Empirical Economics manuscript No.
(will be inserted by the editor)

The Economic Cost of the Arab Spring: the Case of the Egyptian Revolution

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Received: date / Accepted: date

Abstract This paper analyzes the effects that the Arab Spring and the subsequent revolution had on per capita real Gross Domestic Product in Egypt. The estimation procedure that we follow is the *Synthetic Control Method*. After comparing the observed evolution of Egyptian real output in the period 2011-2017 with that of synthetic Egypt, our estimates show *i*) an accumulated loss in the growth rate of per capita real Gross Domestic Product of 12.04% (a yearly average of 1.56%); *ii*) an accumulated loss in the per capita real Gross Domestic Product of 6,279.7 dollars (a yearly average of 897.1 dollars); and *iii*) an accumulated loss in the aggregate real Gross Domestic Product of 582.5 billion dollars (a yearly average of 83.2 billion dollars)

Keywords Case Study · Synthetic Control Method · Treatment Effect · Arab Spring · Egypt.

This study was funded by the Spanish Ministry of Economy and Competitiveness and the European Fund of Regional Development (Grant numbers ECO2015-64467-R and ECO2016-76884-P (MINECO/FEDER)), and by the Basque Government (Grant numbers DEUI-IT-793-13 and DEUI-IT-783-13).

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1 Introduction

The Arab Spring uprisings began in mid-December 2010 in Tunisia, forcing the president Zine El Abidine Ben Ali to resign on January 14, 2011. This overthrow set a precedent for other countries in the region, and protests spread quickly in the Middle East and North Africa to other countries, although the degree of intensity varied across countries. While in some cases such as Egypt, Libya, Yemen and the aforementioned Tunisia their autocratic regimes were overthrown from power, other countries such as Jordan and Morocco also witnessed profound political changes, although their rulers stayed in power. In some other countries, the Arab Spring did not go much beyond street protests and mild reforms, such as was the case in Algeria, Lebanon, Oman, Qatar, Bahrain or Kuwait. The Syrian case can be considered a special one as the uprising became a violent armed conflict still alive at the time of writing this paper [see Khan (2014), Hodler (2012), The Economist (2013)].

As is the case in most social movements, the Arab Spring can also be analyzed from an economic perspective in terms of both causes and consequences. Thus, and concerning the economic causes, Luciani (2016) points to a set of variables which as a whole play their role: low growth, increasing inequality, corruption and cronyism, and rising unemployment especially among the young. There also exists a long held tradition that has focused on studying the economic cost of conflicts in terms of growth, unemployment, inflation, government debt, or current account deficits. Our paper falls within this stream of literature. The reader is referred to Bozzoli *et al.* (2010), a thorough survey on the issue where different methodological aspects are discussed.

Focusing on the economic consequences of the Arab Spring, previous studies have addressed this issue, but most of them have followed a purely descriptive approach, thereby forgoing a more rigorous, quantitative approximation [e.g. see IMF (2013), IIF (2013)].[1] This is the gap that this paper attempts to fill. We aim at estimating the cost in terms of the Gross Domestic Product lost as a result of the Arab Spring and the resulting revolution in Egypt between 2011 and 2017 by using the Synthetic Control Method (SCM) introduced in Abadie and Gardeazabal (2003).[2] We believe that the case of Egypt deserves particular attention for two main reasons. The population in Egypt was the highest in 2010 (84.11 millions) among all those countries which were exposed to the Arab Spring revolution to a greater or lesser extent. In addition, the size of the Egyptian economy, in terms of GDP, was the largest out of such a set of countries in that year (829.1 billion PPP constant 2011 international dollars).

Obviously political stability and economic growth are highly related [see, for example, Fosu (1992), Alesina *et al.* (1996), Benhabib and Rustichini (1996), Asteriou and Price (2001) or Aisen and Veiga (2013)]. Just by tak-

[1] One exception is Groizard *et al.* (2016) which studies foreign tourists' demand for travel to countries experiencing Arab Spring episodes by using a gravity model of bilateral tourism flows for Egypt, Syria, Tunisia and Yemen.

[2] Matta *et al.* (2016) follow a similar approach where Tunisia is the case study.

ing a bird's-eye view of the economic series (say, tourism, per capita GDP or investment to GDP ratio) before and after 2011, an apparent slowdown of the Egyptian economy appears. For instance, tourism, a strategic sector in that economy, represented 7.7% of direct contribution to GDP (and 16.7% of total contribution) and 6.7% of direct contribution to employment (14.8% including indirectly supported employment) in 2010. By the year 2017, however, figures clearly worsened: 5.6% of direct contribution to GDP (and 11.0% of total contribution) and 3.9% of direct contribution to employment (8.5% including indirectly supported employment).[3] Along the same lines, international tourist arrivals reached a historical maximum of 14 million in 2010 and dropped to 9.5 million (a 32% fall) in 2011. After experiencing a mild recovery in 2012 (11.2 million), the figures in 2013, 2014, 2015 and 2016 fell to 9.2 million, 9.6 million, 9.1 million and 5.3 million, respectively.[4] Regarding per capita output, it took four years to recover (and even exceed) the prerevolutionary levels: in 2010 per capita real GDP was 9,857 dollars, steadily falling until 2013 (9,814 dollars) and then started on a path to growth. Finally, the investment to GDP ratio (19.5% in 2010) reached its minimum in 2014 (13.64%) and, despite its positive growth rate since then, it has not yet recovered the 2010 level. With all these easily observable facts in mind, a natural question arises: did the political instability and social distress brought about by the revolutionary process really affect the Egyptian economy? And if so, to what extent, *i.e.* can one provide an estimate of such an effect and its statistical significance?

The Egyptian Revolution itself was preceded by innumerable factors. Focusing on 2010, the previous year, these are some of the figures: 37.39% of the population older than 25 had no schooling (a clear symptom of a failing education system); government corruption ranked position 98 out of 178 in the most corrupt countries list; widespread poverty: 25.2% of the population was below the national poverty line; high youth unemployment: 25.18% among 15-24 year old people; high inflation: 11.3%.[5]

The protests in Egypt started on January 25, 2011. On January 29, President Mubarak announced that he would make some changes to his cabinet, but no relevant change really happened. Protesters continued and, on February 1, President Mubarak announced that he would not seek reelection in September 2011. However, the number of people protesting grew again after this announcement. Several deaths and injuries were reported among protesters. On February 11 Mubarak finally resigned from the Presidency. The Supreme Council of Armed Forces took control and held power until June 2012, when democratic elections were celebrated. The winner of the Presi-

[3] The data come from the World Travel & Tourism Council (`https://www.wttc.org`) [last accessed December 2018].

[4] The data source is the World Development Indicators Databank (`http://databank.worldbank.org`) [last accessed December 2018].

[5] The data come from different sources: Quality of Government Standard Dataset (`http://qog.pol.gu.se`) for education, unemployment and inflation data [last accessed December 2018]; Transparency International's 2010 report (`http://www.transparency.org`) for corruption data [last accessed December 2018]; and World Development Indicators Databank (`http://databank.worldbank.org`) for poverty [last accessed December 2018].

dency was the Muslim Brotherhood's Freedom and Justice Party candidate Muhammad Morsi. After a new law that concentrated power in the president and allowed him legal immunity, his policies were considered as dictatorial by the opposition and new protests emerged in November 2012. In July 2013 the military removed Morsi from power. An interim government drew up a new constitution, and after the 2014 elections, the ex-head of the Egyptian armed forces, Abdel Fattah el-Sisi, became president.

In order to assess the cost of the revolutionary process in economic terms, here we make use of the SCM. This was introduced in Abadie and Gardeazabal (2003), where the economic cost, in terms of GDP loss, of terrorism in the Basque Country (in Spain) was assessed. Since then, the same methodology with slight variations has been extensively applied in numerous comparative case studies. For instance, Horiuchi and Mayerson (2015) study the influence of the 2000 Palestinian Intifada upon Israel's economy. Pinotti (2015) estimates the economic costs of organized crime in Southern Italy. Cavallo *et al.* (2013) study the effect of catastrophic natural disasters on economic growth. Billmeier and Nannicini (2013) study the effect of economic liberalization on real GDP per capita in a worldwide sample of countries. Abadie *et al.* (2015) estimate the economic impact of the 1990 German reunification on West Germany. Grier and Maynard (2016) study the impact of Hugo Chavez's regime on the Venezuelan economy. Abadie *et al.* (2010) estimate the effect of the tobacco control program implemented in California in 1988 on per-capita cigarette sales. Bohn *et al.* (2014) assess the effect of 2007's Legal Arizona Workers Act on the proportion of the Hispanic non-citizen population in the state.

