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The Impact of a Large-Scale Natural Disaster on Local Economic Activity: Evidence from the 2003 Bam Earthquake in Iran

Abstract

This study provides new causal evidence for the impact of a large-scale natural disaster on local economic activity in Iran using nighttime light intensity. We apply the synthetic control method (SCM) and nighttime light (NTL) data from 1992 to 2020 for 31 provinces and 429 counties to study the impact of the 2003 Bam earthquake in the Iranian Kerman Province. According to the results and statistical inference tests for the SCM, Bam County and four neighboring counties experienced a statistically significant boost in economic activity in the years following the earthquake. This increase in local economic activity can be explained by the combination of several factors, such as an unprecedented inflow of national and international disaster relief during the reformist government of President Khatami, the political trust and mobilization of civil society in this period, the cultural importance of Bam, the severity of the earthquake, and the media attention. Additionally, economic activity in Bam County returns to its pre-disaster development path after seven years.

JEL-Codes: E010, H840, O110, O440, O530, Q510, Q540, R110, R120.

Keywords: natural disaster, natural hazard, synthetic control, earthquake, economic development, nighttime light, Iran, Bam.

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1. Introduction

Over the past 30 years (1992-2020), Iran has experienced 143 natural disasters, 16 of which can be classified as large-scale disasters, including floods, earthquakes, droughts, storms, and others. These disasters have affected more than 51 million Iranians, resulting in over 33,000 deaths and an estimated damage of more than US$25 billion, adjusted for inflation using the consumer price index (EM-DAT 2021). Especially due to its geography, Iran is extremely vulnerable to natural hazards. We have chosen to focus on the 2003 Bam earthquake since it was the largest natural disaster in the period of available nighttime data (1992-2020) and because Bam and its cultural landscape are important UNESCO World Heritage Sites[1]. This earthquake is considered one of the deadliest in Iranian history, resulting in the deaths of 26,796 people, affecting over 250,000 people, causing damage of over US$700 million (EM-DAT 2021), adjusted for inflation, and destroying about 80% of the city of Bam (Fallahi 2007).

One of the main contributions of this study is the creation of a counterfactual case for Kerman Province and Bam County to investigate the impact of the earthquake. Previous studies on Iran have mainly focused on the short-term impacts of natural disasters of all sizes (Sadeghi and Emamgholipour 2008; Sadeghi, Emamgholi Sefiddasht, and Zarra Nezhad 2009; Yavari and Emamgholipour 2010; Hosseini, Hosseinioon, and Pooyan 2013; Yuan et al. 2018; Fischer 2021). However, we are interested in examining the long-term effects of large-scale natural disasters. To achieve this, we will use the synthetic control method (SCM) to construct synthetic versions of Kerman Province and Bam County that have been affected by the earthquake. We will then estimate the economic development of the counterfactual province and county, which reflect the development paths that would have been taken if the impact of the disaster did not occur. The difference between the development paths of the affected province and county, in comparison to their synthetic versions, will provide us with estimations of the impact of the 2003 Bam earthquake.

We are measuring economic activity in Iranian provinces and counties using nighttime light (NTL) data from 1992 to 2020 (Li et al. 2020), which has several advantages for our study. First, it not only reflects the development of the formal economy, but also the development of the informal economy, which was on average 17% of Iran's GDP from 1991 to 2017 (Medina and Schneider 2019). Therefore, it provides us with a more comprehensive measure of the true impact of the earthquake on economic activity. Second, NTL data provides a longer time period than the available official gross domestic product (GDP) data on the provincial and county

[1] Website of the United Nations Educational, Scientific and Cultural Organization (UNESCO) about Bam: https://whc.unesco.org/en/list/1208/ (Accessed: 9 September 2022).

