Replicating and Extending the Economic Impact of Political Shocks in Tunisia

From the Arab Spring to the 2021 Power Seizure

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Abstract

This paper replicates and extends the synthetic control analysis of Matta et al. (2016), who estimate the economic cost of the Arab Spring in Tunisia. Using the Synthetic Control Method, we first reconstruct a counterfactual path for Tunisia's GDP per capita in the absence of the 2011 Arab Spring and assess the extent to which the original findings can be reproduced using updated data. We then extend the analysis to a second major political shock, the July 2021 political changes and subsequent institutional reconfiguration, constructing a new synthetic control for Tunisia over the 2011–2021 pre-treatment period. The results show a clear divergence between actual Tunisia and its synthetic counterfactual following both political shocks. The post-2011 gap indicates a substantial and persistent shortfall in GDP per capita relative to the estimated counterfactual, while the post-2021 estimates point to a further negative divergence that persists through 2025. Placebo tests and post-to-pre-treatment RMSPE ratios indicate that the observed post-treatment divergence is large relative to the pre-treatment fit and is relatively unusual among the placebo donor countries. Overall, the findings suggest that Tunisia's economic performance following major political shocks has been weaker than the corresponding synthetic counterfactual, with the post-2021 period associated with a further divergence from the estimated counterfactual growth path.

Keywords Tunisia, Arab Spring, July 2021 political changes, political instability, GDP per capita, synthetic control method, causal inference.

JEL Classification:
C31, D74, F43, O11, P16.

Contents

1 Introduction

Tunisia experienced two major political breaks over the past fifteen years. The first was the Tunisian Revolution in 2010–2011, which marked the beginning of the Arab Spring and led to substantial changes in the country's political and institutional environment. The second occurred in July 2021, following a period of significant political and institutional change associated with the adoption of exceptional measures and a reconfiguration of executive and legislative arrangements. Both episodes represented important shifts in Tunisia's political environment and were followed by periods of relatively weak economic performance. This raises an important empirical question: to what extent did these political shocks affect Tunisia's economic trajectory relative to what would have occurred in their absence?

Estimating the economic consequences of political events is difficult because the relevant counterfactual is not directly observable. In the case of Tunisia, we cannot observe how GDP per capita would have evolved after 2011 in the absence of the Arab Spring, nor how it would have evolved after 2021 in the absence of the subsequent political and institutional changes. The Synthetic Control Method (SCM) provides a useful framework for addressing this problem. Originally developed by Abadie and Gardeazabal (2003), the method constructs a synthetic version of the treated unit as a weighted combination of untreated units. The weights are selected so that the synthetic control reproduces the characteristics and outcome trajectory of the treated unit during the pre-treatment period. Abadie et al. (2010) formalize this approach and show how it can be used to estimate the effect of an intervention in comparative case studies.

The SCM has subsequently been applied to a wide range of economic and policy questions. Its main advantage in a single-country setting is that it provides an explicit data-driven counterfactual rather than relying only on a parametric comparison group. At the same time, the method requires careful construction of the donor pool and predictor set. In particular, Kaul et al. (2016) discuss the consequences of using all pre-intervention outcomes as predictors and highlight important considerations regarding the specification of synthetic controls.

This paper replicates and extends the analysis of Matta et al. (2016), who use the Synthetic Control Method to estimate the economic impact of the Arab Spring on Tunisia. Their analysis constructs a synthetic Tunisia using a set of countries that were not affected by the Arab Spring and compares the evolution of GDP per capita in actual and synthetic Tunisia after 2010. The synthetic control is constructed using the 1990–2010 pre-treatment period, with the post-treatment comparison covering the years following the Arab Spring. Their results indicate a substantial decline in Tunisian GDP per capita relative to its synthetic counterpart after 2011.

Our first objective is to replicate this analysis. We reconstruct the synthetic control for Tunisia over the pre-2011 period and examine whether the main qualitative result survives in our implementation. Using GDP per capita data from the World Development Indicators (World Bank, 2024a), we reproduce the pre-treatment trajectory of Tunisia and compare it with the estimated synthetic counterfactual after the Arab Spring. The resulting synthetic control is composed primarily of a small number of donor countries with relatively large weights, while the remaining donors receive smaller weights. The resulting post-2011 divergence between actual and synthetic Tunisia is consistent with the negative economic effect identified in the original study.

The second objective is to extend the analysis to the July 2021 political break and the subsequent institutional changes. The extension applies the same synthetic control framework to a second treatment period. We use the post-Arab Spring period as the pre-treatment window and construct a new Synthetic Tunisia based on the country's economic trajectory and characteristics before 2021. This allows us to estimate a counterfactual path for Tunisia after 2021 and assess whether actual GDP per capita subsequently diverged from the trajectory predicted by the synthetic control.

The results show a negative post-treatment gap following both political breaks. For the Arab Spring, actual GDP per capita falls below the synthetic counterfactual after 2010, while the pre-treatment trajectories closely track each other. The estimated donor weights indicate that the counterfactual is concentrated among a limited number of countries, with Belize receiving the largest weight in the post-2011 synthetic control. For the analysis of the July 2021 political changes, actual GDP per capita also falls below the

synthetic counterfactual after 2021. The gap becomes increasingly negative in the subsequent years, suggesting that Tunisia's observed economic trajectory was weaker than that of its estimated counterfactual.

We further assess the credibility of these results using placebo tests. We assign the treatment to donor countries and construct placebo synthetic controls using the same procedure as for Tunisia. For the Arab Spring analysis, Tunisia exhibits a substantially larger post-treatment divergence than most placebo countries. The post-to-pre-treatment RMSPE ratio also places Tunisia near the upper end of the placebo distribution. A similar pattern appears in the analysis of the July 2021 political changes, where Tunisia records a higher post-to-pre-treatment RMSPE ratio than most placebo donor countries. These results suggest that the observed post-treatment gaps are relatively large when compared with both the pre-treatment fit and the gaps obtained for placebo countries.

The analysis should nevertheless be interpreted with the limitations of the Synthetic Control Method in mind. A synthetic control provides a counterfactual based on the observed characteristics and outcomes included in the estimation. It cannot fully account for unobserved factors or country-specific shocks that occur after the treatment. In addition, the identification strategy requires the donor countries to remain unaffected by the treatment and to provide a credible approximation of the treated country's counterfactual trajectory. The results therefore measure the divergence between actual Tunisia and its estimated synthetic counterpart rather than identifying the effect of political events under assumptions that are independent of the synthetic control design.

The contribution of this paper is twofold. First, it provides a replication of the synthetic control analysis of the economic consequences of the Arab Spring in Tunisia. Second, it extends the same empirical framework to the July 2021 political break, allowing the economic trajectories associated with two major political shocks to be studied within a common counterfactual framework. The comparison provides evidence that Tunisia's economic underperformance relative to its synthetic counterfactual was not limited to the period immediately following the Arab Spring, but continued following the second political break in 2021.

The remainder of the paper is organized as follows. Sections 2 and 3 presents the Synthetic Control Method and the data. Section 4 presents the replication of the Arab Spring analysis. Section 5 presents the extension to the July 2021 political changes. Section 6 reports the placebo and robustness tests. Section 7 concludes.

2 The Original Study: Matta et al. (2016)

2.1 The Synthetic Control Method

The Synthetic Control Method (SCM) provides a framework for estimating the effect of a major intervention or shock when only one unit is exposed to the treatment. The method was introduced by Abadie and Gardeazabal (2003) and subsequently developed by Abadie et al. (2010). It is particularly useful in comparative case studies where traditional regression-based methods may provide a less convincing counterfactual.

The central problem is straightforward. Suppose that a country experiences a political shock at time T_0. We observe the country's outcome before and after the shock, but we cannot observe what would have happened to the same country after T_0 if the shock had not occurred. This unobserved outcome is the relevant counterfactual. The Synthetic Control Method estimates it by constructing a weighted average of other countries that were not exposed to the treatment.