After comparing the accumulated observed growth rate for per capita real GDP for Egypt and the estimated synthetic Egypt from 2011 to 2017, 7.03% and 19.07% respectively, our main results can be stated as follows:

1. The loss in terms of the growth rate of per capita real GDP as a consequence of the revolution in that seven year period was equal to 12.04% (or, equivalently, an annual average rate of 1.56%).
2. This differential in the growth rates had implications in terms of forgone output. The loss in the per capita real GDP would have been equal to 6,279.7 dollars (an annual average of 897.1 dollars), while the loss in the aggregate real GDP would have been equal to 582.5 billion dollars (an annual average of 83.2 billion dollars).
3. The falls in tourism and travel rents and investment (relative to GDP) are found as two potential underlying mechanisms through which the Egyptian economy was so strongly impacted by the Arab Spring movement and the embedded political instability.

The rest of the paper is organized as follows. Section 2 briefly describes the SCM. Section 3 describes the data and the variables used in our estimation exercise. Section 4 presents the main results. Section 5 is devoted to some robustness check analysis. Section 6 discusses potential mechanisms through which the revolution might have affected real GDP growth. Finally, Section 7 concludes.

2 Synthetic Control Method

The SCM can be briefly described as follows.[6] Assume that a balanced panel data set consisting of $J+1$ *units* (countries, regions, states, cities,...) and $t = 1, 2, ..., T$ *periods* (years, quarters,...) is observed. At some point in time $t = T_0 + 1$, where $1 \leq T_0 < T$, one (and only one) of the units starts experiencing some type of uninterrupted *treatment* (event, shock, law,...) until $t = T$.[7] This allows the researcher to split up the set of T periods between the *pre-treatment periods*, $t = 1, 2, .., T_0$, and the *post-treatment* periods, $t = T_0 + 1, T_0 + 2, ..., T$. Similarly, two types of units emerge: the *treated* unit, which without loss of generality can referred to as $j = 1$, and those in the set of the *donor pool* or the potential control units, $j = 2, 3, ..., J+1$. The purpose of the study can be posed by the following question: what is the effect of the treatment on some post-intervention outcome(s), Y_{1t}, (e.g. per capita GDP, consumption of tobacco, ethnical composition of the labor force, etc.)? The problem is that the counterfactual (i.e. the performance of the treated unit for the post-treatment periods under the hypothesis of the absence of treatment) is naturally unobserved. Therefore, the comparison with the observed performance of the treated unit under treatment might seem unfeasible. More formally, the treatment effect for unit 1 (the treated one) and period t is given by

$$\alpha_{1t} \equiv Y_{1t}^1 - Y_{1t}^0, \tag{1}$$

for $t = T_0 + 1, T_0 + 2, ..., T$, and where Y_{1t}^1 denotes the (observed) potential outcome under treatment, and Y_{1t}^0 denotes the (unobserved) potential outcome under the hypothesis of no treatment. The ingenious way of circumventing this difficulty suggested in Abadie and Gardeazabal (2003) consists of building up a *synthetic* treated unit: a weighted average conveniently obtained among the untreated units in such a manner that it resembles the performance of the treated unit for a vector of pre-treatment characteristics during the pre-treatment periods as closely as possible. The payoff is an estimate of Y_{1t}^0 which in turn allows one to obtain an estimate for α_{1t}.

More formally, the difference between the vector pre-treatment characteristics of the treated unit, $\mathbf{X}_1$ (the *predictors* of the outcome variable, which may include pre-intervention values of the outcome variable) and those of the synthetic control, $\mathbf{X}_1^s$, is given by $\mathbf{X}_1 - \mathbf{X}_1^s = \mathbf{X}_1 - \sum_{j=2}^{J+1} \mathbf{X}_j w_j$, where w_j trivially denotes the weight assigned to control unit j. Optimal weights are found by solving the following problem

$$\begin{array}{ll} \min_{\{w_j\}_{j=2}^{J+1}} & (\mathbf{X}_1 - \mathbf{X}_1^s)' \, V \, (\mathbf{X}_1 - \mathbf{X}_1^s) \\ s.t. & \begin{cases} \mathbf{X}_1^s = \sum_{j=2}^{J+1} \mathbf{X}_j w_j, \\ w_j \geq 0, \text{ for } j = 2, 3, .., J+1, \\ \sum_{j=2}^{J+1} w_j = 1, \end{cases} \end{array} \tag{2}$$

[6] This heavily draws on Abadie *et al.* (2010, 2015).

[7] If the number of treated units were more than one, the method could be applied independently to each of the treated units or to an aggregate of all treated units.

where V is a diagonal, positive semi-definite matrix whose m-th element represents a weight that reflects the relative importance that the researcher assigns to the m-th variable in vector $\mathbf{X}$ as a predictor of the outcome variable, Y.[8]

The optimal weights thus obtained, $\mathbf{w}^*(V) = \{w_j^*(V)\}_{j=2}^{J+1}$, will depend of course on the choice for matrix V. Several alternatives have been considered in the literature. The first one amounts to a nested, double minimization, where matrix V and control weights $\mathbf{w}^*$ are jointly obtained in such a way that $\mathbf{w}^*(V)$ solves the problem in Eq. (2) and V minimizes the pre-treatment mean square prediction error, which is defined as

$$Pre\text{-}MSPE \equiv \sum_{t=1}^{T_0} \left(Y_{1t} - \sum_{j=2}^{J+1} Y_{jt} w_j(V) \right)^2 / T_0. \tag{3}$$

[see Abadie and Gardeazabal (2003), Appendix B]. The second one would represent a subjective choice: let the researcher decide a reasonable choice reflecting his/her previous knowledge regarding the relative importance of each particular predictor among those in $\mathbf{X}$ for the outcome $\mathbf{Y}$ [see Abadie and Gardeazabal (2003)]. A third alternative, usually referred to as cross-validation consists of dividing the pretreatment years into a *training period* (from $t = 1$ to $t = T^*$) and a *validation period* (the remaining periods, i.e. from $t = T^* + 1$ to $t = T_0$). After using predictors measured in the training period, matrix V is selected such that the resulting synthetic control minimizes the mean square prediction error over the validation period.[9] Following this, the matrix V selected in the previous step and predictor data measured in the validation period are used to obtain the optimal $\mathbf{w}$ [see Abadie *et al.* (2015)]. As a final alternative, another data-driven method can be used to set matrix V: after regressing the outcome $\mathbf{Y}$ on the set of predictors $\mathbf{X}$, the elements of matrix V are obtained by comparing the corresponding OLS coefficients (in modulus or squared) over the sum of all coefficients (in modulus or squared, respectively) [see Firpo and Possebom (2016), Ferman and Pinto (2017), Bohn *et al.* (2014)]. This implies that better predictors are assigned higher weights in the construction of V. In this paper we follow the first approach (*i.e.* nested minimization with respect to both V and w).[10]

Once optimal weights, w_j^*, have been obtained, the effect of the intervention on the treated unit for period t is estimated as

$$\hat{\alpha}_{1t} \equiv Y_{1t}^1 - \sum_{j=2}^{J+1} w_j^* Y_{jt}^0, \tag{4}$$

[8] Note that the non-negative elements of matrix V can always be normalized to add up to, say, 1 as this does not affect the optimal choice for the vector of weights $\mathbf{w}$.

[9] This is defined as $(T_0 - T^*)^{-1} \sum_{t=T^*+1}^{T_0} \left(Y_{1t} - \sum_{j=2}^{J+1} Y_{jt} w_j^* \right)^2$. Intuitively, the cross-validation technique selects the matrix V that minimizes out-of-sample prediction errors.

[10] In particular, we use the R **MSCMT** package, version 1.3.3 which has proven to outperform other computational procedures implemented in R, Stata© and Matlab© in terms of computational time and accuracy [see Becker and Klößner (2017, 2018)].

for $t = T_0 + 1, T_0 + 2, ..., T$, and where (by construction and if the donor pool has been correctly specified) no Y^0_{jt} is affected by the treatment or intervention experienced by unit 1.