levels and has consistent political borders over the whole time period. Using SCM and localized data can provide a more accurate representation of the true impact of a natural disaster while accounting for external shocks, such as economic sanctions, that may affect the entire country. This is the first study on the case of Iran to measure the costs of natural disasters by creating counterfactual cases for affected provinces and counties. It has an advantage over previously used approaches because the estimated synthetic control will reflect the development of the provinces and counties in the absence of the disaster. Additionally, this study is the first to use SCM to investigate spatial spillovers into neighboring geographical units. The main findings are that Bam County and four neighboring counties experienced a boost in economic activity in the years following the disaster, returning to their pre-disaster development paths within ten years. These findings are consistent with previous theoretical models (Albala-Bertrand 1993; Skidmore and Toya 2002; Chhibber and Laajaj 2008; Klomp 2016) and empirical evidence, which show an increase of economic performance after natural disasters; for example: Albala-Bertrand (1993) for the case of 27 developing countries; Noy (2009) for his sample of OECD countries; Loayza et al. (2012) for the case of flood disasters in their sample of 94 countries; Klomp (2016) for the long-term impact of geophysical disasters in his sample of 147 countries; Onuma et al. (2021) for the average effect of all disasters in their sample of 173 countries; and Felbermayr et al. (2022) for the case of excessive precipitation in their worldwide sample.

We have identified several factors that are responsible for this increase in local economic activity in the case of the Bam earthquake, namely an unprecedented inflow of national and international disaster relief during the reformist government of President Khatami, the political trust and mobilization of civil society in this period, the cultural importance of Bam, the severity of the earthquake, and the media attention. The paper is structured as follows: Section 2 presents an overview of the theoretical and empirical literature. Section 3 explains the data and methodology. Section 4 presents the results including statistical inference and robustness checks. Section 5 discusses the findings and explains different contributing factors behind the estimated booming effect after the Bam earthquake. Section 6 concludes.

2. Literature Review

A significant body of literature has both theoretically and empirically examined the relationship between economic performance and natural disasters, however, with heterogeneous results that depend on the characteristics of the countries and disasters (Noy 2009; Loayza et al. 2012; Cavallo et al. 2013; Felbermayr and Gröschl 2014; Klomp and Valckx 2014; Klomp 2016; Noy and duPont IV 2018; Fabian, Lessmann, and Sofke 2019; Onuma, Shin, and Managi 2021; Felbermayr et al. 2022).

2.1 Theoretical Literature

Theoretical backgrounds are discussed by Albala-Bertrand (1993) and Skidmore and Toya (2002) who show how the impact of natural disasters can positively affect economic growth. They hypothesize that this growth is due to capital stock accumulation, human capital accumulation, or improvements in technological capacity. Despite the destruction of capital, disasters increase the return on human capital relative to investment capital and increase total factor productivity through the adoption of newer and more productive technologies. This is also supported by Klomp (2016) who argues with Schumpeter's creative destruction theory, which means that the disaster shocks can work as an accelerator for upgrading the destroyed capital stock. Moreover, Noy and duPont IV (2018) focus on the long-term consequences of natural disasters and argue that several factors should be taken into consideration when assessing likely post-disaster long-term outcomes, for example the type and severity of the event, the underlying composition of the economy, and the total area impacted. They also state that there is no clear consensus concerning the long-term economic consequences of natural disasters. Based on the findings of several empirical studies, they argue that the long-term consequences of disasters can fall into four categories: no long-term impact, positive impact, negative impact, or mixed/nuanced impact (where different aggregates are impacted differently).

2.2 Previous Global Studies

Empirical evidence for different impacts of natural disasters on the economy in the short and long run is provided in several studies that show how the type and size of a disaster and country characteristics, such as the level of economic development, the level of institutional development, and geographical aspects, among others, are responsible for these differences. An early study by Albala-Bertrand (1993) shows positive GDP growth rates after large-scale natural disasters in 27 developing countries in the two years following the events. After one year, 17 countries had even higher growth rates than before the events, and after two years, 6 countries reported further acceleration of growth. A study by Noy (2009) also focuses on the short-term effects of natural disasters on the macroeconomy. He shows that countries with higher literacy rates, better institutions, higher per capita incomes, more openness to trade, and higher levels of government spending are able to better withstand the initial shock and prevent further spillovers into the macroeconomy. His results suggest a positive impact of natural disaster damage on economic growth in OECD countries and a negative impact in developing countries.

