.819	0.182
Observations		8,633			8,637		
Adj. R^2		0.444			—		
Within R^2 (Mello)		—			0.423		

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered SEs at the country level.
Mello p-values inferred from reported coefficients and SEs (normal approximation).

Table A.2: Event study comparison across GDP components: selected post-treatment coefficients

	Replication		Mello (2024)		
	Coeff.	(SE)	Coeff.	(SE)	Diff.
Private Consumption					
$\ln y_{t-4}$	-2.831***	(0.693)	-2.665***	(0.651)	-0.166
Host	0.035	(0.859)	-0.098	(0.801)	0.133
$l = +1$	-0.186	(0.515)	-0.169	(0.515)	-0.017
$l = +2$	0.166	(0.539)	0.214	(0.559)	-0.048
$l = +3$	-0.133	(1.041)	-0.198	(0.982)	0.065
$l = +4$	-0.144	(1.040)	-0.149	(1.087)	0.005
$l = +8$	-0.048	(0.528)	-0.184	(0.527)	0.136
$l = +16$ (binned)	0.201	(0.535)	0.186	(0.538)	0.015
N	8,589		8,549		
Government Consumption					
$\ln y_{t-4}$	-3.777**	(1.492)	-3.349***	(1.278)	-0.428
Host	-0.677	(0.646)	-0.155	(0.265)	-0.522
$l = +1$	0.202	(0.311)	0.384	(0.368)	-0.182
$l = +2$	0.137	(0.399)	0.080	(0.501)	0.057
$l = +3$	0.298	(0.827)	0.264	(0.884)	0.034
$l = +4$	0.133	(0.701)	0.082	(0.752)	0.051
$l = -0.196$	(1.344)	-0.640	(1.507)	0.444	
$l = +16$ (binned)	-0.000	(0.484)	-0.060	(0.520)	0.060
N	8,589		8,549		
Capital Formation					
$\ln y_{t-4}$	-7.816***	(1.749)	-7.795***	(1.624)	-0.021
Host	-1.587	(1.334)	-1.606	(1.404)	0.019
$l = +1$	-0.239	(0.505)	0.229	(0.515)	-0.468
$l = +2$	1.110	(1.235)	1.552	(1.128)	-0.442
$l = +3$	1.112	(1.373)	1.228	(1.370)	-0.116
$l = +4$	-0.156	(2.012)	-0.029	(2.008)	-0.127
$l = +8$	2.351	(1.679)	1.892	(1.932)	0.459
$l = +16$ (binned)	0.157	(1.217)	0.185	(1.256)	-0.028
N	8,589		8,549		
Exports					
$\ln y_{t-4}$	-3.772***	(0.694)	-3.730***	(0.754)	-0.042
Host	1.885**	(0.859)	1.249	(0.983)	0.636
$l = +1$	3.772	(2.630)	3.183	(2.631)	0.589
$l = +2$	5.810**	(2.627)	5.124*	(2.767)	0.686
$l = +3$	4.271*	(2.398)	3.844	(2.359)	0.427
$l = +4$	5.422	(3.670)	5.049	(3.631)	0.373
$l = -0.899$	(2.567)	-1.381	(2.643)	0.482	
$l = +16$ (binned)	0.815	(1.669)	0.501	(1.726)	0.314
N	8,589		8,549		
Imports					
$\ln y_{t-4}$	-6.146***	(0.951)	-6.056***	(0.952)	-0.090
Host	-0.360	(1.800)	-0.390	(1.909)	0.030
$l = +1$	1.516	(1.221)	1.719	(1.201)	-0.203
$l = +2$	1.307	(1.233)	1.429	(1.245)	-0.122
$l = +3$	3.179	(2.009)	3.138	(1.947)	0.041
$l = +4$	4.178*	(2.137)	4.326**	(2.084)	-0.148
$l = +8$	1.440	(2.104)	1.331	(2.131)	0.109
$l = +16$ (binned)	2.168	(2.881)	2.266	(2.872)	-0.098
N	8,589		8,549		

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered SEs at the country level.
Selected post-treatment lags shown ($l = +1$ to $+4$, $+8$, $+16$). Full coefficients in replication materials.
Mello p-values inferred from reported coefficients and SEs (normal approximation).