Let Tunisia denote the treated country and let R denote a set of potential donor countries. For each donor country $r \in R$, let Y_{rt} denote the outcome of interest at time t, in this case GDP per capita. A synthetic Tunisia is constructed as a weighted average of the donor countries:

$$Y_t^{SC} = \sum_{r=1}^{R} w_r Y_{rt}, \tag{1}$$

where the weights satisfy

$$w_r \geq 0 \qquad \text{and} \qquad \sum_{r=1}^{R} w_r = 1. \tag{2}$$

The weights therefore define a convex combination of the donor countries. Each possible vector of weights $W = (w_1, \ldots, w_R)$ generates a different synthetic control. The objective is to select the vector of weights that makes synthetic Tunisia as similar as possible to actual Tunisia before the treatment.

The pre-treatment matching concerns both the outcome of interest and a set of economic and social characteristics. Let X_1 denote a vector of pre-treatment characteristics for Tunisia and X_0 the corresponding matrix for the donor countries. The optimal weights are chosen to minimize the discrepancy between Tunisia and its synthetic counterpart:

$$W^* = \arg\min_{W} \left(X_1 - X_0 W\right)' V \left(X_1 - X_0 W\right), \tag{3}$$

subject to the non-negativity and adding-up restrictions on the weights. The matrix V determines the relative importance assigned to the different predictors.

The intuition is important. The objective is not to find a single country that looks like Tunisia. Instead, SCM combines several countries, potentially assigning a large weight to some countries and a zero weight to others. The resulting weighted average is designed to reproduce Tunisia's pre-treatment economic trajectory and relevant characteristics. If the synthetic control provides a close approximation to actual Tunisia before the shock, the subsequent divergence between the two series can be interpreted as evidence about the effect of the treatment.

For Tunisia, the treatment effect at time t can therefore be expressed as

$$\widehat{\tau}_t = Y_t^{Tunisia} - Y_t^{SC}, \qquad t > T_0. \tag{4}$$

A negative value means that actual Tunisia performed below its synthetic counterpart after the treatment. In the context of this paper, this corresponds to GDP per capita being lower than the estimated counterfactual path in the absence of the political shock.

An important feature of SCM is that inference does not rely primarily on conventional regression standard errors. Instead, researchers commonly use placebo or falsification tests. The treatment is artificially reassigned to countries that were not exposed to the shock, and the same synthetic control procedure is repeated for these placebo units. The post-treatment divergence observed for Tunisia can then be compared with the distribution of divergences obtained for the placebo countries. Matta et al. (2016) follow this approach in their analysis of the Arab Spring.

The quality of the pre-treatment fit is also important when interpreting these placebo comparisons. A large post-treatment gap is less informative if the synthetic control already fits the treated country poorly before the intervention. For this reason, SCM applications often compare the magnitude of the post-treatment discrepancy relative to the pre-treatment discrepancy. This provides a way of distinguishing an unusually large post-treatment divergence from a country for which the synthetic control was simply a poor fit from the beginning.

Finally, the credibility of the SCM estimates depends on several assumptions. The donor countries should not themselves be affected by the treatment, and the synthetic control should provide a credible approximation of the treated country in the absence of the shock. The method also relies on the assumption that relevant differences between the treated unit and its synthetic counterpart can be captured by the observed predictors and pre-treatment outcomes. These assumptions are important in the Tunisian application because several countries may have experienced indirect consequences of the Arab Spring or other shocks during the post-treatment period.

2.2 The Impact of the Arab Spring on Tunisia

Matta et al. (2016) apply the Synthetic Control Method to estimate the macroeconomic cost of the Arab Spring in Tunisia. Their motivation is that, despite the major political and economic importance of the

Arab Spring, there was limited quantitative evidence on its aggregate economic consequences. Tunisia provides a particularly suitable case for a synthetic control analysis because the country experienced a relatively clearly defined political shock in 2010–2011, while GDP per capita and other economic indicators are available for a relatively long pre-treatment period.

The treatment is defined as the Tunisian Revolution and the beginning of the Arab Spring in 2011. The authors use annual data covering Tunisia and a large set of potential donor countries from 1990 to 2013. The pre-treatment period extends from 1990 to 2010, while the post-treatment period covers 2011–2013. The outcome of interest is GDP per capita measured in purchasing power parity terms. The Synthetic Control Method is used to construct a counterfactual path for Tunisian GDP per capita representing the trajectory that Tunisia might have followed in the absence of the Arab Spring. Matta et al. (2016) describe this synthetic country as "Synthetic Tunisia."

A key feature of their donor-pool construction is that they do not restrict the potential controls to countries in the Middle East and North Africa. Although countries from the region might appear attractive because of their geographic and cultural similarity to Tunisia, many of them were themselves affected directly or indirectly by the Arab Spring. The authors therefore use a global pool of potential controls and remove countries that experienced important shocks during the post-2010 period. Their final donor pool contains 114 countries. Matta et al. (2016) argue that the global donor pool also makes it easier to obtain countries with GDP per capita levels comparable to Tunisia.

The predictors are selected to reproduce both Tunisia's economic structure and its development characteristics before the Arab Spring. The authors include measures of the composition of expenditure, namely consumption, investment, imports, and exports, as well as the composition of production through agriculture, industry, and services. They also include life expectancy at birth and secondary school enrollment as indicators of human development. These variables are obtained from the World Development Indicators. Matta et al. (2016) use averages over 1990–2000 and 2001–2010 for most economic variables. This allows the synthetic control to reproduce not only the average level of these variables but also some of their evolution over the pre-treatment period.

To obtain a close match in GDP per capita, the authors additionally include four averages of GDP per capita corresponding to 1990–1994, 1995–1999, 2000–2004, and 2005–2010. This specification produces a particularly close pre-treatment match between Tunisia and its synthetic counterpart. The authors also discuss the importance of not mechanically including every lag of the outcome as a predictor, referring to the methodological concern raised by Kaul et al. (2016).

The resulting Synthetic Tunisia is composed of 14 countries with positive weights. The largest weights are assigned to Belize, Mauritius, India, Sri Lanka, the Republic of Congo, and Poland. Belize receives the largest weight at 19.7 percent, followed by Mauritius with 17.5 percent and India with 16.4 percent. Sri Lanka receives 10.3 percent, the Republic of Congo 8.7 percent, and Poland 8.1 percent. The remaining countries receive substantially smaller weights. This composition illustrates the main feature of SCM: the counterfactual does not correspond to any individual country, but to a weighted combination of countries that collectively reproduce the characteristics of Tunisia before the treatment.

The resulting synthetic control closely reproduces Tunisia's pre-2011 economic trajectory. For example, the average GDP per capita of Tunisia and Synthetic Tunisia is almost identical in each of the four pre-treatment periods used by the authors. The same is true for several structural characteristics. The synthetic control also approximates Tunisia in terms of investment, consumption, imports, exports, agriculture, services, life expectancy, and secondary school enrollment. In contrast, the simple average of the 114 potential donor countries differs substantially from Tunisia. This provides evidence that the SCM optimization successfully selects a combination of countries that is much more comparable to Tunisia than an unweighted donor average. (Matta et al., 2016)

The central result emerges after 2010. Before the Arab Spring, actual Tunisia and Synthetic Tunisia follow very similar paths. After 2010, however, the two series diverge, with actual Tunisian GDP per capita remaining below its synthetic counterpart. Matta et al. (2016) estimate that GDP per capita was approximately US$600 lower than the synthetic counterfactual in 2011, corresponding to a loss of 5.5 percent. The estimated gap was US$574, or 5.1 percent, in 2012 and increased to approximately US$735,

or 6.4 percent, in 2013. Thus, the largest immediate deterioration occurred in 2011, while Tunisia did not subsequently recover the gap relative to its synthetic counterfactual. (Matta et al., 2016)

The authors interpret these results as evidence that the Arab Spring generated a substantial negative effect on Tunisia's aggregate economic performance. Importantly, the estimated effect is not simply a decline in GDP relative to the previous year. It is a decline relative to the estimated counterfactual trajectory of Synthetic Tunisia. The distinction is important because Tunisia's economy could continue to grow while still performing substantially worse than it would have in the absence of the shock.