The natural question that arises at this point is that of causal inference, or how to assess the significance of the estimate. Or, in other words, whether the difference in Eq. (4) is really driven by the treatment at issue. To this end Abadie *et al.* (2010) carry out what they called "in-space placebo studies", extending the concept introduced in Abadie and Gardeazabal (2003). Assume that the effect were estimated for *every single unit* $j = 2, 3, ..., J + 1$ in the donor pool, thereby obtaining a distribution of effect estimates. If the estimated effect $\hat{\alpha}_{1t}$ is truly due to the treatment under study, one would expect that the probability of finding an effect of larger magnitude among those obtained in the placebo analysis should be low because, by construction, none of the units in the donor pool was treated. Similarly, one could conduct "in-time placebo studies": focusing on the treated unit, but this time assuming different treatment periods, should imply a low probability of finding a treatment effect of greater magnitude than the one estimated for the true treatment period [see Abadie *et al.* (2015)].

3 Data and variables

Regarding the sample period, this goes from 1990 to 2017, which is further split between the pre-treatment and the post-treatment periods, 1990-2010 and 2011-2017, respectively, so that 2011 is set as the treatment year [see Lesch (2011)]. Ideally, a long enough pre-treatment period would be desirable to the extent that it led to a better fit between the treated and the synthetic units. Extending the pre-treatment period, however, poses two problems. First, the availability of long, reliable economic time series data is an issue when departing from OECD or developed economies. And, second, expanding the pre-treatment period beyond some given year might not be recommendable if the treated unit and the control units experienced diverging or non-homogeneous trends in earlier periods.

In a first stage, the countries in the donor pool have been restricted so that they can be considered as members of a "club" with some common key features which make such a set homogeneous to some extent. Otherwise, the resulting synthetic treated country unit might be economically meaningless despite possibly resulting in a substantial improvement (i.e. a reduction) in the pre-treatment mean squared prediction error. Given the role played by the tourism sector in the Egyptian economy, a natural criterion to select the donor pool is to consider only those countries in which tourism represents a sizable fraction of their respective economies. Thus, according to *World Bank Open Data*, we first selected the list of 94 countries for which tourism and travel rents relative to GDP and for the period 1995-2010 represent at least one half of that of the Egyptian economy, 15.82% [see `https://tcdata360.worldbank.org`, last accessed December 2018].

In a second stage, some of these countries have been dropped for diverse reasons. First, some countries (Iraq, Tunisia and Syria) have been removed as the revolutionary processes embedded in the Arab Spring also succeeded there. Second, Sri Lanka has been taken out of the pool as it was involved in an armed conflict [see Spencer (2016)]. In all those cases, including such countries in the donor pool would have prevented us from obtaining a reliable synthetic unit. Otherwise, the treatment experienced by such countries would influence the performance of the synthetic Egypt, thereby precluding a sensible causality inference. Third, some countries (Estonia, Croatia, Slovenia, Bosnia and Herzegovina, Czech Republic, Georgia, Germany and Montenegro) have been eliminated as they were newly created during the sample period. Fourth, Dominican Republic, Cape Verde, Lesotho, Kiribati, Laos and Saint Kitts and Nevis have been withdrawn from the pool because the available statistical data was quite poor as information on some of the growth predictors was incomplete or even completely missing.

We set per capita real GDP as our outcome variable. The series [*GDP per capita, PPP (constant 2011 international $)*] allows us to make sound international comparisons, and has been obtained from the World Data Bank, available at `https://data.worldbank.org` [last accessed December 2018]. The joint choice of *i*) the sample period and *ii*) the outcome variable poses another restriction on the countries which are candidates to be part of the donor pool as the variable must be available for *all* units (treated and untreated) and *all* time periods. As a result, Bahrain, Cambodia, Cuba, Hungary, Maldives, Sao Tome and Principe, and Venezuela were dropped from the donor pool. The final result in short gives us a total of 69 countries: Egypt plus 68 control units in the donor pool [see Table 1 for details].

Concerning the predictors, our choice of covariates follows three basic principles: *i*) economic meaning, *ii*) availability for all units, and *iii*) predictive power. Concerning the last one of the three, a potential growth predictor is accepted as such in so far as it increases the quality of the synthetic unit, the quality being assessed in terms of reduced Pre-MSPE as our measure of goodness of fit [see Eq. (3)].

First, we do not include the whole series of lagged values (*i.e.* pre-treatment values) of the outcome variable as a means to improve the quality of the synthetic unit as opposed to some other works in the literature [see Billmeier and Nannicini (2013), Bohn *et al.* (2014), Gobillon and Magnac (2016), Hinrichs (2012) and Gardeazabal and Vega-Bayo (2017) among others]. As pointed out by Kaul *et al.* (2018), using all outcome lags as separate predictors make all other predictors irrelevant, regardless of how important all other predictors are for accurately predicting post-treatment values of the outcome, potentially threatening the estimator's unbiasedness. Along such lines, we only introduce five lagged values of per capita real GDP corresponding to 1990, 1995, 2000, 2005 and 2010. Second, we also include four averages of per capita real GDP corresponding to four periods: 1990-1995, 1996-2000, 2001-2005 and 2006-2010. Third, we additionally include four averages of the ratio of tourism and travel rents relative to GDP for the same four periods just pointed out. Data have been obtained from *World Bank Open Data* [see `https://tcdata360.worldbank.org`, last accessed December 2018]. Fourth, as an attempt to further make the resulting synthetic Egypt more reliable, in that the members with positive weight are more alike, we set the mean of Islamic population for the period 2006-2010 as an extra growth predictor. Thus, in particular, we have used the total (in per cent terms) of adherents to Islam [see Teorell *et al.* (2018), p. 73]. Fifth, educational attainment is also included among the set of growth predictors. More specifically, we use the averages of educational attainment of males between 45 and 54 years old for the periods 2001-2005 and 2006-2010 [see Teorell *et al.* (2018), p. 325]. Sixth, we have also allowed in life expectancy at birth [see Aghion *et al.* (2011)]. In particular we consider the average values for two periods, 1990-1994 and 1995-1999. Data have been obtained from the *World Bank Open Data* [see `https://data.worldbank.org`] [last accessed December 2018]. Seventh, the averages of the investment to GDP ratio for the periods 1996-2000 and 2001-2005 are also part of the growth predictor set. Data have been retrieved from the *World Bank Open Data* [see `https://data.worldbank.org`] [last accessed December 2018]. And, eighth, we have finally included the average of the imports to GDP ratio for 2001-2005 among the growth predictors, the data having been obtained from the *World Bank Open Data* [see `https://data.worldbank.org`] [last accessed December 2018].

In the process of selecting the appropriate predictors, some potential candidates have been discarded, whether because (to the best of our knowledge) data are not available for all the countries (e.g. stock of capital per capita) or because their inclusion would lead to an increase in the Pre-MSPE. For instance, this is the case of some economic indicators such as the consumption and export shares of GDP; the number of visitors (both total and relative to national population); the averages of inflation, unemployment and per capita GDP growth rates. And it is also the case of some socio-political indicators (e.g. social fragmentation and corruption indices).

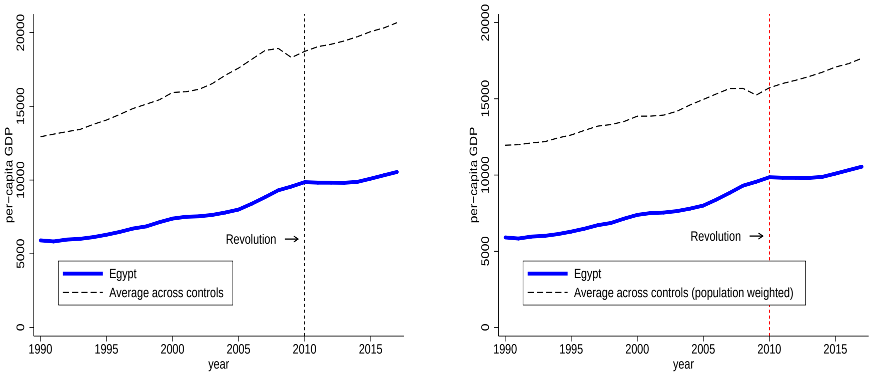
The result is a balanced, annual country-level, panel data consisting of 69 countries and 28 yearly observations for each.