Further empirical evidence of the mixed impact of natural disasters on economic performance can also be found in other studies. Loayza et al. (2012) show that the impact of natural disasters depends on the type and severity of the natural disasters and the economic sector affected. Their results suggest that flood disasters have a positive effect on GDP growth, using panel data with five-year averages from 1961-2005 for 94 countries. Klomp (2016) shows a negative impact on economic growth for most disaster types, measured by changes in nighttime lights, but he also presents a positive long-term impact of geophysical disasters in a sample of 147 countries over the period 1992-2008. Onuma et al. (2021) take into account many of the previously discussed aspects and study the effect of natural disasters on economic growth in the short (0-5 years), middle (6-10 years), and long term (11-30 years), using a sample of 173 countries for the period 1990-2010, while taking into account the type and severity of the disaster and the income level of the affected countries. The sample of all natural disasters shows a positive effect in the short and medium term, while the sample of all large-scale (catastrophic) natural disasters have a negative effect in the short, medium, and long term. Their results suggest that geophysical disasters have a positive effect in the long run in upper middle-income countries and a negative effect in high income countries. Finally, Felbermayr et al. (2022) found a positive effect of excessive precipitation on local economic activity using a worldwide sample.

There are also several studies that highlight the negative impact of natural disasters on growth (Bertinelli and Strobl 2013; Felbermayr and Gröschl 2014; Elliott, Strobl, and Sun 2015; Fabian, Lessmann, and Sofke 2019; Joseph 2022). However, some of these studies are case studies focusing on specific countries or specific natural disasters. A meta-regression analysis by Klomp and Valckx (2014), which examines the relationship between natural disasters and economic growth per capita, reveals a negative genuine effect of disasters on growth with differences depending on disasters and country samples. They also find some evidence that a part of the negative impact of natural disasters found in these studies is caused by publication bias. Several studies have also shown the huge advantage of using nighttime light data to evaluate the economic impact of natural disasters and the recovery process (Bertinelli and Strobl 2013; Elliott, Strobl, and Sun 2015; Klomp 2016; Fabian, Lessmann, and Sofke 2019; Nguyen and Noy 2020; Felbermayr et al. 2022; Joseph 2022). The topic of post-disaster spillovers has gained more attention in recent years with a handful of published studies (Felbermayr et al. 2022; Fischer 2021; Lenzen et al. 2019; Barbosa and Lima 2019). According to these studies, the indirect spillover effects of natural disasters, much like direct effects, are heterogeneous and depend on the country characteristics and disasters.

The synthetic control method (SCM) has already been used in several studies in the context of natural disasters, for example, to study its impact on economic growth, employment, population size, tourist arrivals, university enrolment, migration, and government spending (Coffman and Noy 2011; Cavallo et al. 2013; Barone and Mocetti 2014; duPont IV and Noy 2015; Cerqua and Di Pietro 2017; Lynham, Noy, and Page 2017), and beyond (Smith 2015; Cheong, Kwak, and Yuan 2017; De Roux and Riehl 2022). Like studies using other methodologies, the results are mixed. Coffman and Noy (2011) investigated the 1992 hurricane on the Hawaiian island of Kauai and found reduced employment and population size. The real per capita income of the factual Kauai was larger than its synthetic counterpart for about 8 years after the disaster. Barone and Mocetti (2014) examined the impact of two earthquakes in Italy using regional data and their results suggest a positive effect of one earthquake on GDP per capita and a negative effect in the other. They argue that the differences are the results of different levels of pre-quake institutional quality. duPont IV and Noy (2015) follow a similar approach and studied the impact of the 1995 Kobe earthquake in Japan and found reduced population size and GDP per capita in the long term, an increase in local government expenditures, and an increase of migration into the region in the years following the disaster. Lynham et al. (2017) investigated the 1960 tsunami in Hawaii and show a decrease in population size, number of employees, and sugar production, suggesting on overall negative impact on the economy in the long term. Contrary to previous regional-level studies, Cavallo et al. (2013) use country-level data and do not find any significant effect of natural disasters on economic growth. They construct synthetic controls for each country that experienced a large-scale natural disaster in the period 1970-2008, covering 196 countries.

2.3 Previous Studies on Iran

While the majority of studies on natural disasters in the case of Iran are related to health, geography, engineering, and natural disaster management, there are also empirical studies on their effects on GDP per capita, savings, and investments (Sadeghi and Emamgholipour 2008; Sadeghi, Emamgholi Sefiddasht, and Zarra Nezhad 2009; Yavari and Emamgholipour 2010). Using time-series analysis with country-level data, the authors found negative impacts of natural disasters on Iran's non-oil GDP, per capita investments, and per capita GDP in the short run. Fischer (2021) uses several spatial panel models and found that there is no statistically significant direct impact of natural disasters on GDP per capita growth, using the period 2010-2016 that included only one large-scale natural disaster (the 2014 flood). When focusing on the disaster type, the study found some evidence for a positive association between flood disasters and GDP per capita growth. The study also found positive spatial spillover into neighboring provinces.