2.3 Robustness and Interpretation of the Original Results

Because the Synthetic Control Method is not a conventional regression estimator, Matta et al. (2016) do not rely on standard regression-based p-values to assess the significance of their main estimates. Instead, they conduct a series of placebo and sensitivity tests.

First, they perform placebo tests by applying the SCM procedure to the 114 donor countries and treating each country as if it had experienced the Arab Spring in 2011. The resulting placebo gaps provide a reference distribution against which the Tunisian gap can be evaluated. The authors note that the placebo gaps are heterogeneous, partly because some countries are not well reproduced by their synthetic controls during the pre-treatment period. They therefore normalize the post-treatment gap by the pre-treatment fit and compare the resulting ratios across countries. This allows them to distinguish a large treatment-period gap from a generally poor synthetic-control fit. (Matta et al., 2016)

Second, the authors conduct a series of sensitivity analyses. They sequentially remove countries receiving positive weights from the baseline synthetic control and reconstruct Synthetic Tunisia. The resulting synthetic trajectories remain close to the baseline specification, suggesting that the main result is not driven by one particular donor country. They also conduct time-series placebo tests by assigning fictitious treatment dates before the actual Arab Spring. In particular, they repeat the analysis using 2000 as a placebo treatment date and find no comparable divergence between Tunisia and its synthetic counterpart after the fictitious shock. (Matta et al., 2016)

The authors also examine whether the results depend on the choice of predictors. They add institutional variables and later introduce net fuel exports and ores and metal exports to the baseline specification. These modifications change the composition of the synthetic control to some extent but leave the main post-2011 divergence broadly unchanged. This is particularly relevant given the importance of oil prices and the mining sector during the period. (Matta et al., 2016)

Finally, Matta et al. (2016) compare the SCM results with an alternative Autoregressive Distributed Lag model. The regression results indicate that GDP per capita growth fell by approximately 5.8 percent in 2011, with the 2011 effect statistically significant. The magnitude is close to the decline estimated using the synthetic control approach. The authors therefore conclude that the two empirical approaches provide broadly consistent evidence that the largest immediate economic impact occurred in 2011 and that Tunisia did not subsequently catch up with its synthetic counterfactual. (Matta et al., 2016)

The paper also investigates the mechanism behind the aggregate GDP loss. Using separate synthetic-control analyses for investment, consumption, and net exports, the authors identify investment as the main channel. Actual investment as a share of GDP fell substantially below its synthetic counterpart after 2011. They estimate that investment was approximately 3.9 percentage points of GDP below its counterfactual on average over 2011–2013. Net exports also deteriorated relative to the counterfactual, while consumption did not exhibit a comparable deterioration. The authors associate the investment decline primarily with increased political and economic uncertainty, which may have encouraged firms and investors to postpone investment decisions. (Matta et al., 2016)

Overall, the original study provides a clear empirical benchmark for the analysis developed in this paper. Its main finding is that the Arab Spring was associated with a substantial and persistent gap between Tunisia's actual GDP per capita and the GDP per capita of a carefully constructed synthetic counterfactual. The estimated loss reached 5.5 percent in 2011, 5.1 percent in 2012, and 6.4 percent in 2013. The placebo, sensitivity, predictor-specification, and alternative-regression exercises all support the

broad conclusion, although the authors acknowledge that SCM cannot completely eliminate concerns about unobserved factors and country-specific shocks. (Matta et al., 2016)

This original framework provides the basis for the replication conducted in the next section and, subsequently, for extending the analysis to the July 2021 political break.

3 Data and Methods

3.1 Data Construction and Sources

The empirical analysis follows as closely as possible the data construction and variable definitions of Matta et al. (2016). The objective is to reproduce the original empirical exercise using a newly constructed dataset rather than relying directly on the data files used in the original study. This approach allows us to verify the reproducibility of the original results and provides a consistent dataset that can subsequently be used for the extension of the analysis.

The main source of macroeconomic and socioeconomic indicators is the World Bank's World Development Indicators (WDI) database. Whenever possible, the data were retrieved programmatically through the World Bank API. Using the API allows the data collection process to be reproducible and considerably reduces the risk of transcription errors associated with manually downloading and entering observations. The indicators were retrieved for Tunisia and the potential donor countries over the period required by the empirical analysis, with particular attention to the 1990–2013 period used in the original study.

The variables were constructed following the definitions reported by Matta et al. (2016). The dataset includes GDP per capita and the economic and social characteristics used to construct the synthetic control. These include consumption, gross capital formation, imports, exports, agricultural value added, industrial value added, services value added, life expectancy, and secondary school enrollment. The corresponding variables are transformed into the same ratios, averages, and time periods used in the original specification whenever the underlying data allow for an exact replication.

A particular difficulty concerns the governance indicators. The governance data used in the analysis were not available through the relevant API in a form that allowed us to retrieve the required historical observations directly. We therefore downloaded these data manually from the original data source and incorporated them into the replication dataset. This is the only major component of the dataset for which the data collection process could not be fully automated through an API. The manually downloaded data were subsequently processed using the same country identifiers, years, and variable definitions as the rest of the dataset.

This procedure is important for the reproducibility of the analysis. The complete R code used to construct the dataset and reproduce the empirical results is made available together with the underlying data. This allows the reader to inspect the complete data pipeline, from the initial data retrieval to the final estimation of the synthetic control. In particular, the code documents the API requests, data cleaning procedures, variable transformations, donor-pool construction, and estimation steps.

3.2 Construction of the Synthetic Control Model

After constructing the replication dataset, we follow the empirical strategy of Matta et al. (2016) as closely as possible. Tunisia is defined as the treated unit, while the donor pool consists of countries that were not directly or indirectly exposed to the Arab Spring or other major shocks that could contaminate the counterfactual during the post-treatment period.

The treatment period is defined as 2011, corresponding to the Tunisian Revolution and the beginning of the Arab Spring. The pre-treatment period therefore covers 1990–2010, while the post-treatment period covers 2011–2025. This follows the original study and allows the replication to reproduce the same treatment timing and time horizon.

The synthetic control is constructed as a weighted average of the countries in the donor pool. Let Y_{it} denote GDP per capita for country i in year t. The counterfactual GDP per capita for Tunisia is given by

$$Y^{SC}_{Tunisia,t} = \sum_{j=1}^{J} w_j Y_{jt}, \tag{5}$$

where J is the number of countries in the donor pool and the weights satisfy

$$w_j \geq 0, \qquad \sum_{j=1}^{J} w_j = 1. \tag{6}$$

The vector of weights is selected using only information available before the Arab Spring. Following Matta et al. (2016), the optimization procedure seeks to make Synthetic Tunisia as similar as possible to actual Tunisia during the pre-treatment period, both in terms of GDP per capita and the economic and social characteristics used as predictors.

The predictor set follows the original study. In particular, the model incorporates measures of the structure of the economy, including consumption, investment, imports, exports, agriculture, industry, and services, together with life expectancy and secondary school enrollment. The construction also uses GDP per capita averages over several sub-periods of the pre-treatment period. These variables are intended to ensure that the synthetic control reproduces not only the level of GDP per capita but also the broader economic structure and development characteristics of Tunisia before 2011.

The optimal vector of weights is obtained by minimizing the distance between Tunisia and its synthetic counterpart over the pre-treatment period. Once the weights have been estimated, they are kept fixed during the post-treatment period. The resulting synthetic series therefore represents the estimated path that Tunisia would have followed in the absence of the Arab Spring, conditional on the information used to construct the counterfactual.