4 Results

The time path for per capita real GDP for Egypt and the corresponding average (both non-weighted and population-weighted) for all the countries in the donor pool is shown in Figure 1. The respective growth rates are quite similar in the pre-treatment years except for a drop in the average growth rate of the control countries (which even becomes negative) in 2009. This means that the average of those countries (in particular, the population-weighted average) might seem in principle a good candidate for the synthetic Egypt. Note, however, that the levels (which represent our outcome variable) are quite different (in particular in the non-weighted case), so that there is still some room for improvement.

Figure 1
Trends in per capita real GDP: Egypt vs. donors

(a) (b)



Key to Figure 1. Time paths for per capita real GDP for Egypt and the average of the 68 countries in the donor pool. Panel (a): non-weighted average. Panel (b): population weighted average.

Following the SCM above outlined, therefore, a more accurate synthetic Egypt is obtained. Our main results are presented in Tables 1, 2, 3 and 4, and in Figures 2 and 3.

Table 1 shows the 68 countries in the donor pool and their corresponding estimated weight vector, $\mathbf{w}^*$, of which only 10 are strictly positive. Among those, Gambia and Mauritius are the ones with the largest weights (24.18% and 20.35%, respectively), while Seychelles and Uruguay play the lowest roles (1.90% and 2.61%, respectively); and, in between, Mongolia (14.30%), Albania (10.44%), Comoros (10.02%), Lebanon (8.05%), Panama (4.72%) and Bahamas (3.42%). The resulting Pre-MSPE is 3369.772.

Table 1. Synthetic Egypt

Country	Weight	Country	Weight	Country	Weight	Country	Weight
Albania	10.436	Fiji	0	Malaysia	0	Saudi Arabia	0
Antigua(*)	0	France	0	Mali	0	Senegal	0
Argentina	0	Gambia	24.178	Malta	0	Seychelles	1.896
Australia	0	Greece	0	Mauritius	20.354	Singapore	0
Austria	0	Grenada	0	Mexico	0	South Africa	0
Bahamas	3.420	Guyana	0	Mongolia	14.303	Spain	0
Barbados	0	Honduras	0	Morocco	0	Sweden	0
Belize	0	Iceland	0	Namibia	0	Tanzania	0
Brazil	0	India	0	Nepal	0	Thailand	0
Botswana	0	Indonesia	0	New Zealand	0	Tonga	0
Bulgaria	0	Israel	0	Norway	0	Trinidad(***)	0
Chile	0	Italy	0	Panama	4.724	Turkey	0
Comoros	10.022	Jamaica	0	Peru	0	UK	0
Costa Rica	0	Japan	0	Philippines	0	USA	0
Cyprus	0	Jordan	0	Portugal	0	Uruguay	2.613
Dominica	0	Kenya	0	St. Lucia	0	Vanuatu	0
Ecuador	0	Lebanon	8.054	St. Vincent(**)	0	Vietnam	0

Key to Table 1. Countries in the donor pool and their weights (in per-cent terms) for synthetic Egypt. (*)Antigua and Barbuda. (**)Saint Vincent and the Grenadines.(***)Trinidad and Tobago. Pre-MSPE = 3369.772

Table 2 shows the predictor and the outcome variables for Egypt, the synthetic Egypt, and the corresponding (population-weighted) means of the 68 control countries. As can be seen, considering Egypt and its synthetic, the fit for all the growth predictors is quite remarkable (and substantially better than that obtained by the averages of the control countries), with two exceptions: the average of the proportion of Islamic population for 2006-2010, and the average of the ratio of imports of goods and services to GDP for 2001-2005. Despite this seemingly poor performance, and as pointed out above, they have been included as they contribute to reducing the pre-intervention mean squared prediction error.

Table 2 also shows the optimal weights of predictors [i.e. the diagonal elements of matrix V in Eq. (2)] normalized so that the sum equals 100 and where, for the sake of space saving, those V_m's less than 0.1% have been omitted. Despite some predictors being assigned low weights, they are maintained as long as they contribute to reducing the pre-treatment mean squared prediction error. The sum of the V_m's corresponding to the averages of per capita real GDP for the four periods considered equals 74.4, and the sum of the V_m's corresponding to five lagged values of per capita real GDP included equals 25.6. This should be no surprise whatsoever: lagged values (and their averages) are, by construction, their own best predictors, so that the rest of predictors are assigned a lower (but non-negligible) weight.

Table 2
Economic Growth Predictors Before the Revolution

	Egypt	Synthetic Egypt	Donor Pool	V		Egypt	Synthetic Egypt	Donor Pool	V
y_{1990}	5909.2	5844.2	11957.3	0.5	$T/Y_{(iii)}$	16.6	19.1	10.2	–
y_{1995}	6292.7	6337.6	12629.3	3.0	$T/Y_{(iv)}$	18.3	21.3	9.2	–
y_{2000}	7388.4	7361.0	13861.9	10.2	$Islam_{(iv)}$	86.4	46.5	3.7	–
y_{2005}	8001.5	8059.6	14960.9	8.3	$Educ_{(iii)}$	6.7	6.6	7.5	–
y_{2010}	9857.5	9817.0	15725.8	3.6	$Educ_{(iv)}$	7.3	7.1	8.1	–
$y_{(i)}$	6024.7	6012.4	12219.5	10.5	$LEB_{(a)}$	65.4	63.8	66.3	–
$y_{(ii)}$	6916.5	6934.2	13364.5	12.5	$LEB_{(b)}$	67.6	65.1	67.8	–
$y_{(iii)}$	7697.3	7693.2	14309.1	51.4	$I/Y_{(ii)}$	19.3	19.2	23.4	–
$y_{(iv)}$	9192.4	9192.5	15532.3	–	$I/Y_{(iii)}$	17.2	21.6	24.0	–
$T/Y_{(i)}$	11.5	14.1	1.6	–	$Q/Y_{(iii)}$	26.3	49.5	24.2	–
$T/Y_{(ii)}$	13.4	15.4	10.3	–					

Key to Table 2. y_t: per capita real GDP for year t; $y_{(k)}$: average per capita real *GDP* for period k; $T/Y_{(k)}$: average tourism and travel rents to *GDP* ratio for period k; $Islam_{(k)}$: average of proportion of Islamic adherents for period k; $Educ_{(k)}$: average years of education of males between 45 and 54 years old; $LEB_{(k)}$: average life expectancy at birth for period k; $I/Y_{(k)}$: average investment to *GDP* ratio for period k; $Q/Y_{(k)}$: average imports to *GDP* ratio for period k. Periods are denoted as follows i: 1990-1995; ii: 1996-2000; iii: 2001-2005; iv: 2006-2010; a: 1990-1994; b: 1995-1999. All shares are expressed in per cent terms. Averages across control countries in the donor pool in columns 4 and 9 are population-weighted. Columns 5 and 10 show the optimal predictor weights in per cent terms; values below 0.1% are omitted.

Along these lines, we also tried 3 alternative predictor specifications (referred to as Case 1-Case 3 in Table 3). In Case 1 we have included all lagged values of the outcome variable. In Case 2 we have included only 7 lagged values (with a separation of 3 years in between): more precisely, 1992, 1995, 1998, 2001, 2004, 2007 and 2010. Finally, in Case 3 we have included no lags whatsoever. In all these cases, we have kept the rest of predictors described in Table 2. Our conclusion after this robustness analysis is threefold: first, increasing the number of lagged values of the outcome variable beyond the original 5-year evenly separated values included in Table 2 does not improve the fit (the mean squared prediction error does not fall). Second, reducing the number of lagged values below those included in Table 2 worsens the fit. And, third, as expected, changes in the mean squared prediction error are accompanied by changes in the optimal weights.