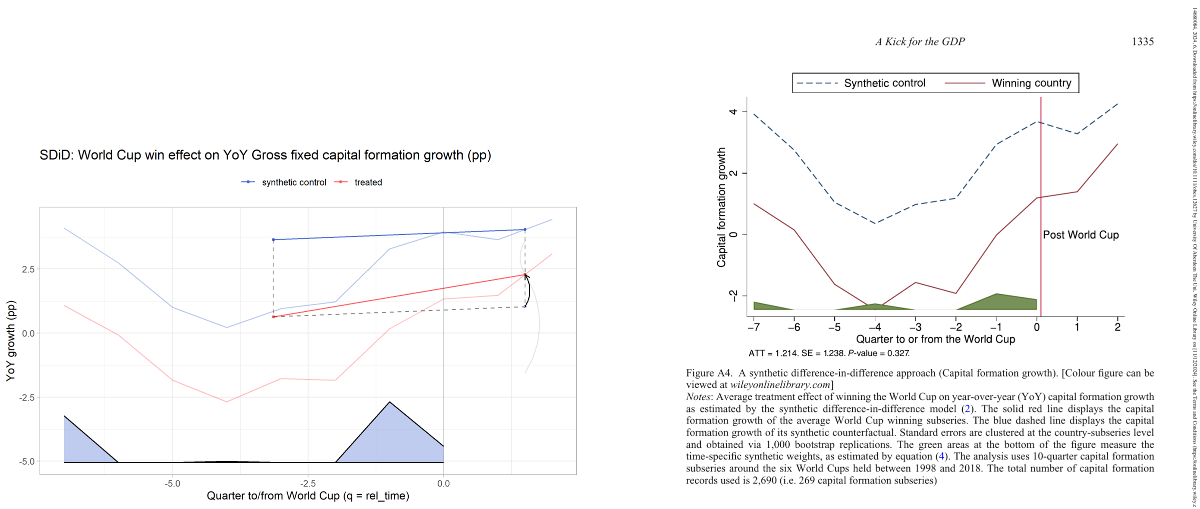


(a) Replication: ATT $= -0.331$ pp, SE $= 0.591$, $p = 0.576$

(b) Mello (2024): SE $= 0.463$, $p = 0.498$

Figure A.2: SDiD: effect of winning the World Cup on YoY government consumption growth

Notes: Solid line = average treated (winning) subseries; dashed line = synthetic control. Bootstrap SEs from 1,000 replications.

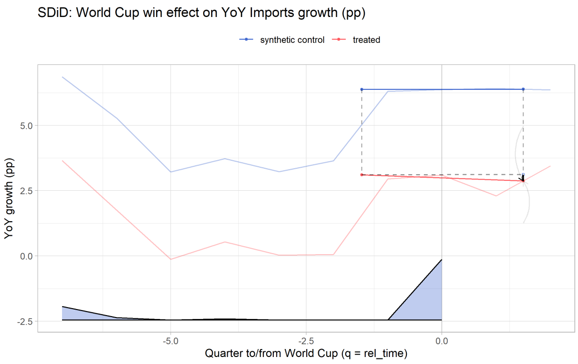


(a) Replication: ATT $= 1.251$ pp, SE $= 1.120$, $p = 0.264$

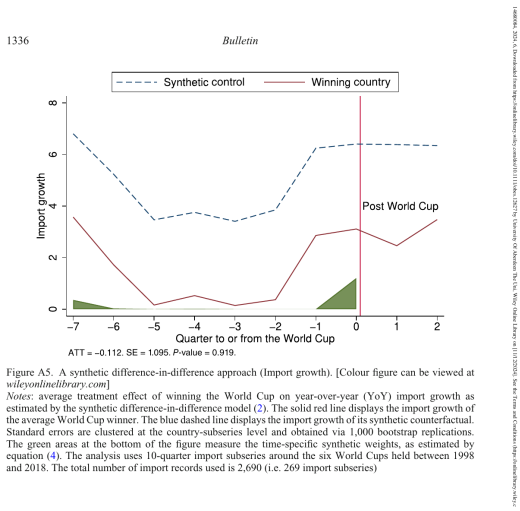
(b) Mello (2024): SE $= 1.238$, $p = 0.327$

Figure A.3: SDiD: effect of winning the World Cup on YoY capital formation growth

Notes: Solid line = average treated (winning) subseries; dashed line = synthetic control. Bootstrap SEs from 1,000 replications.



(a) Replication: ATT $= -0.247\,\text{pp}$, SE $= 1.169$, $p = 0.832$



(b) Mello (2024): SE $= 1.095$, $p = 0.919$

Figure A.4: SDiD: effect of winning the World Cup on YoY import growth

Notes: Solid line = average treated (winning) subseries; dashed line = synthetic control. Bootstrap SEs from 1,000 replications.