The estimated effect of the treatment is then calculated as the gap between actual Tunisia and Synthetic Tunisia:

$$\widehat{\tau}_t = Y_{Tunisia,t} - Y^{SC}_{Tunisia,t}, \qquad t = 2011, \ldots, 2025. \tag{7}$$

A negative value of $\widehat{\tau}_t$ indicates that actual Tunisian GDP per capita was below its estimated counterfactual level. We also report the proportional gap between the two series in order to facilitate comparison across years and with the estimates reported by Matta et al. (2016).

The empirical implementation is conducted entirely in R. The code reproduces the different stages of the analysis, including data preparation, construction of the donor pool, estimation of the synthetic control weights, calculation of the counterfactual GDP per capita series, and construction of the treatment-effect estimates. The same framework is subsequently used for the additional analyses presented in this paper.

An important objective of this procedure is to distinguish the replication of the original methodology from the extensions introduced later in the paper. The baseline model is therefore constructed to reproduce the original study as closely as possible. Any subsequent modifications to the donor pool, predictor set, treatment period, or outcome are explicitly identified as extensions rather than being incorporated into the baseline replication.

4 Replication Results: The Arab Spring

4.1 Reconstructing Synthetic Tunisia

We begin by reconstructing the Synthetic Tunisia used to evaluate the economic consequences of the Arab Spring. The estimation follows the methodology described in Matta et al. (2016), while using the updated dataset constructed for this replication. Tunisia is treated as the exposed unit from 2011 onward, and the synthetic control is estimated using information from the 1990–2010 pre-treatment period.

Table 1 reports the estimated donor weights. The composition of our Synthetic Tunisia differs from that reported by Matta et al. (2016). In our estimates, Mauritius, Peru, Vietnam, Sri Lanka, and Belize account for a large share of the total weight, whereas Poland and India, which received substantial weights in the

original study, receive weights close to zero in the replication. These differences are not necessarily evidence of a different economic mechanism. They reflect, in part, differences in the underlying GDP data. The original study uses GDP series expressed in 2011 purchasing power parity (PPP), whereas our replication uses the updated 2021 PPP series. Revisions to historical GDP levels and the corresponding changes in the data vintage can alter the relative pre-treatment trajectories of donor countries. As a result, the countries providing the closest match to Tunisia before the treatment period can also change, leading to different estimated donor weights.

Despite these differences in composition, the quality of the pre-treatment match remains strong. Table 2 compares Tunisia with its synthetic counterpart across the main predictors. GDP per capita is reproduced particularly closely in both pre-treatment sub-periods, with average GDP per capita of approximately $7.74 thousand for Tunisia and $7.75 thousand for Synthetic Tunisia over 1990–2000, and $10.86 thousand and $10.88 thousand respectively over 2001–2010. The synthetic control also provides a close approximation for several structural characteristics, including investment, trade openness, and the sectoral composition of output. Overall, the results indicate that the new donor weights provide a satisfactory pre-treatment counterfactual despite the changes relative to the original study.

Table 1: Country Weights in the Synthetic Tunisia (Arab Spring)

Country	Weight (%)
Mauritius	31.64
Peru	16.72
Viet Nam	16.14
Sri Lanka	14.19
Belize	9.48
El Salvador	4.42
Indonesia	3.21
Ecuador	1.53
Congo, Rep.	1.13
Tajikistan	0.55
Malaysia	0.17
India	0.11
Paraguay	0.11
Togo	0.06

Note: Donor countries assigned a non-trivial weight (at least 0.05%) in the baseline Arab Spring synthetic control, fit on 1990-2010.

Table 2: Averages of Economic and Social Characteristics of GDP (Arab Spring)

Predictor	Treated	Synthetic	Sample Mean
gcf_9000	25.98	25.00	22.48
gcf_0110	24.11	24.55	24.16
cons_9000	78.13	78.01	81.94
cons_0110	78.68	78.61	79.98
imp_9000	45.12	44.97	40.86
imp_0110	48.40	48.87	45.81
exp_9000	41.02	40.33	34.92
exp_0110	45.60	44.65	41.42
agr_9000	13.03	15.09	15.38
agr_0110	8.72	9.84	11.27
serv_9000	46.94	49.46	49.60
serv_0110	55.73	53.60	52.41
life_exp	72.22	70.32	67.84
sec_enroll	68.67	70.81	72.93
special.gdp_pc_ppp_k.1990.2000	7.74	7.75	18.57
special.gdp_pc_ppp_k.2001.2010	10.86	10.88	23.21

Note: Tunisia vs. Synthetic Tunisia vs. simple average of the donor pool, pre-2011.

4.2 The Post-2011 Economic Gap

Figure 1 plots actual GDP per capita in Tunisia against the reconstructed Synthetic Tunisia from 1990 to 2025. The two series are closely aligned throughout the pre-treatment period, providing visual evidence of the quality of the counterfactual. Following 2011, however, the two trajectories diverge, with actual Tunisia remaining below its synthetic counterpart.

This pattern reproduces the central qualitative finding of Matta et al. (2016). The Arab Spring is followed by a persistent gap between the observed Tunisian trajectory and the estimated counterfactual. The difference between the two series is already visible in 2011 and becomes larger over subsequent years.

Our results also indicate that the divergence extends substantially beyond the three-year post-treatment window considered in the original study. While Matta et al. (2016) estimate GDP per capita losses of 5.5 percent in 2011, 5.1 percent in 2012, and 6.4 percent in 2013, our extended series shows that the gap does not close after 2013. Instead, the difference between actual and synthetic Tunisia remains persistent over the subsequent period and continues through 2025.

To make the replication directly comparable with the original study, Table 3 restricts the analysis to the 2011–2013 period. The comparison shows that the sign of the estimated effect is unchanged and that the magnitude remains of the same general order as the original estimates. At the same time, our estimates display a somewhat faster widening of the gap over the three-year period. This difference should be interpreted in light of the revised data and the resulting changes in the composition of the synthetic control.

Table 3: Comparison to the Paper's Published Estimates (2011–2013 window only)

Year	This replication (%)	Paper's published loss (%)	Difference (pp)
2011	-9.57	-5.50	-4.07
2012	-10.46	-5.10	-5.36
2013	-12.74	-6.40	-6.34

Note: Paper's published loss: 5.5% (2011), 5.1% (2012), 6.4% (2013) of Synthetic Tunisia's GDP per capita. Caveat: current WDI data is PPP-based on 2021 international $ (paper used 2011 international $) and historical GDP series have since been revised, so exact magnitudes are not expected to match; this table checks whether the sign and rough scale of the paper's result hold up under current data.