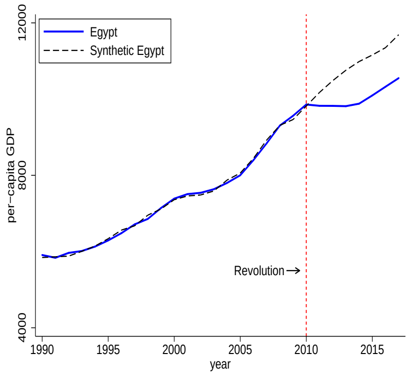
Table 3
Synthetic Egypt for alternative predictor specifications

Country	*Case 1*	*Case 2*	*Case 3*
Albania	10.44	12.91	0.00
Bahamas	3.42	3.67	0.00
Belize	0.00	0.00	0.30
Comoros	10.02	35.05	16.70
Costa Rica	0.00	0.00	8.41
Dominica	0.00	0.00	6.56
Gambia	24.18	0.00	0.00
Kenya	0.00	0.00	18.63
Lebanon	8.05	8.00	0.05
Mauritius	20.35	18.90	28.90
Mongolia	14.30	10.16	0.00
Panama	4.72	6.94	0.00
Peru	0.00	0.00	4.10
Seychelles	1.90	0.61	0.00
South Africa	0.00	0.00	9.62
Uruguay	2.61	3.74	6.71
Pre-MSPE	3369.77	3507.22	9500.83

Key to Table 3. Countries in the donor pool and their weights (in per-cent terms) for synthetic Egypt under alternative predictor specifications.

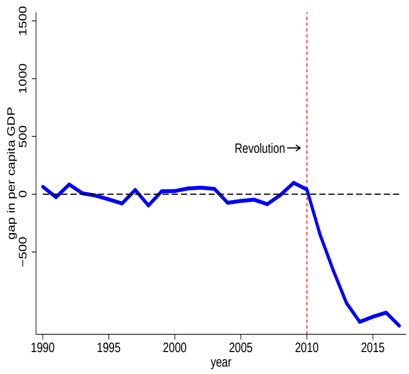
Figure 2 shows the time paths for per capita Gross Domestic Product for both Egypt and the synthetic Egypt. The fit between the two during the pre-treatment period, 1990-2010, looks quite accurate, which is nothing but the graphical consequence of the numerical results just shown above in Table 2, with an average annual growth rate of per capita real GDP for that period of 2.6% (both for Egypt and the synthetic Egypt). Starting 2011, however, a substantial gap between the predicted trend for the synthetic Egypt and Egypt appears: the growth rate of per capita real GDP fell during all the treatment period here considered, 2011-2017, even becoming negative in 2011-2013. Figure 3 shows the time path of the treatment effect, that is to say, the difference in Eq. (4) in terms of gap in per capita real GDP.

Figure 2
Trends in per capita real GDP:
Egypt vs. synthetic Egypt



Key to Figure 2. Time paths of per capita real GDP for Egypt and the synthetic Egypt for both the pre- and the post-treatment periods.

Figure 3
Trend in per capita real GDP gap:
Egypt vs. synthetic Egypt



Key to Figure 3. Time path for the gap of per capita real GDP. See Eq. (4).

Figures 2 and 3 show the qualitative implications quite neatly. But, what are the quantitative implications? Table 4 gives the answer, both in terms of forgone growth and forgone output. The observed growth rate of the per capita real GDP between 2011 and 2017 was equal to 7.028%, while that for the synthetic Egypt in the same period was equal to 19.067%. In other words, the loss in terms of the growth rate of per capita real GDP during the 2011-2017 period was equal to 12.039%. See columns 2-4 for further detail. This gap in the growth rates had consequences in terms of output: had it not been for the political and economic instability caused by the revolution, the accumulated per capita real GDP in the period 2011-2017 would have been 6,279.7 dollars higher (measured in PPP 2011 international dollars), which amounts to 897.1 dollars per year on average. And, in aggregate terms, the accumulated real GDP in that period would have been 582.5 billion higher (measured in the same units, equivalent to 83.2 billions per year on average). See columns 5 and 6. As pointed out in the Introduction, these figures make considerable sense if one bears in mind that tourism, in terms of share of GDP, is one of the main economic sectors in Egypt, and it is also certainly the most sensitive to turmoils and political instability. Thus, it can be concluded that by the year 2017 Egypt had not yet recovered its pre-revolution economic position, despite the observed upward sloped trend of per capita GDP starting in 2014 [see Figure 2].

Table 4

Period	g	g^s	Δg	Δy	ΔY $(\times 10^9)$
2011	-0.341	3.635	-3.976	-350.028	-30.1
2012	-0.014	3.030	-3.045	-659.740	-57.9
2013	-0.084	2.614	-2.698	-941.997	-84.6
2014	0.668	2.121	-1.452	-1104.510	-101.4
2015	2.184	1.562	0.622	-1060.268	-99.4
2016	2.263	1.728	0.536	-1024.524	-98.0
2017	2.190	2.997	-0.807	-1138.593	-111.1
2011-17	7.028	19.067	-12.039	-6279.660	-582.5
Annual average	0.975	2.524	-1.560	-897.094	-83.2

Key to Table 4. g: annual growth rate (%) of per capita real GDP for Egypt; g^s: annual growth rate (%) of per capita real GDP for synthetic Egypt; $\Delta g \equiv g - g^s$: difference in growth rates (%) between Egypt and synthetic Egypt; Δy: loss in per capita real GDP; ΔY: loss in real GDP. Both Δy and ΔY are measured in PPP 2011 international dollars.

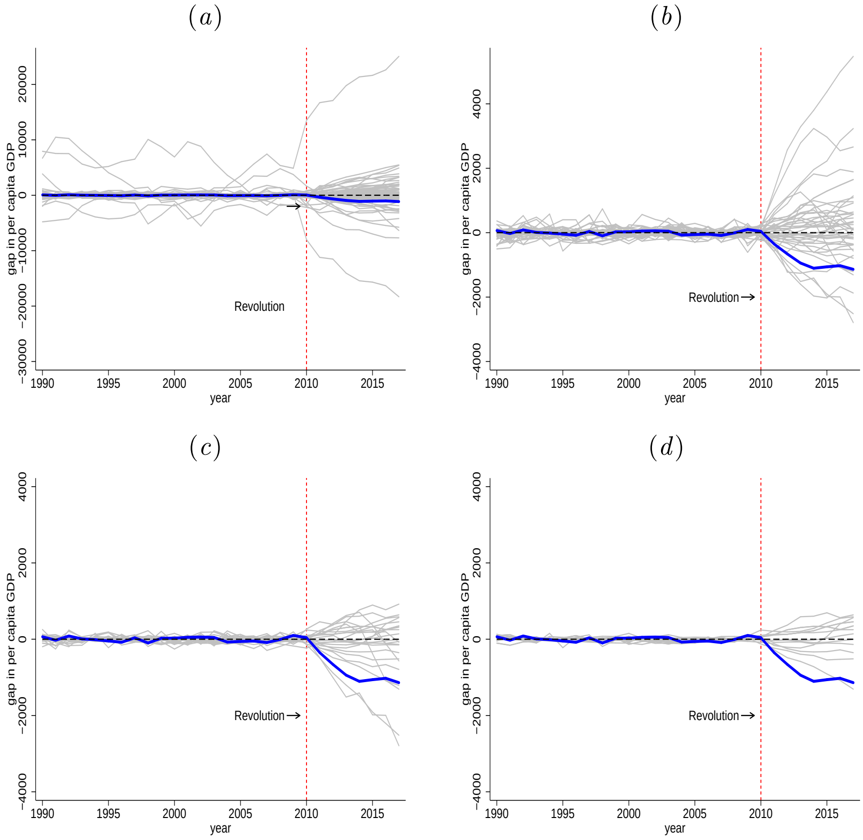
5 Robustness

• **In-space placebo test.** One could always wonder whether the results shown in the previous section are really caused by the treatment under consideration, or they are nothing but a mere statistical fluke. The usual way to clear up the doubt consists of conducting some placebo analysis [see, for instance, Abadie *et al.* (2010) and Abadie *et al.* (2015)]. We first tried the *in-space* placebo analysis. In this case, this means that Egypt was moved to the donor pool and then we applied the SCM to every other country in the pool built up with nations not exposed to a revolution similar in nature to that in Egypt. Therefore, the exercise allows one to obtain a distribution of effects for the countries which did not experience the same treatment: our results would be validated if the probability of finding other significant treatment effects were low enough.