Moreover, Hosseini et al. (2013) report the social and economic consequences of two major earthquakes in Iran, namely the 1990 Manjil-Rudbar earthquake and the 2003 Bam earthquake. They present the destruction in the affected areas and show how the disasters affected the psychological well-being of its inhabitants. In addition, they discuss different laws and policies related to disaster management. In a case study comparison including Iran, Yuan et al. (2018) show how earthquakes can facilitate civil society engagement in developing countries. Overall, their results suggest that civil society engagement experienced a sharp spike directly after the disaster, but most of the volunteers left the affected area after several months. The study also discusses the reactions of the governments and challenges in coordination between involved agents.

In addition to earthquake disasters, there is also a discussion in the literature about weather-related disasters which are often associated with climate change. Vaghefi et al. (2019) prognose that Iran is likely to experience more extended periods of extreme maximum temperatures in the southern part of the country and more extended periods of extreme weather events, including dry and wet conditions. Their projections show a climate of extended dry periods interrupted by intermittent heavy rainfalls, which will increase the chances of flooding. Climate change in Iran has already had social and economic consequences, such as inter-province migration (Farzanegan, Gholipour, and Javadian 2022) and increasing housing and residential land prices (Farzanegan, Feizi, and Gholipour 2021). The former study showed that higher levels of air pollution have a positive and significant impact on net outmigration in Iranian provinces between 2011 and 2016 and the latter examined the effect of drought on housing and residential land prices in Iran, using panel data from 2006–2015 on the province level.

Overall, we can see that there is already a large amount of literature addressing the problem of natural disasters in Iran. However, these studies have mainly discussed the immediate impact of natural disasters on various indicators, addressing consequences in the short term. None of these studies have estimated a counterfactual Iran or the affected region, which could help identify the causal impact of the disaster. One of the main challenges of causal analysis, as mentioned by Holland (1986), is that the unit under intervention or exposure cannot be obtained without the mentioned treatment. Thus, the challenge of causal inference is the best estimation of a counterfactual or synthetic region that perfectly reproduces the development picture of the affected region before experiencing the disaster. We will fill this gap by using the SCM and provide empirical evidence for the impacts of a large-scale natural disaster in the intermediate and long-term.

3. Methodology and Data

This study utilizes nighttime light data as a measurement for economic activity, which has already been widely used in the context of natural disasters and beyond (Ghosh et al. 2009; 2013; Chen and Nordhaus 2011; Henderson, Storeygard, and Weil 2012; Bertinelli and Strobl 2013; Elliott, Strobl, and Sun 2015; Klomp 2016; Tanaka and Keola 2017; Fabian, Lessmann, and Sofke 2019; Farzanegan and Hayo 2019; Nguyen and Noy 2020; Farzanegan and Fischer 2021; Felbermayr et al. 2022; Joseph 2022). Additionally, we will employ the synthetic control method, which has previously been used in the context of sudden shocks to an economy on the provincial level (Abadie and Gardeazabal 2003; Barone and Mocetti 2014; Horiuchi and Mayerson 2015; duPont IV and Noy 2015; Bilgel and Karahasan 2017; Lynham, Noy, and Page 2017; Sun and Yu 2020)[2].

3.1 Methodology

We use the SCM with data at the provincial and county levels because the effect of natural disasters on the national economy of a country might be small, except for very small countries (Albala-Bertrand 1993; Bertinelli and Strobl 2013; Klomp 2016; Noy and duPont IV 2018; Fabian, Lessmann, and Sofke 2019). In the case of Iran, we would expect that even large-scale natural disasters that affect only one province or a sparsely populated province will hardly be measurable in the national GDP. This also gives us the possibility to keep factors that affected all Iranian provinces and counties at the same time constant. In a cross-country or time-series comparison, we will not know if the effects on economic activity come from a natural disaster or another major shock.