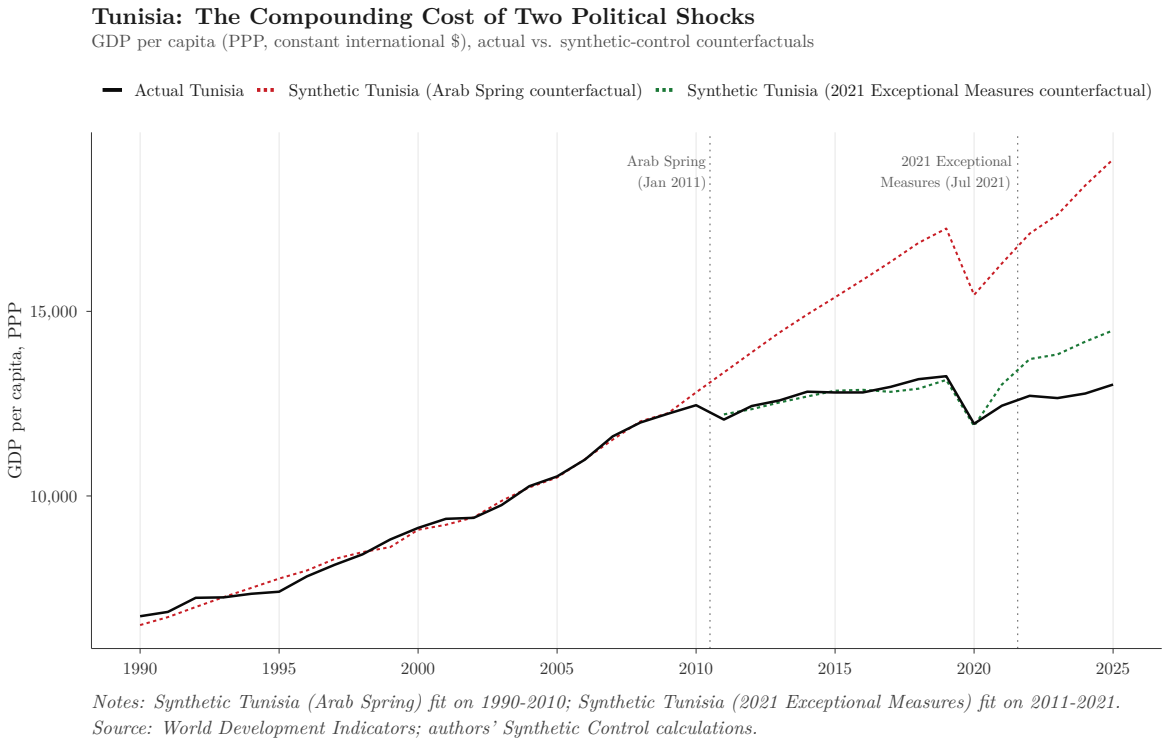

Figure 1: The Compounding Cost of Two Political Shocks in Tunisia

5 Extension: The July 2021 Political Changes

The Arab Spring counterfactual estimated using the 1990–2010 pre-treatment period cannot separately identify the economic consequences of later political events. Once the synthetic control has been constructed using the pre-2011 trajectory, the counterfactual provides a benchmark for what Tunisia's GDP per capita might have looked like in the absence of the Arab Spring, but it cannot distinguish between the effects of the 2011 shock and those of subsequent political or economic events.

This limitation becomes particularly relevant after July 2021, when Tunisia entered a new phase of political and institutional change associated with the adoption of exceptional measures. To study this second political break separately, we construct an independent synthetic control using Tunisia's post-Arab-Spring trajectory as the relevant pre-treatment period. The model is therefore estimated over 2011–2021, with 2021 treated as the final pre-treatment year and the July 2021 political changes marking the beginning of the treatment period.

This second specification answers a different counterfactual question. Rather than asking how Tunisia would have performed in the absence of the Arab Spring, it asks how Tunisia might have evolved after 2021

had the July 2021 political break not occurred, conditional on the economic trajectory observed between 2011 and 2021.

The shorter donor-pool period requires additional exclusions. Several potential donor countries experienced major political, institutional, or economic shocks around the treatment period that could compromise their suitability as controls. We therefore exclude Sri Lanka following its 2022 sovereign default and economic crisis, Peru following the political crisis surrounding the removal of President Pedro Castillo, Niger following the July 2023 military coup, Myanmar following the February 2021 military coup, Afghanistan following the Taliban takeover in August 2021, Ethiopia following the Tigray conflict, Haiti following the severe political and institutional crisis beginning in 2021, Belarus following its political crisis and subsequent sanctions, Kazakhstan following the January 2022 unrest, and Ecuador following its security and energy crises during 2022–2024. The exclusion principle follows the logic used by Matta et al. (2016): countries experiencing major contemporaneous shocks that could affect the outcome independently of the treatment should not be used to construct the counterfactual.

Table **??** reports the donor weights obtained from this second synthetic control. The resulting counterfactual provides a close approximation to Tunisia during the 2011–2021 pre-treatment period.

Figure 1 presents both counterfactuals simultaneously. The Arab Spring Synthetic Tunisia provides the long-run benchmark beginning in 2011, while the second synthetic control provides the counterfactual specifically associated with the 2021 political break. The second synthetic control follows actual Tunisia closely up to the treatment period and subsequently diverges from it. The timing of this second divergence is consistent with the July 2021 political break.

Taken together, the two counterfactuals provide evidence of two distinct periods of divergence. The first begins after the Arab Spring, while the second emerges after the July 2021 political break. The results therefore suggest that the economic underperformance associated with the post-2011 period cannot be treated as a single uninterrupted effect. The 2021 political break is associated with an additional divergence between actual Tunisia and the counterfactual constructed from its pre-2021 trajectory.

The two synthetic controls should nevertheless be interpreted as answering different counterfactual questions. The first estimates the trajectory of Tunisia in the absence of the Arab Spring, while the second estimates the trajectory in the absence of the July 2021 political break conditional on the post-2011 experience. The difference between the two counterfactuals therefore should not be interpreted mechanically as two independent causal effects that can simply be added together. Instead, they provide complementary evidence on the economic consequences associated with two separate political shocks.

6 Robustness Checks and Methodological Choices

6.1 Leave-one-out Analysis

Following the robustness strategy of Matta et al. (2016), we conduct leave-one-out exercises to assess whether the estimated Arab Spring effect depends disproportionately on a particular donor country. We re-estimate the synthetic control after sequentially removing each of the countries receiving positive weights in the baseline specification.

The resulting counterfactual trajectories remain close to the baseline Synthetic Tunisia throughout the post-treatment period. The main divergence between actual and synthetic Tunisia therefore does not disappear when individual donor countries are excluded. This suggests that the baseline result is not driven by a single country in the donor pool.

6.2 In-Space Placebo Tests

We next conduct in-space placebo tests by applying the same synthetic control procedure to the countries in the donor pool. Each eligible donor country is treated as if it had experienced the political shock at the same time as Tunisia. The resulting placebo gaps are then compared with the gap estimated for Tunisia.

Figures 2 and 3 present the placebo gaps for the Arab Spring and July 2021 analyses, respectively. In both exercises, Tunisia exhibits a large and persistent post-treatment divergence relative to the placebo countries.

To account for differences in pre-treatment fit, we also compare the post-treatment RMSPE with the pre-treatment RMSPE. This produces the post-to-pre-treatment RMSPE ratio used in the SCM literature and discussed by Abadie et al. (2010). A higher ratio indicates that the post-treatment divergence is large relative to the discrepancy already present during the pre-treatment period.

For the Arab Spring analysis, Tunisia has a post-to-pre-treatment RMSPE ratio of 22.79, the highest among the 22 units included in the placebo exercise. Estonia ranks second with a ratio of 12.09, followed by Chile with 8.02. The separation between Tunisia and the other placebo units is therefore substantial.

For the July 2021 political changes, Tunisia also records the highest RMSPE ratio among the 13 units included in the placebo exercise, with a value of 6.10. Sweden follows with 5.75, while Finland and Albania record ratios of 5.06 and 4.47, respectively.

These placebo results indicate that the post-treatment divergence observed for Tunisia is unusually large relative to the pre-treatment fit and relative to the divergences obtained for the placebo countries. They therefore provide additional support for the interpretation of the main results, while remaining subject to the assumptions underlying synthetic control inference.