The results are shown in Figure 4.a. Each gray line depicts the estimated gap of per capita real GDP for each of the 68 runs of the test, while the thicker blue line denotes the estimated gap for Egypt. The fit for the pre-treatment period for Egypt is quite precise and quite approximate for most of the control countries: the pre-treatment mean squared prediction error (Pre-MSPE) for Egypt, equals 3,369.77, while the median and the mean for the other countries equal 46,471.55 and 1,464,671 respectively. Nevertheless, it is also apparent that our outcome variable during the pre-treatment years, 1990-2010, is not well approximated for some of the countries in the donor pool as convex combinations of the rest of control units. And this naturally reduces confidence in the results of post-treatment analysis and placebo tests.

Following the same procedure as in Abadie *et al.* (2010), we exclude in turn those control countries whose performance during the pre-treatment period is relatively worse than that of Egypt in terms of Pre-MSPE. Thus, Figure 4.b shows the result of dropping those countries with Pre-MSPE twenty times or more higher than Egypt's, so that 28 countries are eliminated: this implies that there is a reduction i) in the number of countries with substantial deviations from a zero gap before 2011, and also ii) in the number of countries with an abnormal non-zero gap in the post-treatment years. Reducing the threshold level, of course, strengthens this natural intuition. For instance, Figure 4.c and Figure 4.d show the results of excluding control units with Pre-MSPE five times or more and Pre-MSPE twice or more higher than Egypt's respectively, so that 18 additional countries are dropped in the former case, while 10 more countries are left out in the latter.

Figure 4
In-Space placebo test



Key to Figure 4. per capita real GDP gap in Egypt and placebo gaps. Panel (a): all 68 control countries. Panel (b): 40 control countries after dropping countries with Pre-MSPE 20 times higher or more than Egypt. Panel (c): 22 control countries after dropping countries with Pre-MSPE 5 times higher or more than Egypt. Panel (d): 12 control countries after dropping countries with Pre-MSPE 2 times higher or more than Egypt.

As a means to objectively assess the significance of the effect (gap) of Egypt, we build up the distribution of the average treatment effect, ATE, which is defined as

$$ATE_j \equiv \frac{\sum_{t=T_0+1}^{T} \left(Y_{jt} - \sum_{p=1,p\neq j}^{J+1} Y_{pt} w_{jp}^{*} \right)}{T - T_0},$$

where w_{jp}^{*} trivially denotes the optimal weight for control unit p and for synthetic unit j. Focusing on only those countries whose Pre-MSPE is less than or equal to 2 times that of Egypt, the sample is reduced to 13 units (Egypt itself plus 12 controls).[11] The result is that Egypt's (negative) ATE is the lowest, so that the probability of finding an ATE larger than or equal to Egypt's is as low as 0.077. As a complementary method to test the significance of Egypt's effect, we obtain the entire distribution of the ratios of post- to pre-treatment mean squared prediction error, R_j, which is defined as

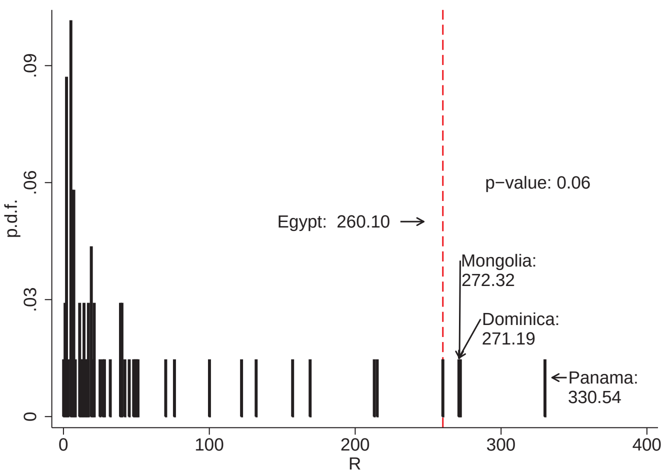
$$R_j \equiv \frac{\sum_{t=T_0+1}^{T}\left(Y_{jt}-\sum_{p=1,p\neq j}^{J+1} Y_{pt}w_{jp}^{*}\right)^2/(T-T_0)}{\sum_{t=1}^{T_0}\left(Y_{jt}-\sum_{p=1,p\neq j}^{J+1} Y_{pt}w_{jp}^{*}\right)^2/T_0}. \tag{5}$$

If the SCM has correctly identified the synthetic Egypt and the treatment effect, one would expect that such a ratio would be significantly higher for Egypt than for any of the countries in the donor pool. Figure 5 shows the histogram for the distribution of R for the 69 countries (including, therefore, Egypt and the 68 control units) in our sample. The ratio R for Egypt equals 260.10, which is surpassed only by Panama (330.54), Mongolia (272.32) and Dominica (271.19); and the resulting p-value [or probability of finding a ratio R higher than or equal to Egypt's], $p(R_1)$, is 0.058, where

$$p(R_1) \equiv \frac{\sum_{k=1}^{J+1}\mathbf{1}[R_k \geq R_1]}{J+1},$$

$\mathbf{1}(*)$ denoting the indicator function of event $*$.

Figure 5
Distribution of R

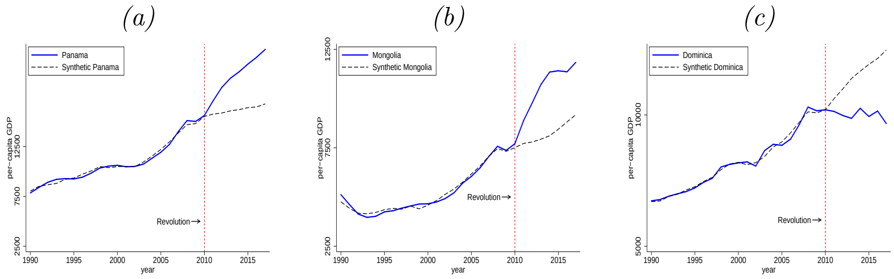


Key to Figure 5. Distribution of R.

[11] Acemoglu *et al.* (2016) adopt a slightly more restrictive criterion as only control units with a Pre-MSPE less than or equal to $\sqrt{3}$ times that of the treated unit are considered to test the statistical significance of the treatment effect.

The seemingly abnormal cases of Panama, Mongolia and Dominica deserve some explanation. Figure 6 shows the equivalent to Figure 2 for these three countries where the signs of the gaps between observed paths of per capita real GDP and those of the synthetic countries are clearly appreciated. Panama displayed an outstandingly high growth rate between 2011 and 2017 (42.48%). However, among the countries upon which its synthetic is built only India, which represents 20.1% of its synthetic, exhibited a higher accumulated growth rate than Panama (45.91%). But, at the same time, the growth rates of Argentina, Bulgaria, Tonga and Uruguay (representing 4.3%, 21.6%, 10.0% and 26.6% of synthetic Panama respectively) were significantly lower than Panama's: 1.19%, 21.46%, 8.86% and 20.31% respectively. And the growth rate of Lebanon was negative (-18.75%), accounting for 17.4% of synthetic Panama. Mongolia experienced a huge growth rate of per capita real GDP (53.61%) in the post-treatment period, the highest among the countries in the donor pool [followed by India and Panama (45.91% and 42.48% respectively)]. The reason behind this extraordinary economic expansion (for instance, per capita real GDP grew 15.2% in 2011) can be sought mainly in the booming mining industry, the strength of commodity exports and high government spending [see Narangoa (2012), and Ganbold and Ali (2017)]. Consequently, no synthetic country could replicate Mongolia's observed per capita real GDP path. For instance, although India exhibited a 45.91% growth rate, it only represents 2.33% of synthetic Mongolia. And control countries with higher weights than India displayed significantly lower growth rates. For example, Bulgaria and Tanzania, representing 37.6% and 33.40% of counterfactual Mongolia, grew at 21.46% and 28.35%, respectively, in the same period. Finally, the observed per capita real GDP in Dominica fell by 5.15 percentage points between 2011 and 2017. Two factors mainly explain the negative evolution of the Dominican economy: the financial crisis following 2008, and the natural disasters that hit the Caribbean region in 2015 and 2017, especially harmful for economies whose reliance on agriculture and tourism infrastructure is critical [see Gold *et al.* (2010) and IMF (2018)].