A.3 Extension Event Study Comparison

Table A.3: Event study coefficients: winner vs. finalist vs. semi-finalist (all relative-time indicators)

	Winner		**Finalist**		**Semi-finalist**	
	Coeff.	(SE)	Coeff.	(SE)	Coeff.	(SE)
Pre-treatment						
$l = -16$	0.771	(0.671)	1.038**	(0.397)	0.405	(0.414)
$l = -15$	0.499	(0.479)	1.371*	(0.778)	0.280	(0.719)
$l = -14$	0.392	(0.623)	1.073	(0.673)	0.060	(0.668)
$l = -13$	0.380	(0.444)	1.078*	(0.608)	−0.013	(0.592)
$l = -12$	0.019	(0.485)	0.977*	(0.561)	0.101	(0.604)
$l = -11$	−0.178	(0.590)	0.961*	(0.552)	0.105	(0.618)
$l = -10$	0.218	(0.730)	1.041	(0.745)	0.168	(0.576)
$l = -9$	0.043	(0.581)	1.018**	(0.476)	0.441	(0.513)
$l = -8$	0.219	(0.665)	0.487	(0.474)	0.302	(0.395)
$l = -7$	0.348	(0.556)	0.467	(0.357)	0.255	(0.425)
$l = -6$	0.250	(0.575)	0.460	(0.383)	0.072	(0.433)
$l = -5$	0.615	(0.564)	0.863**	(0.390)	0.244	(0.401)
$l = -4$	0.073	(0.515)	0.768	(0.508)	−0.030	(0.504)
$l = -3$	−0.188	(0.481)	0.233	(0.432)	−0.349	(0.513)
$l = -2$	−0.512	(0.453)	−0.096	(0.360)	−0.650	(0.503)
$l = -1$	0.071	(0.227)	−0.029	(0.263)	−0.342	(0.296)
Post-treatment						
$l = +1$	0.325	(0.269)	0.275	(0.231)	0.198	(0.174)
$l = +2$	0.597	(0.387)	0.347	(0.277)	0.404*	(0.204)
$l = +3$	0.305	(0.319)	−0.285	(0.340)	−0.234	(0.274)
$l = +4$	0.287	(0.319)	−0.006	(0.327)	−0.310	(0.346)
$l = +5$	0.042	(0.380)	−0.084	(0.384)	−0.354	(0.423)
$l = +6$	0.188	(0.407)	0.236	(0.295)	−0.102	(0.462)
$l = +7$	−0.044	(0.659)	0.312	(0.411)	−0.050	(0.432)
$l = +8$	0.066	(0.775)	−0.391	(0.527)	−0.584	(0.484)
$l = +9$	0.486	(0.381)	−0.564	(0.593)	−0.477	(0.448)
$l = +10$	−0.051	(0.394)	−0.437	(0.344)	−0.592*	(0.323)
$l = +11$	0.110	(0.441)	0.153	(0.438)	−0.238	(0.389)
$l = +12$	0.213	(0.483)	0.744	(0.492)	0.765	(0.493)
$l = +13$	−0.445	(0.585)	0.693	(0.585)	0.438	(0.438)
$l = +14$	−0.276	(0.589)	0.735	(0.612)	0.573	(0.459)
$l = +15$	−0.377	(0.615)	0.262	(0.656)	0.327	(0.506)
$l = +16$	0.073	(0.463)	0.263	(0.251)	0.148	(0.326)
Treated countries	6		9		14	
Treatment events	10		23		43	
Observations	8,633		8,633		8,633	
Within R^2	0.012		0.012		0.011	

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Country-clustered SEs.
Reference category: $l = 0$ (Q2 of World Cup year). Endpoints binned at ±16.
Winner = rank 1; Finalist = rank 1–2; Semi-finalist = rank 1–4.