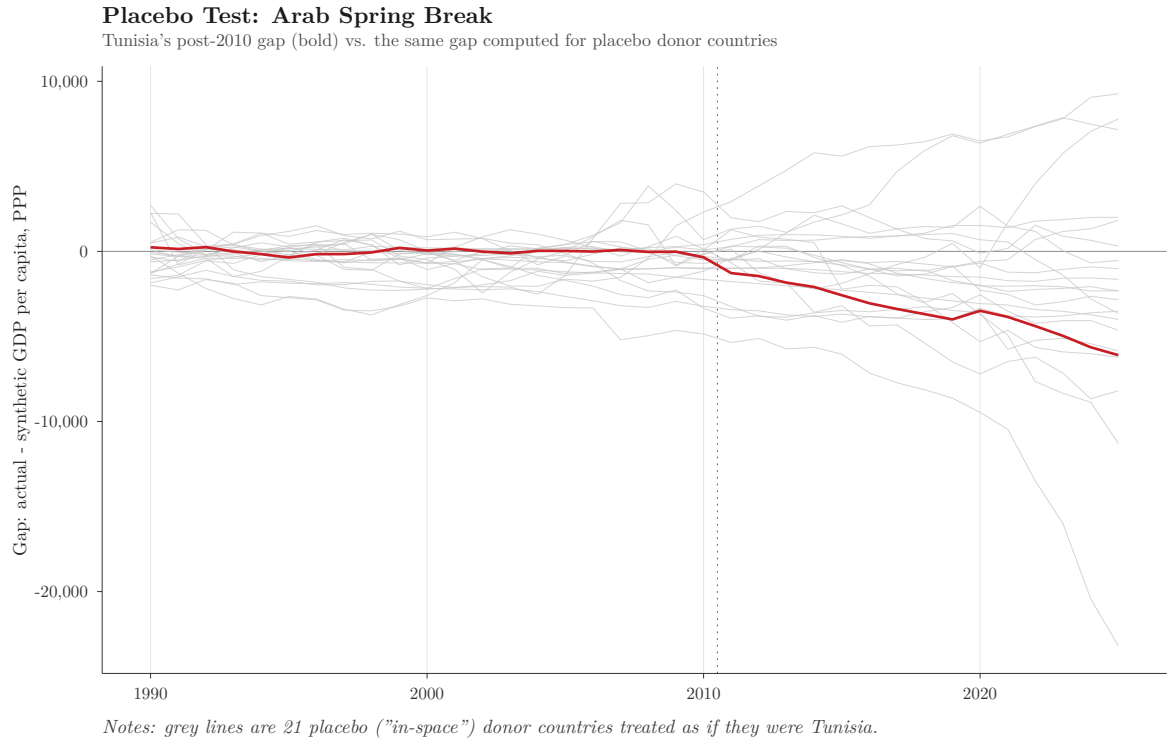

Figure 2: Placebo Test for the Arab Spring Break

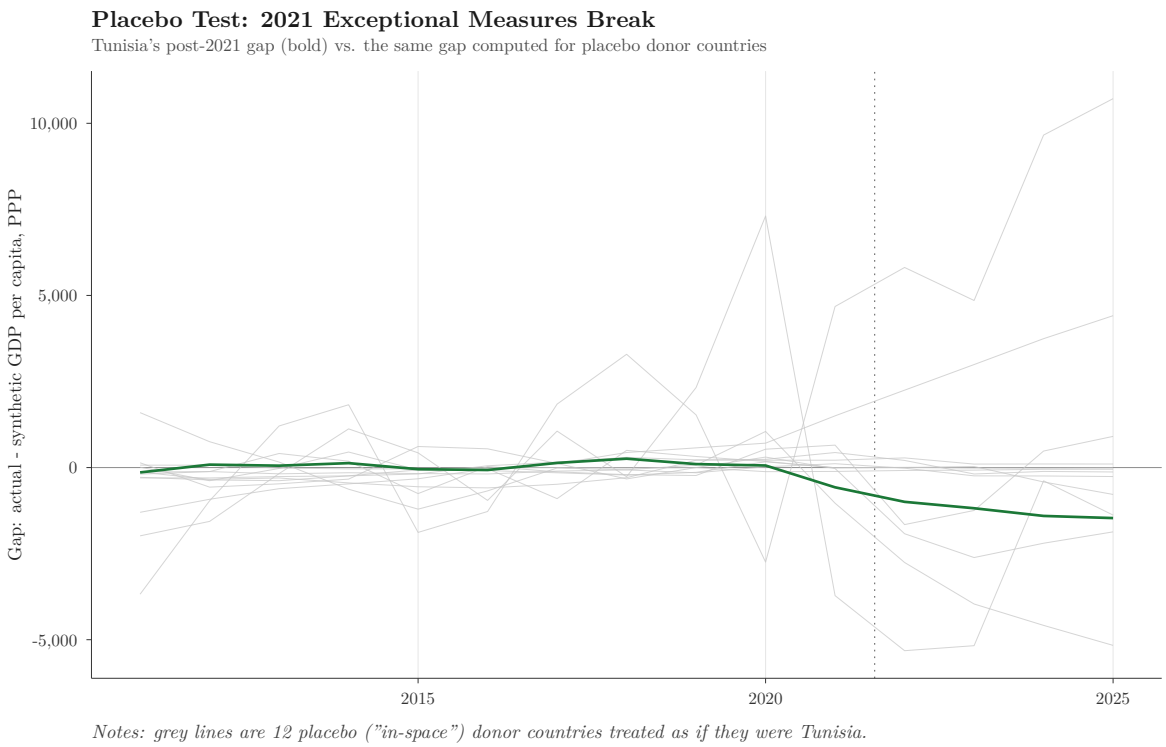

Figure 3: Placebo Test for the July 2021 Power Seizure

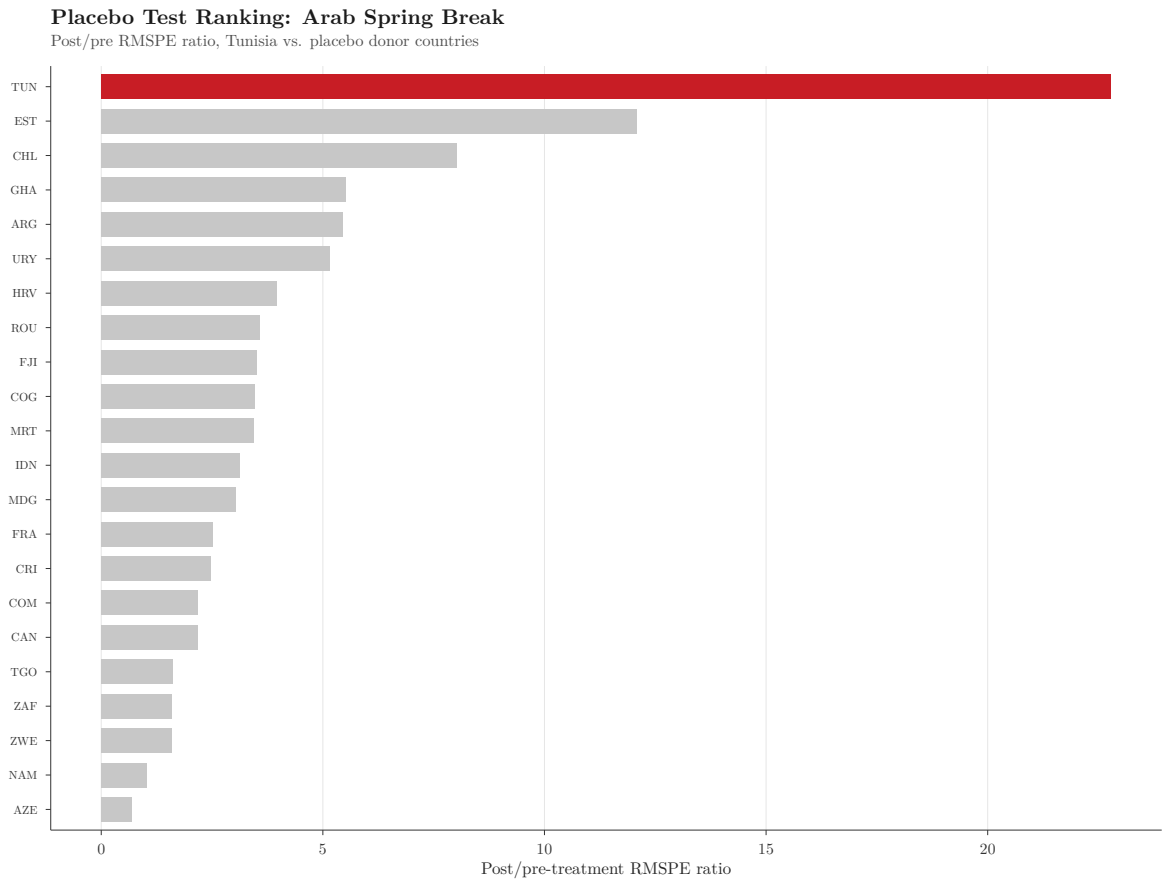

Figure 4: Placebo Test Ranking for the Arab Spring Break

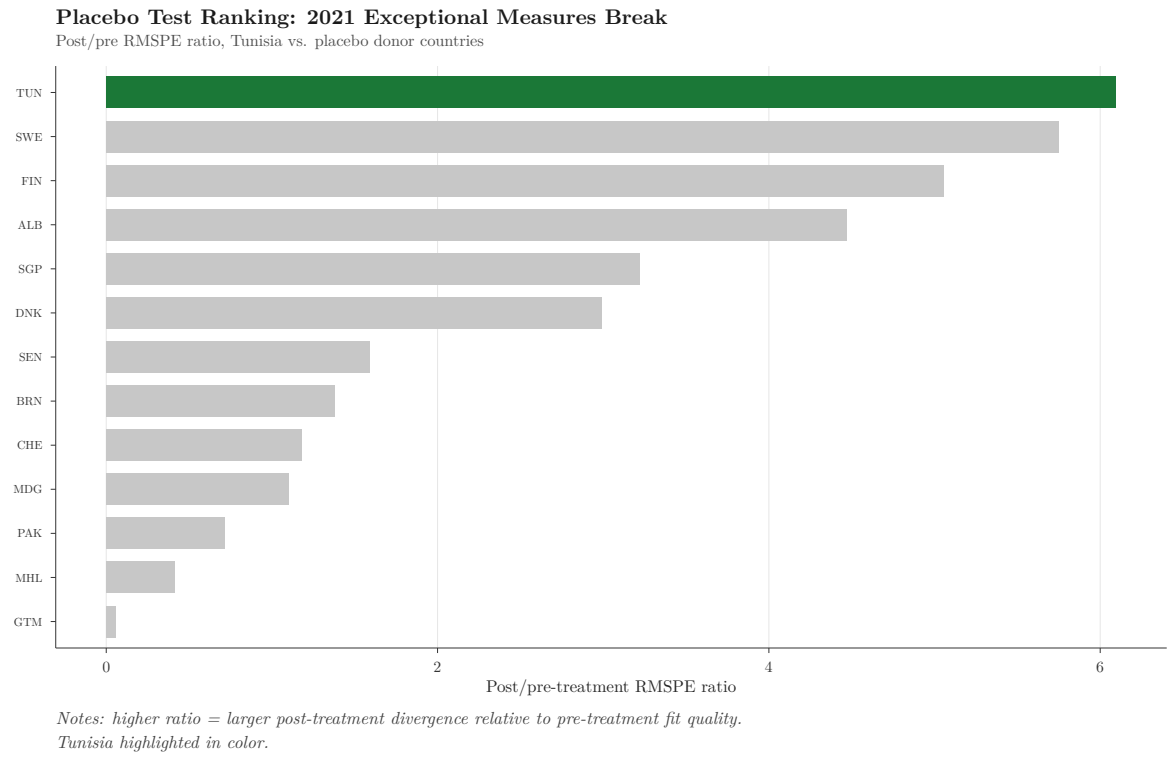

Figure 5: Placebo Test Ranking for the July 2021 Power Seizure

6.3 Departures from the Original Specification

Although the replication follows Matta et al. (2016) as closely as possible, several methodological differences arise from the use of updated data and the extension of the analysis.

First, we use two GDP per capita sub-period predictors rather than the four sub-period averages used in the original specification. This adjustment is driven by the numerical properties of the current data and the resulting synthetic-control optimization. It is also consistent with the methodological concern discussed by Kaul et al. (2016) regarding the use of a large number of lagged outcome variables as predictors.

Second, we report the treatment effect primarily in terms of percentage gaps rather than attempting to reconstruct the original international-dollar PPP price basis. Historical data revisions and changes in the published price series make a direct reconstruction of the original price basis difficult. Percentage gaps provide a more transparent comparison between the original estimates and the estimates obtained using the current data.

Third, the placebo exercises use the full set of eligible donor countries available after the relevant exclusions. The Arab Spring placebo exercise contains 22 units, while the July 2021 political changes placebo exercise contains 13 units. This approach allows the estimated Tunisian gap to be compared with the complete set of eligible placebo units rather than with a randomly selected subset.

6.4 Limitations of the Extended Post-Treatment Analysis

The extension of the Arab Spring analysis from the original 2011–2013 window to 2025 provides information about the persistence of the estimated gap, but it also introduces additional identification concerns.

In particular, the extended period includes several major global shocks, most notably the COVID-19 pandemic and the global terms-of-trade disturbances following Russia's invasion of Ukraine. These events affected Tunisia and many countries in the donor pool. The synthetic control framework can account for common movements when they are shared by Tunisia and the donor countries, but it cannot fully resolve situations in which these shocks affect countries differently.

The common decline in actual and synthetic Tunisia around 2020 illustrates this issue. Both series respond to the COVID-19 shock, which suggests that part of the global disturbance is captured by the counterfactual. Nevertheless, the longer the post-treatment period becomes, the greater the possibility that country-specific shocks contaminate the estimated gap.