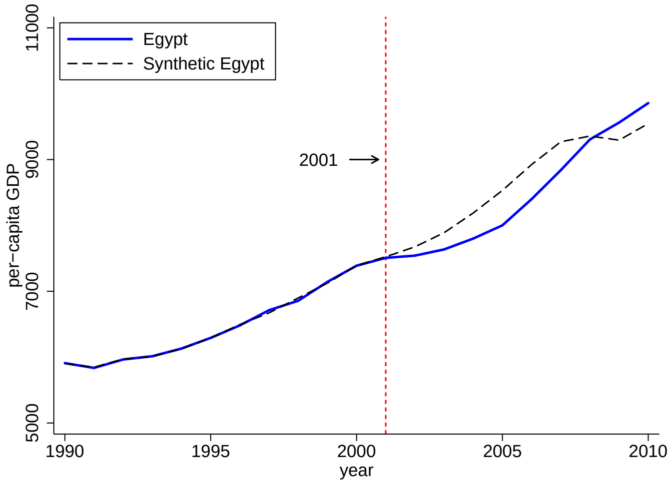
Figure 6
Trends in per capita real GDP: observed vs.
synthetic countries with R higher than Egypt



Key to Figure 6. Time path of per capita real GDP for Panama (a), Mongolia (b) and Dominica (c) and their synthetics.

- **In-time placebo test.** We also run an *in-time* placebo analysis: if the SCM has been implemented and the results are sound, no statistically significant effect should be detected had the treatment hypothetically occurred in some previous period to which it effectively took place. For instance, Figure 7 shows the results for an hypothetical treatment in the year 2001, and the date has not been chosen at random. At first glance, the seemingly negative effect which arises as a consequence of the hypothetical treatment in 2001 (and which seems to vanish by 2008) might be explained by the September 11 terrorist attack, and the recovery after a seven year period, by the so called "peace-dividend" effect. That is to say, once the conflict ceases to exert its negative impact on the economy, this returns to its original path [see Gardeazabal (2012)].

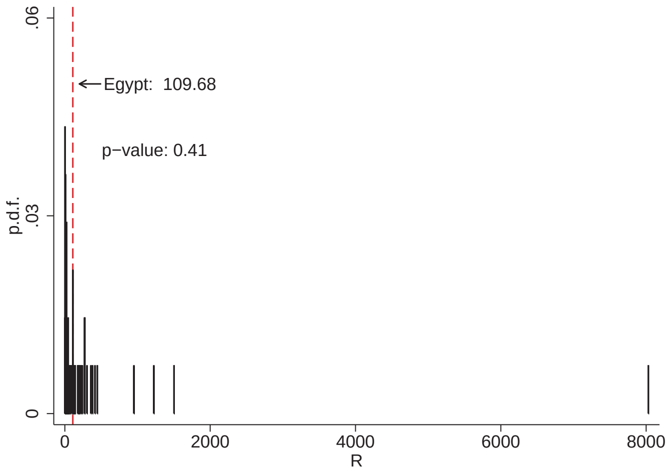
Figure 7
In-time placebo test for 2001



Key to Figure 7. In-time placebo test under the counterfactual that the Egyptian revolution had occurred in 2001.

Even though we find this explanation valid, we must formally test the significance of such a hypothetical treatment effect. In other words, one must proceed to run the corresponding in-space placebo, but this time setting the treatment date in 2001. The same way we proceeded above, focusing on the countries with a Pre-MSPE less than or equal to 2 times Egypt's, we find eleven countries out of thirteen with higher than or equal ATE (in absolute value) to Egypt's: the probability of finding a treatment effect in 2001 higher than or equal to Egypt's would be 84.6%. If, in a complementary way, we computed the entire distribution of the post- to pre-MSPE ratios, we would find a p-value of 0.41. This means that the probability of finding a higher than or equal treatment effect to Egypt's for a hypothetical treatment in 2001 is 41%, or that Egypt's treatment effect is by no means significant under standard significance levels. Figure 8 shows the analogue to Figure 5. Our result is clearly reinforced: the SCM has correctly identified the consequences in terms of per capita real GDP of the Arab spring for Egypt.

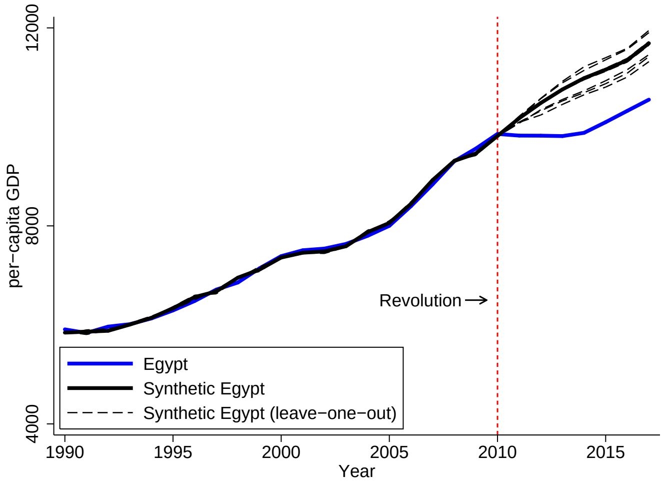
Figure 8
In-time placebo: Distribution of R



Key to Figure 8. Distribution of R.

- **Leave-one-out test.** For completeness, we also run a final robustness check. Following Abadie *et al.* (2015), we re-estimate the baseline model ten times to construct a synthetic Egypt leaving out in each iteration one of the ten countries that received a positive weight (namely, Albania, Bahamas, Comoros, Gambia, Lebanon, Mauritius, Mongolia, Panama, Seychelles and Uruguay). As acknowledged by the authors, by dropping such control units the goodness of fit is sacrificed to some degree, but in turn this sensitivity analysis allows us to verify to what extent the results are driven by any particular control country. The outcome of the exercise is displayed in Figure 9.

Figure 9
Leave-One-Out distribution



Key to Figure 9. Time paths of per capita real GDP for Egypt (blue line), the synthetic Egypt with all control countries with positive weights in Table 1 (black line), and the synthetic Egypt excluding one of such control countries at a time (dashed lines).

The leave-one-out synthetic control that shows the smallest and the largest effects (in terms of accumulated loss of per capita real GDP) of the revolution are those that exclude Bahamas and Albania [Table 5], thereby providing a sort of confidence interval. For instance, if Albania were excluded from the donor pool, the accumulated loss of per capita real GDP would be $7547.1 (equivalent to an annual average of $1078.2); and if, alternatively, Bahamas were left out, the loss would be $4252.0 (equivalent to an annual average of $607.4), while the result obtained if no control unit were eliminated was $6279.7 (equivalent to an annual average of $897.1) [see Table 4].

Table 5
Leave-one-out test

		Leaving out Albania *(maximum effect)*				Leaving out Bahamas *(minimum effect)*			
Period	g	g^s	Δg	Δy	ΔY	g^s	Δg	Δy	ΔY
2011	−0.34	4.01	−4.35	−390.1	−33.5	2.81	−3.15	−266.9	−22.9
2012	−0.01	3.54	−3.55	−753.0	−66.1	1.48	−1.50	−417.9	−36.7
2013	−0.08	3.26	−3.34	−1106.1	−99.3	2.09	−2.17	−639.9	−57.5
2014	0.67	2.69	−2.02	−1334.3	−122.5	1.85	−1.19	−768.1	−70.5
2015	2.18	1.63	0.55	−1301.5	−122.0	1.47	0.72	−708.6	−66.5
2016	2.26	1.68	0.59	−1263.9	−120.9	1.88	0.39	−683.0	−65.4
2017	2.19	3.11	−0.92	−1398.1	−136.4	2.82	−0.63	−767.6	−74.9
2011-17	7.03	21.67	−14.64	−7547.1	−700.9	15.31	−8.28	−4252.0	−394.3
Annual average	0.98	2.84	−1.88	−1078.2	−100.1	2.06	−1.08	−607.4	−56.3

Key to Table 5. See Key to Table 4. Y is measured in billions.

6 The Arab Spring and growth: underlying mechanisms

Perhaps an open question might be that of the underlying mechanisms through which the Arab Spring revolutionary process might have dampened GDP growth in Egypt.[12] Here we discuss the potential roles played, in particular, by the falls in tourist activity and investment, two of the growth predictors introduced in Section 4. As a way of shedding light on this issue, we repeated the exercise carried out in Sections 3 and 4, but changing the outcome variable this time, thereby considering two alternatives: first, tourism activity; and, second, investment.