A.4 Underperformer Event Study: GDP

Table A.4: Underperformer event study: GDP coefficients (all relative-time indicators)

	Coeff.	(SE)	t-stat	
Pre-treatment				
$l = -16$	0.435	(1.006)	0.432	
$l = -15$	0.489	(1.105)	0.443	
$l = -14$	0.871	(0.917)	0.949	
$l = -13$	0.036	(0.959)	0.037	
$l = -12$	−0.195	(0.806)	−0.241	
$l = -11$	−0.515	(0.880)	−0.586	
$l = -10$	−0.664	(1.008)	−0.659	
$l = -9$	−0.566	(0.919)	−0.616	
$l = -8$	−0.698	(1.008)	−0.692	
$l = -7$	−0.664	(0.989)	−0.671	
$l = -6$	−0.703	(0.993)	−0.708	
$l = -5$	−0.163	(1.069)	−0.152	
$l = -4$	0.327	(0.981)	0.333	
$l = -3$	0.367	(0.762)	0.481	
$l = -2$	0.356	(0.497)	0.718	
$l = -1$	0.124	(0.298)	0.415	
Post-treatment				
$l = +1$	0.495	(0.283)	1.749	*
$l = +2$	0.460	(0.646)	0.712	
$l = +3$	0.909	(0.961)	0.946	
$l = +4$	0.535	(1.133)	0.472	
$l = +5$	0.396	(1.220)	0.325	
$l = +6$	0.372	(1.231)	0.302	
$l = +7$	0.094	(1.230)	0.076	
$l = +8$	0.311	(0.981)	0.317	
$l = +9$	0.394	(1.124)	0.350	
$l = +10$	0.478	(1.039)	0.460	
$l = +11$	0.357	(1.059)	0.337	
$l = +12$	0.176	(1.215)	0.144	
$l = +13$	−0.397	(1.035)	−0.384	
$l = +14$	−0.656	(1.133)	−0.579	
$l = +15$	−0.062	(1.035)	−0.060	
$l = +16$	0.135	(0.931)	0.145	
Treated countries	19			
Treatment events	23			
Observations	8,633			
Within R^2	0.012			

$^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$. Country-clustered SEs.
Reference category: $l = 0$ (Q2 of World Cup year). Endpoints binned at ±16.
Treatment: top-10 pre-tournament ELO rating, eliminated in group stage.

A.5 Underperformer: Individual GDP Overlay

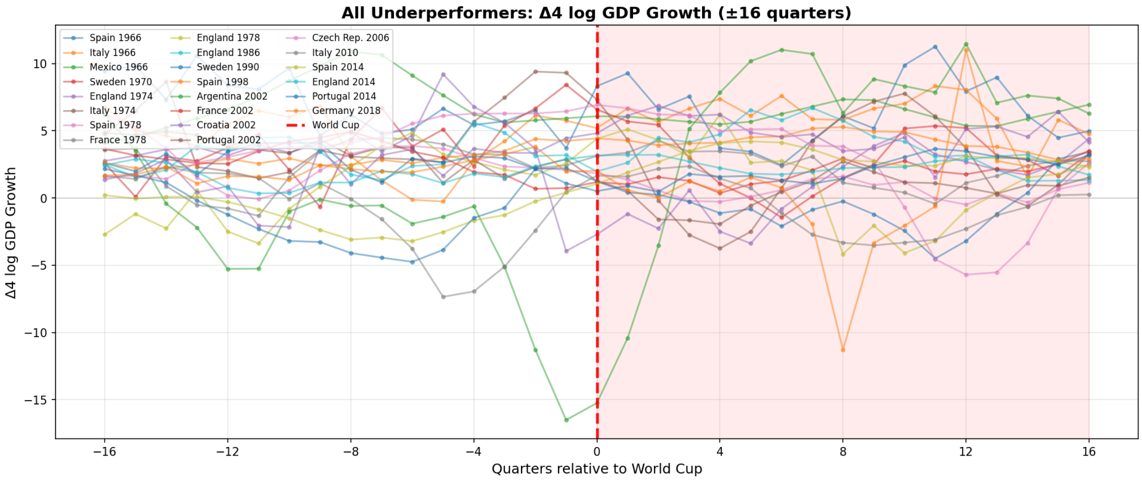


Figure A.5: All underperformers: individual Δ_4 log GDP growth (± 16 quarters)

Notes: Each line represents an individual underperformance event. Dashed vertical line marks the World Cup quarter ($l = 0$). Shaded region: post-treatment window. Treatment = top-10 pre-tournament ELO rating, eliminated in group stage.