For this reason, the long-run divergence should be interpreted primarily as evidence of persistent relative underperformance rather than as a precise estimate of the cumulative causal effect of the Arab Spring. The three-year comparison with the original study provides the closest replication benchmark, while the longer series provides evidence on the persistence of the divergence.

7 Conclusion

This paper replicates and extends the Synthetic Control Method analysis of Matta et al. (2016) on the economic consequences of the Arab Spring in Tunisia. The analysis has two objectives. First, we reconstruct the original counterfactual for Tunisia using updated data and the same general empirical strategy as the original study. Second, we apply the same framework to the July 2021 political changes and subsequent institutional reconfiguration.

The replication confirms the main qualitative finding of Matta et al. (2016). The reconstructed Synthetic Tunisia closely follows actual Tunisia during the pre-2011 period, providing a strong pre-treatment fit. After the Arab Spring, however, actual GDP per capita falls below its synthetic counterpart. When restricting the comparison to the 2011–2013 period studied in the original paper, the estimated gap remains negative and of a similar order of magnitude. The precise estimates differ from the published results, which is expected given revisions to historical data and the resulting changes in the composition of the synthetic control. Nevertheless, the central finding of a substantial post-2011 divergence survives.

The extended post-2011 series provides additional information on the persistence of this divergence. Rather than closing after the three-year period considered by Matta et al. (2016), the gap between actual and synthetic Tunisia remains visible over the subsequent years and persists through 2025. This result should be interpreted with caution because the extended period includes several major global and country-specific shocks. Nevertheless, the persistence of the gap indicates that the economic consequences associated with the post-2011 period were not limited to a short-lived contraction.

The second part of the analysis considers the July 2021 political break. By constructing an independent Synthetic Tunisia using the 2011–2021 period as the pre-treatment window, we obtain a counterfactual that captures Tunisia's economic trajectory following the Arab Spring but before the July 2021 political event. Actual GDP per capita subsequently falls below this second counterfactual. The timing of the divergence is consistent with an additional period of economic underperformance following the political break.

The placebo exercises provide further support for the main empirical patterns. Tunisia records the highest post-to-pre-treatment RMSPE ratio among the placebo units in both the Arab Spring and July 2021 political changes analyses. The corresponding gaps are therefore unusually large relative to the pre-treatment discrepancies and to the divergences obtained when the same methodology is applied to other countries. The time-placebo tests also provide no comparable divergence when fictitious treatment dates are assigned to 2000 and 2008.