The SCM was developed by Abadie et al. (2003; 2010; 2015) and is used to study shocks on an outcome variable, which in our case is the natural logarithm of the sum of nighttime lights. The shock is the 2003 Bam earthquake which suggests that the disaster year is 2003 and the affected unit ($j=1$) is Kerman Province. The remaining provinces will be used as the donor pool ($j=2$ to $j=J+1$). We do the same on the county level, where Bam County is the affected unit. The advantage of the SCM is that we are using the combination of several unaffected units to approximate the pre-disaster characteristics of the affected unit, which is much more accurate than using any single unaffected unit. We also need a sample that is a balanced panel dataset,

[2] The SCM was also used in several studies about Iran, using country-level data, to determine the impact of revolution, war, and sanctions (Gharehgozli 2017; Farzanegan 2022a; 2022b).

where all units are observed at the same time periods $t=1,\ldots,T$. In addition, it should include a positive number of pre-disaster periods, T_0, and a positive number of post-disaster periods, T_1, where $T=T_0+T_1$. Unit 1 ($j=1$) is exposed to the disaster during the period $T_0+1,\ldots,T$, and the disaster has no effect during the period $1,\ldots,T_0$. With this approach, we will measure the effect of the Bam earthquake on the post-disaster outcome.

According to Abadie et al (2015), a synthetic control is defined as the weighted average of the units in the donor pool. It can be represented by a $J\times 1$ vector of weights $W=(w_2,\ldots,w_{J+1})'$, with $0\leq w_j\leq 1$ for $j=2,\ldots,J$ and $w_2+\ldots+w_{J+1}=1$. We are choosing a synthetic control by choosing a particular value for W. It will be selected using Mill's Method of Difference[3], so that the characteristics of the affected unit are best reflected by the characteristics of the synthetic control. The values of the pre-disaster characteristics, X_1, of the affected unit that we aim to match as closely as possible are included in a $k\times 1$ vector and the values of the same variables for the units in the donor pool, X_0, are included in a $k\times J$ matrix. The pre-disaster characteristics in X_1 and X_0 may also include pre-disaster values of the outcome variable. The vector X_1-X_0W describes the difference between the pre-disaster characteristics of the affected unit and the synthetic control. A synthetic control, W^*, that minimizes the size of this difference will be selected.

Abadie et al (2015) operationalize it in the following way. For $m=1,\ldots,k$, let X_{1m} be the value of the m-th variable for the affected unit and let X_{0m} be a $1\times J$ vector containing the values of the m-th variable for the units in the donor pool. The authors choose W^* as the value of W that minimizes:

$$\sum_{m=1}^{k} v_m (X_{1m} - X_{0m}W)^2 \tag{1}$$

The variable v_m is a weight that reflects the relative importance that is assigned to the m-th variable when the difference between X_1 and X_0W is measured. The aim is that the synthetic controls reproduce the values that variables with large predictive power on the outcome variable take for the affected unit. Thus, those variables should be assigned large v_m weights, which will be chosen with a cross-validation method. The value Y_{jt} is the outcome of unit j at time t and Y_1 is a $T_1\times 1$ vector that collects the post-disaster values of the outcome for the affected unit, which is $Y_1=(Y_{1\,T0+1},\ldots,Y_{1\,T})'$. In addition, Y_0 is a $T_1\times J$ matrix, where the column j contains the post-disaster values of the outcome for unit $j+1$. With the comparison of the post-disaster outcomes

[3] Mill's Method of Difference is an approach and logical argument to determine causes and effects. Within this approach, two or more instances of an event (effect) are compared to see what they do not have in common. If they have all but one thing in common, that one thing is identified as the cause (Baronett 2013, 602–37).

between the affected unit and the synthetic control, Y_1-Y_0W^*, we receive the synthetic control estimator of the effect of the disaster. For the post-disaster period t (with $t \geq T_0$), the estimator is given by:

$$Y_{1\,t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{2}$$

Additionally, the corresponding variables X_0 and X_1 are the predictors of the post-disaster outcomes which are not affected by the disaster. However, the applicability of the method may be limited by the presence of unmeasured factors affecting the outcome variable as well as by heterogeneity in the effects of observed and unobserved factors. With a linear factor model, Abadie et al. (2010) show that matching on pre-disaster outcomes helps to control for unobserved factors and for the heterogeneity of the effect of the observed and unobserved factors on the outcome if the number of pre-disaster periods in the dataset is large. They argue that only units that are alike in both observed and unobserved determinants of the outcome variable, as well as in the effect of those determinants on the outcome variable, should produce similar trajectories of the outcome variable over extended periods of time. A difference in the outcome variable following the disaster can be interpreted as being produced by the disaster itself if the unit representing the case of interest (in our case, the province or county affected by the natural disaster) and the synthetic control unit similarly behave over extended periods of time before the disaster.