A.6 SDiD Component Figures: Underperformers

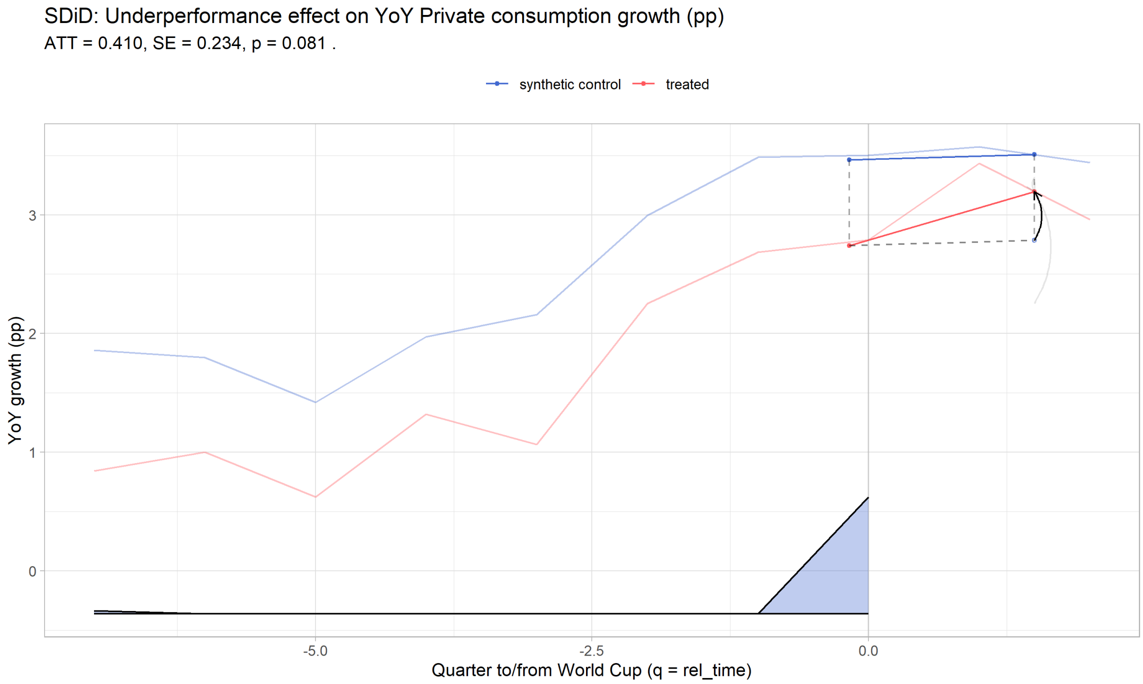


Figure A.6: SDiD: effect of underperformance on private consumption growth

Notes: ATT = 0.410 pp, SE = 0.234 (bootstrap, 1,000 replications), $p = 0.081$. 10 treated, 259 control subseries.