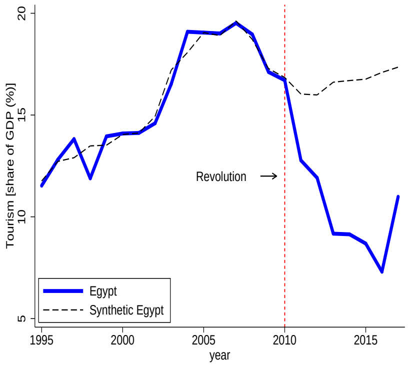
Given the lack of data for tourism and travel rents as a fraction of GDP for years before 1995, the pre-treatment period was reduced to 16 years, as opposed to the 21 years considered in the previous sections. Keeping the same set of control countries [see Table 1], this time it turned out that the counterfactual would be given by a different synthetic Egypt, both in terms of countries with positive weights and of the size of weights. Specifically, this is the resulting list of countries and their associated optimal weights: Belize (11.5%), Costa Rica (33.1%), Gambia (1%), Guyana (3.2%), Honduras (8.9%), Lebanon (7.1%), Mali (6.2%), Mauritius (10.3%), Mongolia (6.3%), Morocco (1.7%), St. Lucia (0.8%) and Tanzania (9.9%).[13] Graphically, the result is shown in Figures 10 and 11 (i.e. the counterparts of Figures 2 and 3 respectively). The former describes the time paths for the tourism and travel rents of Egypt and its counterfactual, while the latter depicts the difference between the two (i.e. the gap), and in both cases as proportions (in percent terms) of GDP. The

[12] The suitability of introducing this discussion was kindly suggested to us by an anonymous referee.

[13] For the sake of space saving the corresponding counterpart to Table 2 has not been included in this paper, but it is available upon request from the authors.

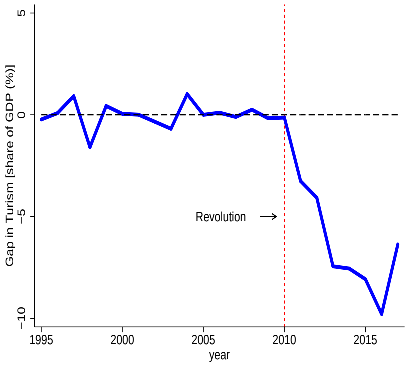
mere visual inspection of the figures suggests two remarks: first, the good fit in the pre-treatment periods [the resulting Pre-MSPE equals 0.3367, see Eq. (3)]; and, second, the apparently strong negative effect which is summarized in an annual average gap of -6.65% for the period 2011-2017.

Figure 10
Trends in tourism and travel rents:
Egypt vs. synthetic Egypt



Key to Figure 10. Time paths of tourism and travel rents relative to GDP for Egypt and the synthetic Egypt for both the pre- and the post-treatment periods.

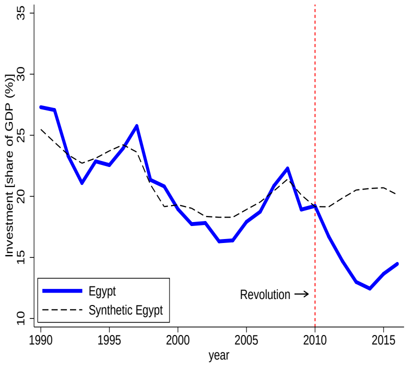
Figure 11
Trend in tourism and travel rents gap:
Egypt vs. synthetic Egypt



Key to Figure 11. Time path for the gap of tourism and travel rents relative to GDP.

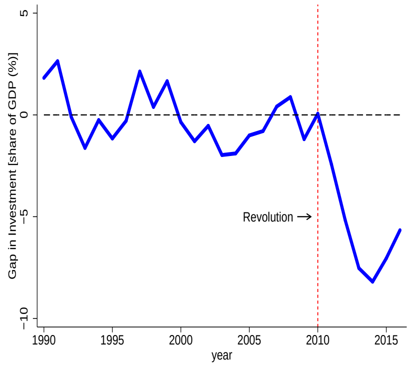
As for the effect of the revolutionary process on investment, the partial unavailability of data for this variable made us change both the sample period (eliminating year 2017) and the donor pool as some countries had to be excluded: Antigua and Barbuda, Dominica, Grenada, Trinidad and Tobago, Saint Vincent, Vietnam, Saint Lucia, Tonga,Vanuatu, Fiji, Gambia and Seychelles, leaving a total of 56 control countries. Notice that some of the removed countries were assigned positive weights in at least one of the two previous synthetics. On this occasion, the resulting synthetic Egypt is given by the following combination of countries and weights: Malaysia (13.7%), Singapore (7.5%), South Africa (38.3%), Thailand (6.1%) and United Kingdom (34.3%). Despite being not as good a fit in the pre-treatment periods as in the case of tourism rents [Pre-MSPE = 1.6870], the SCM still detects a negative effect on the part of the Arab Spring on investment equivalent to an annual average gap of -6.01% for the period 2011-2016.

Figure 12
Trends in investment:
Egypt vs. synthetic Egypt



Key to Figure 12. Time paths of investment relative to GDP for Egypt and the synthetic Egypt for both the pre- and the post-treatment periods.

Figure 13
Trend in investment gap:
Egypt vs. synthetic Egypt



Key to Figure 13. Time path for the gap of investment relative to GDP.

7 Conclusions

In 2011 a revolutionary movement started in Tunisia that quickly spread in the Middle East and North Africa. These popular uprisings, known as Arab Spring, asked for democratic reforms in countries that in general suffered from dictatorships. In this paper we study the case of Egypt, where president Mubarak was overthrown, which gave rise to a transition period characterized by political instability. As is commonly known, political instability and economic growth are highly related. In the case of Egypt, tourism, one of the main economic sectors, has been deeply impacted. Thus, for example, whereas international tourism (number of arrivals) totaled 14 million in 2010, in 2011 it dropped to 9.5 million, standing at 5.3 million in 2016.

In this paper, making use of the SCM, we seek to assess the economic cost of the revolutionary process for the period 2011-2017. The SCM consists of building up a synthetic treated unit (Egypt in our case) as a weighted average obtained amongst the untreated units or controls in such a manner that it mimics the performance of the treated unit for a vector of pre-treatment characteristics during the pre-treatment periods as fairly as possible. The outcome that we try to emulate is per capita real GDP, and the set of predictors that we use for this purpose consists of some lags in the outcome variable and some of its time averages as well as other covariates often used in economic growth literature.

The fit between Egypt and the synthetic Egypt during the pre-treatment period appears fairly accurate. Starting 2011, however, a substantial gap between the predicted trend for the synthetic Egypt and Egypt appears. A summary of the quantitative implications follows: the observed average annual growth rate of the per capita real GDP between 2011 and 2017 was equal to 0.975%, while that for the synthetic Egypt in the same period was equal to 2.524%. To put it in a different way, the accumulated loss in terms of the growth rate of per capita real GDP in that period was equal to 12.04%. This gap in growth rates had consequences in terms of output: due to the revolution, the accumulated loss in the per capita real GDP was equal to 6,279.7 dollars, *i.e.* an average of 897.1 dollars per year. And, in aggregate terms, the accumulated loss in real GDP amounted to $582.5 billion, or a yearly average loss of 83.2 billion dollars.

In order to know whether the results are really caused by the treatment under consideration some check tests were conducted, reinforcing our conclusion that the SCM has correctly identified the consequences of the Arab spring for Egypt in terms of real GDP. Finally, we have also identified at least two of the channels by which the revolutionary process ended up damaging the Egyptian economy, namely the respective falls in tourism and travel rents, and investment.

Compliance with Ethical Standards

Conflict of Interest: Cruz A. Echevarría declares that he has no conflict of interest. Javier García-Enríquez declares that he has no conflict of interest.
Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Acknowledgements We are deeply indebted to Javier Gardeazabal for his comments and suggestions on an earlier draft, to Martin Becker for his valuable help with the R code, and to the editor and two anonymous referees. The usual disclaimer applies.

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