Taken together, the results provide evidence of two distinct periods of divergence in Tunisia's economic trajectory. The first follows the Arab Spring, while the second follows the July 2021 political break. The two synthetic controls answer different counterfactual questions and should therefore not be interpreted as mechanically separable or additive causal effects. Rather, the first counterfactual measures Tunisia's performance relative to a trajectory without the Arab Spring, while the second evaluates the country's post-2011 trajectory relative to a counterfactual without the 2021 political break.

The findings also highlight the value and limitations of the Synthetic Control Method for studying political shocks. The approach provides a transparent counterfactual and allows the magnitude and timing of economic divergence to be examined in a single-country setting. At the same time, the validity of the estimates depends on the quality of the donor pool, the pre-treatment fit, and the absence of differential post-treatment shocks that are not captured by the synthetic control. These limitations become particularly

relevant when the post-treatment period is extended over many years.

Overall, the evidence suggests that Tunisia's economic underperformance relative to its synthetic counterfactual extends across both major political breaks considered in this paper. The replication supports the central conclusion of Matta et al. (2016) that the Arab Spring was followed by a substantial economic gap, while the extension indicates that a further divergence emerged following the July 2021 political break. These results provide a basis for further research on the mechanisms linking political instability to investment, productivity, employment, and long-run economic growth in Tunisia.

Replication and Transparency Statement

All data and replication materials used in this paper are publicly available whenever possible. Sources, datasets, and calculations will be made available together with the manuscript.

AI-based tools were used for language editing, LaTeX assistance, and programming support. All data construction, modelling choices, empirical analysis, interpretation, and conclusions were independently conducted and verified by the author.

Appendix

A.1. Placebo Tests

Table 4: Placebo Test Ranking: Arab Spring Break

Rank	Country	Post/Pre RMSPE Ratio
1	Tunisia	22.79
2	Estonia	12.09
3	Chile	8.02
4	Ghana	5.51
5	Argentina	5.45
6	Uruguay	5.15
7	Croatia	3.96
8	Romania	3.57
9	Fiji	3.51
10	Congo, Rep.	3.46
11	Mauritania	3.45
12	Indonesia	3.12
13	Madagascar	3.04
14	France	2.52
15	Costa Rica	2.47
16	Comoros	2.18
17	Canada	2.17
18	Togo	1.60
19	South Africa	1.58
20	Zimbabwe	1.58
21	Namibia	1.03
22	Azerbaijan	0.68

Note: Post/pre-treatment RMSPE ratio, Tunisia vs. placebo donor countries. Higher = larger post-treatment divergence relative to pre-treatment fit quality. Tunisia ranks 1 of 22 units.

Table 5: Placebo Test Ranking: 2021 Exceptional Measures Break

Rank	Country	Post/Pre RMSPE Ratio
1	Tunisia	6.10
2	Sweden	5.75
3	Finland	5.06
4	Albania	4.47
5	Singapore	3.22
6	Denmark	2.99
7	Senegal	1.59
8	Brunei Darussalam	1.38
9	Switzerland	1.18
10	Madagascar	1.10
11	Pakistan	0.71
12	Marshall Islands	0.42

13	Guatemala	0.06

Note: Post/pre-treatment RMSPE ratio, Tunisia vs. placebo donor countries (2011-2021 pre-period). Tunisia ranks 1 of 13 units.

A.2. July 2021 Political Changes: Synthetic Control

Table 6: Country Weights in the Synthetic Tunisia (2021 Exceptional Measures)

Country	Weight (%)
Belize	39.28
Costa Rica	6.63
Tonga	6.42
Solomon Islands	5.75
Congo, Dem. Rep.	4.86
Kiribati	4.02
Curacao	3.68
Bosnia and Herzegovina	2.31
Marshall Islands	2.03
Cabo Verde	1.75
Sao Tome and Principe	1.73
Kyrgyz Republic	1.67
Mozambique	1.18
Viet Nam	0.94
El Salvador	0.69
Brazil	0.66
Madagascar	0.51
Tajikistan	0.46
Argentina	0.41
Azerbaijan	0.41
Colombia	0.41
Albania	0.40
Kuwait	0.39
Armenia	0.35
Cambodia	0.30
Malawi	0.30
Puerto Rico (US)	0.30
Paraguay	0.29
Fiji	0.28
Serbia	0.28
Mexico	0.27
Maldives	0.26
Guatemala	0.25
San Marino	0.24
Namibia	0.23
Bolivia	0.22
Chile	0.22
Gabon	0.22

Montenegro	0.22
Zimbabwe	0.22
Oman	0.20
Palau	0.20
Uzbekistan	0.20
Moldova	0.19
North Macedonia	0.19
Mauritius	0.19
South Africa	0.19
Angola	0.18
Congo, Rep.	0.18
Ghana	0.18
Mongolia	0.18
Hong Kong SAR, China	0.17
Aruba	0.16
Lao PDR	0.16
Lesotho	0.16
Uruguay	0.16
Georgia	0.15
Malaysia	0.15
Slovak Republic	0.15
Comoros	0.14
Portugal	0.14
Samoa	0.14
Bulgaria	0.13
Botswana	0.13
Indonesia	0.13
Pakistan	0.13
Seychelles	0.13
Bangladesh	0.12
Cameroon	0.12
India	0.12
Mauritania	0.12
Senegal	0.12
Slovenia	0.12
Bhutan	0.11
Cote d'Ivoire	0.11
Dominican Republic	0.11
Spain	0.11
Croatia	0.11
Hungary	0.11
Italy	0.11
Estonia	0.10
Kenya	0.10
Latvia	0.10
Panama	0.10
Togo	0.10
Turkiye	0.10
Belgium	0.09
Benin	0.09
Czechia	0.09

France	0.09
Guinea	0.09
Israel	0.09
New Zealand	0.09
Poland	0.09
Romania	0.09
United Arab Emirates	0.08
Canada	0.08
Finland	0.08
United Kingdom	0.08
Korea, Rep.	0.08
Lithuania	0.08
Rwanda	0.08
Timor-Leste	0.08
Australia	0.07
Austria	0.07
Burkina Faso	0.07
Malta	0.07
Saudi Arabia	0.07
Sierra Leone	0.07
Sweden	0.07
Tanzania	0.07
Germany	0.06
Denmark	0.06
Iceland	0.06
Netherlands	0.06

Note: Donor countries assigned a non-trivial weight (at least 0.05%) in the 2021 Exceptional Measures synthetic control, fit on 2011-2021.

A.3. Data and Code Availability

The data and R code used to construct the dataset, estimate the synthetic controls, conduct the placebo and robustness analyses, and produce the tables and figures are publicly available at:

https://baraalafi.com

The replication materials include the data used in the empirical analysis as well as the R scripts required to reproduce the main results. Data retrieved through the World Bank API can be reconstructed directly from the provided code. The governance indicators, which were not available through the relevant API, are provided separately in the replication materials.

References

Abadie, A., & Gardeazabal, J. (2003). The Economic Costs of Conflict: A Case Study of the Basque Country. *American Economic Review*, 93(1), 112–132.

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association*, 105(490), 493–505.

Kaul, A., Klößner, S., Pfeifer, G., & Schieler, M. (2016). Synthetic Control Methods: Never Use All Pre-Intervention Outcomes as Economic Predictors. Saarland University, mimeo.

Matta, S., Appleton, S., & Bleaney, M. (2016). The Impact of the Arab Spring on the Tunisian Economy. *World Bank Policy Research Working Paper* No. 7856.

World Bank. (2024). *World Development Indicators*. https://databank.worldbank.org/source/world-development-indicators

World Bank. (2024). *Worldwide Governance Indicators*. https://databank.worldbank.org/source/worldwide-governance-indicators