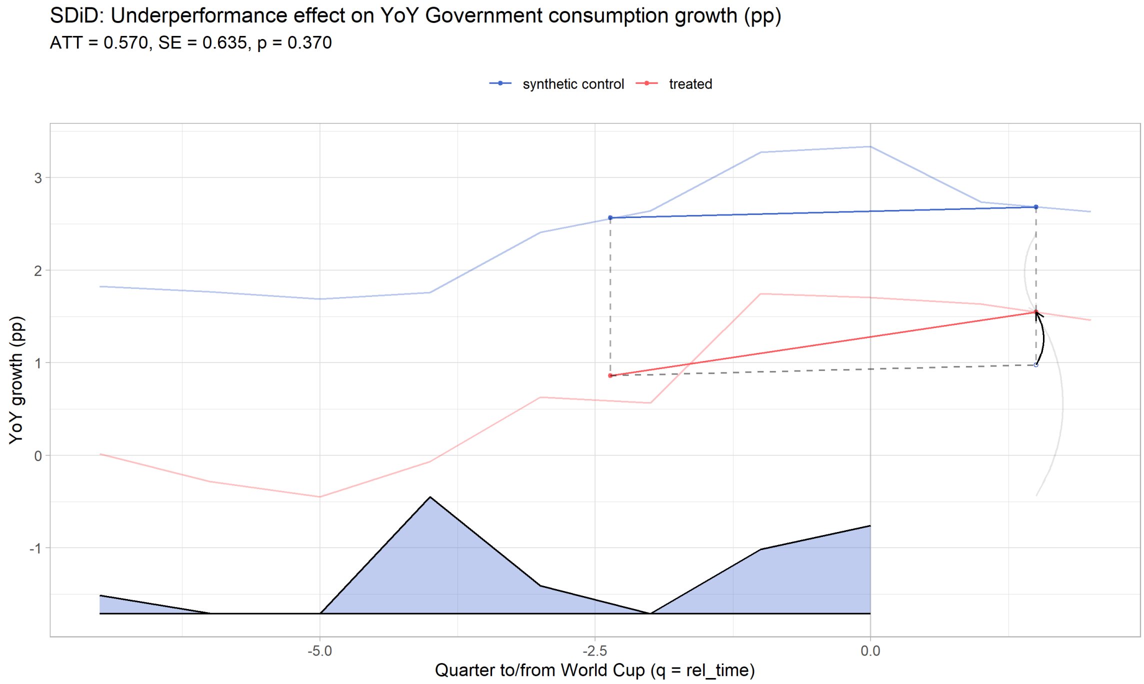


Figure A.7: SDiD: effect of underperformance on government consumption growth

Notes: ATT = 0.570 pp, SE = 0.635 (bootstrap, 1,000 replications), $p = 0.370$. 10 treated, 259 control subseries.

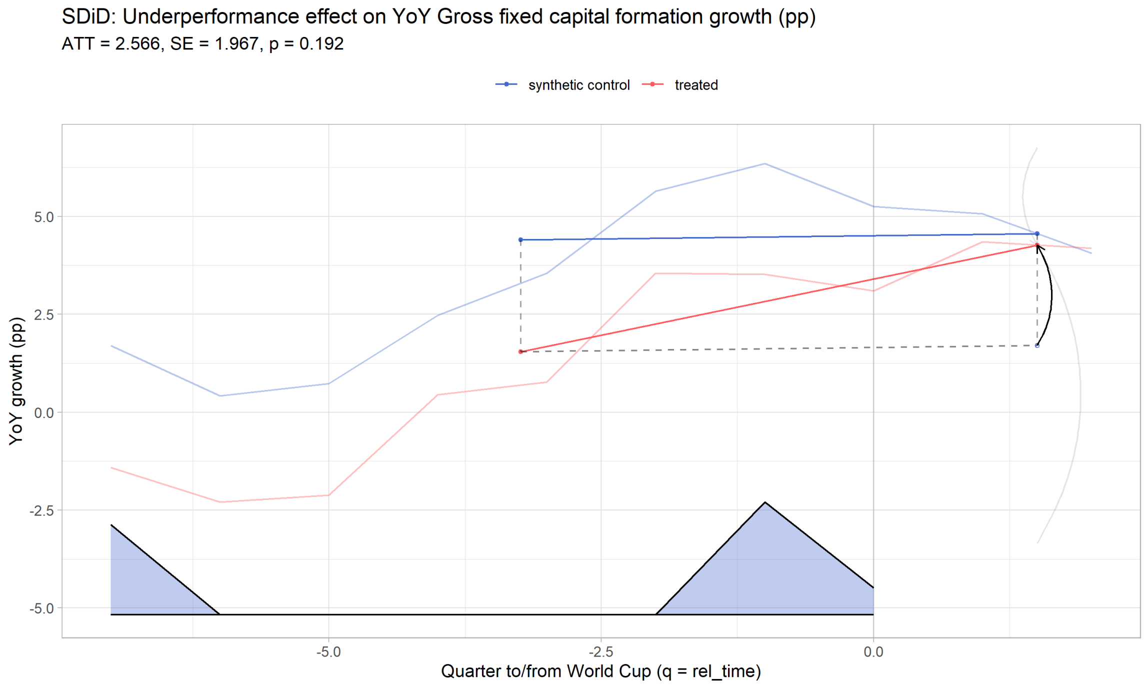


Figure A.8: SDiD: effect of underperformance on capital formation growth

Notes: ATT = 2.566 pp, SE = 1.967 (bootstrap, 1,000 replications), $p = 0.192$. 10 treated, 259 control subseries.

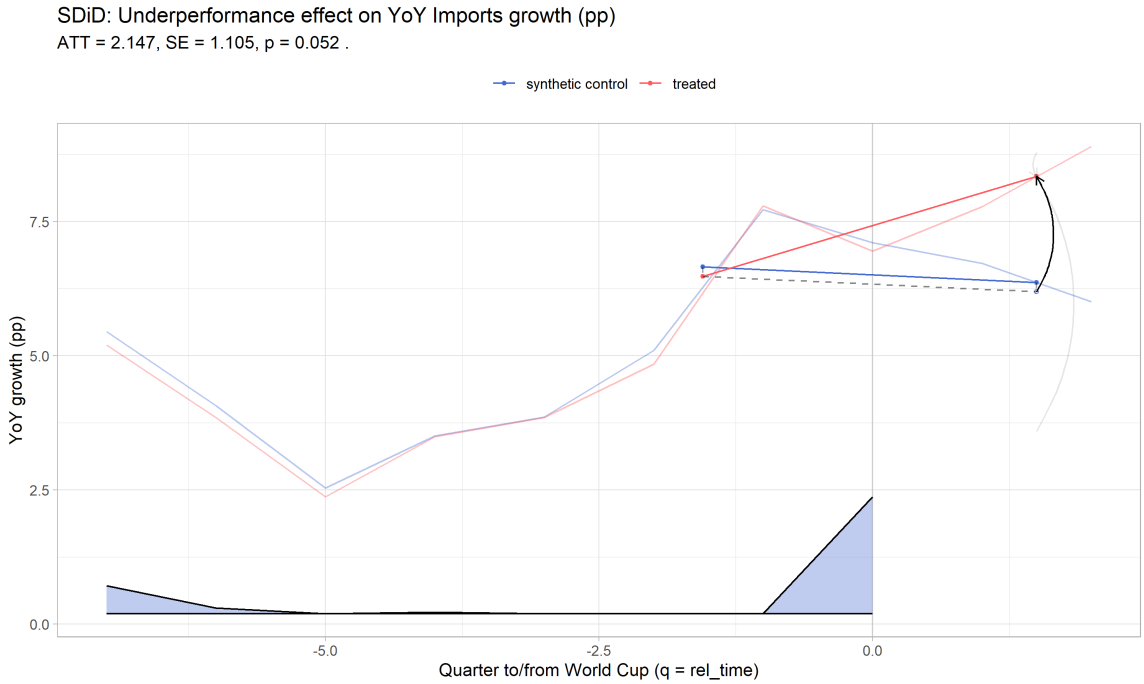


Figure A.9: SDiD: effect of underperformance on import growth

Notes: ATT $= 2.147\,$pp, SE $= 1.105$ (bootstrap, 1,000 replications), $p = 0.052$. 10 treated, 259 control subseries.

A.7 Data Appendix

A.7.1 Variable Definitions

Table A.5: Variable Definitions and Sources

Variable	**Definition and Source**
GDP	Gross Domestic Product, chain-linked volume, rebased, USD PPP converted. Source: OECD QNA (B1_GS1).
Private consumption	Household final consumption expenditure, chain-linked volume, rebased, USD PPP converted. Source: OECD QNA (P31S14_S15).
Gov. consumption	General government final consumption expenditure, chain-linked volume, rebased, USD PPP converted. Source: OECD QNA (P3S13).
Investment	Gross fixed capital formation, chain-linked volume, rebased, USD PPP converted. Source: OECD QNA (P51).
Exports	Exports of goods and services, chain-linked volume, rebased, USD PPP converted. Source: OECD QNA (P6).
Imports	Imports of goods and services, chain-linked volume, rebased, USD PPP converted. Source: OECD QNA (P7).
Population	Total population. Source: OECD annual population statistics, interpolated to quarterly frequency.
Δ_4 ln growth	Year-over-year log growth: $Y_{it} = \ln X_{it} - \ln X_{i,t-4}$. Approximates percentage growth while ensuring additivity of components.
Winner	Indicator for country winning World Cup in quarter t or within ± 16 quarters.
Host	Indicator for country hosting World Cup in year containing quarter t.

A.7.2 World Cup Results 1966-2022

Table A.6: FIFA World Cup Results 1966–2022

Year	Host	Winner	Runner-up	Third Place	Fourth Place
1966	England	England	West Germany	Portugal	Soviet Union
1970	Mexico	Brazil	Italy	West Germany	Uruguay
1974	West Germany	West Germany	Netherlands	Poland	Brazil
1978	Argentina	Argentina	Netherlands	Brazil	Italy
1982	Spain	Italy	West Germany	Poland	France
1986	Mexico	Argentina	West Germany	France	Belgium
1990	Italy	West Germany	Argentina	Italy	England
1994	USA	Brazil	Italy	Sweden	Bulgaria
1998	France	France	Brazil	Croatia	Netherlands
2002	Japan/South Korea	Brazil	Germany	Turkey	South Korea
2006	Germany	Italy	France	Germany	Portugal
2010	South Africa	Spain	Netherlands	Germany	Uruguay
2014	Brazil	Germany	Argentina	Netherlands	Brazil
2018	Russia	France	Croatia	Belgium	England
2022	Qatar	Argentina	France	Croatia	Morocco

A.7.3 Rank Correlation between ELO and FIFA Rankings

Table A.7: Rank correlation between ELO and FIFA rankings among World Cup participants

WC Year	**N teams**	**Spearman ρ**	**Mean |rank diff|**
1994	24	0.70	4.1
1998	32	0.63	6.4
2002	32	0.84	4.2
2006	32	0.85	4.1
2010	32	0.86	3.6
2014	32	0.89	3.3
2018	31	0.90	3.2
2022	31	0.89	3.0

Notes: Rankings are among World Cup participants only. Spearman ρ is the rank correlation between ELO and FIFA pre-tournament rankings. FIFA rankings begin in 1992, so no comparison is available before 1994.

A.7.4 Country Coverage

Table A.8: GDP Country coverage in the event-study sample

Country	**ISO3**	**Period**	**Obs.**
Argentina	ARG	1994-Q1 – 2021-Q4	112
Australia	AUS	1962-Q1 – 2021-Q4	240
Austria	AUT	1962-Q1 – 2021-Q4	240
Belgium	BEL	1962-Q1 – 2021-Q4	240
Bulgaria	BGR	1997-Q1 – 2021-Q4	100
Brazil	BRA	1998-Q2 – 2021-Q4	95
Canada	CAN	1962-Q1 – 2021-Q4	240
Switzerland	CHE	1962-Q1 – 2021-Q4	240
Chile	CHL	1997-Q1 – 2021-Q4	100
Colombia	COL	1995-Q1 – 2021-Q4	108
Costa Rica	CRI	1992-Q1 – 2021-Q4	120
Czechia	CZE	1996-Q1 – 2021-Q4	104
Germany	DEU	1962-Q1 – 2021-Q4	240
Denmark	DNK	1962-Q1 – 2021-Q4	240
Spain	ESP	1962-Q1 – 2021-Q4	240
Estonia	EST	1996-Q1 – 2021-Q4	104
Finland	FIN	1962-Q1 – 2021-Q4	240
France	FRA	1962-Q1 – 2021-Q4	240
United Kingdom	GBR	1962-Q1 – 2021-Q4	240
Greece	GRC	1962-Q1 – 2021-Q4	240
Croatia	HRV	1996-Q1 – 2021-Q4	104
Hungary	HUN	1996-Q1 – 2021-Q4	104
Indonesia	IDN	1991-Q1 – 2021-Q4	124
India	IND	1997-Q2 – 2021-Q4	99
Ireland	IRL	1962-Q1 – 2021-Q4	240
Iceland	ISL	1962-Q1 – 2021-Q4	240
Israel	ISR	1996-Q1 – 2021-Q4	104
Italy	ITA	1962-Q1 – 2021-Q4	240
Japan	JPN	1962-Q1 – 2021-Q4	240
South Korea	KOR	1962-Q1 – 2021-Q4	240
Lithuania	LTU	1996-Q1 – 2021-Q4	104
Luxembourg	LUX	1962-Q1 – 2021-Q4	240
Latvia	LVA	1996-Q1 – 2021-Q4	104
Mexico	MEX	1962-Q1 – 2021-Q4	240
Netherlands	NLD	1962-Q1 – 2021-Q4	240
Norway	NOR	1962-Q1 – 2021-Q4	240
New Zealand	NZL	1962-Q1 – 2021-Q4	240
Poland	POL	1996-Q1 – 2021-Q4	104
Portugal	PRT	1962-Q1 – 2021-Q4	240
Romania	ROU	1996-Q1 – 2021-Q4	104
Russia	RUS	1996-Q1 – 2021-Q3	103

Continued on next page

Table A.8 – *Continued from previous page*

Country	**ISO3**	**Period**	**Obs.**
Saudi Arabia	SAU	2011-Q1 – 2021-Q4	44
Slovakia	SVK	1994-Q1 – 2021-Q4	112
Slovenia	SVN	1997-Q1 – 2021-Q4	100
Sweden	SWE	1962-Q1 – 2021-Q4	240
Turkey	TUR	1962-Q1 – 2021-Q4	240
United States	USA	1962-Q1 – 2021-Q4	240
South Africa	ZAF	1962-Q1 – 2021-Q4	240

Notes: 48 countries. Full-coverage countries (1962-Q1 to 2021-Q4) account for 26 of 48 countries (6,240 of 8,633 observations). Winner countries (BRA, DEU, ESP, FRA, GBR, ITA) contribute 1,295 observations.

B Electronic appendix

Data, code, and figures are provided in electronic form and are available at:
`https://github.com/saiboT-Damaske/The-Effect-of-Winning-a-World-Cup`

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