When selecting the 2003 Bam earthquake as a case study, we considered several requirements that are necessary to apply the SCM. We needed a sufficient number of pre-disaster periods to determine the synthetic control and we also needed enough years after the event so that we could evaluate the impact. Additionally, we needed to find a natural disaster that only affected one or a few provinces simultaneously so that we could have enough donor provinces that were not affected by the shock. In the province-level analysis, we chose Kerman Province with the disaster year 2003. For the analysis, we restrict the donor pool to include only provinces that were not directly or indirectly affected by the disaster or other major shocks during the study period. We exclude provinces from the donor pool that experienced one of the other 16 large-scale natural disasters in the same year or were neighboring provinces of Kerman. Therefore, we exclude the neighboring provinces Fars, Hormozgan, Sistan and Baluchestan, South Khorasan, and Yazd. In the county-level analysis, we investigate the impact on Bam County and its neighbors. As there are 429 counties, and thus more donor pool counties available, we restrict the donor pool more conservatively and remove all counties and neighboring counties that experienced one of the large-scale disasters over the whole period of available data. The included counties are presented in Table A1 in the Appendix.

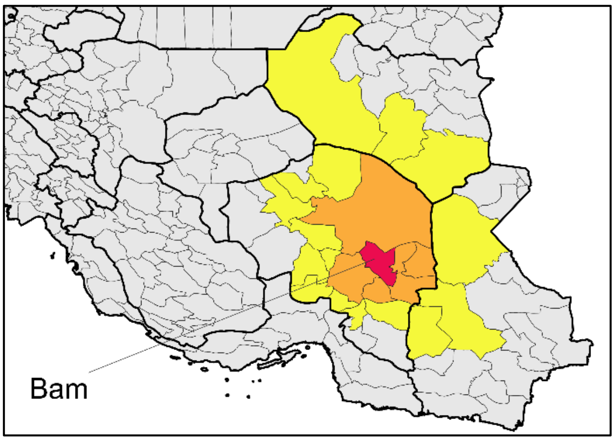
3.2 Data: Outcome Variable and Predictors

According to the International Disaster Database (EM-DAT 2021), Iran has experienced 143 natural disasters in the period from 1992 to 2020. To select the case study, we first limited the number of natural disaster events to large-scale events by using a definition similar to previous studies (Gassebner, Keck, and Teh 2010; Klomp 2016): (i) the number of killed is not less than 1,000; (ii) the number of total affected (injured, affected, and homeless) is not less than 100,000; or (iii) the amount of damages is not less than US$1 billion. This leaves us with 16 large-scale natural disasters and we chose the case study of Bam because it is not only the deadliest earthquake in the sample, but it also provides us with enough years before and after the disaster to apply the SCM.

In December 2003, the historic city of Bam was shaken by an earthquake that measured 6.6 on the Richter scale. The city of Bam is located in Bam County of Kerman Province, which is in southeastern Iran, as presented in Figure 1. It was one of the deadliest earthquakes in Iranian history, killing 26,796 people, injuring more than 20,000 people, leaving more than 60,000 people homeless, and destroying about 80% of Bam and 100% of the buildings in the town of Baravat (Fallahi 2007; Hosseini, Hosseinioon, and Pooyan 2013; EM-DAT 2021). Additionally, the earthquake damaged important infrastructure such as the water supply network, sewage, power lines, telecommunication systems, healthcare centers, educational buildings, irrigation and agricultural systems, gardens, streets, and roads, as well as cultural centers and other cultural heritage sites, such as Bam’s historical citadel. It is estimated that more than 265,000 people were affected by this disaster and the total costs are estimated to be about US$700 million (Ghafory-Ashtiany and Hosseini 2008; EM-DAT 2021). In contrast to residential structures, industrial structures suffered less damage, including cracks in walls and oil spills (Eshghi and Razzaghi 2005).

Figure 1: Provinces and counties affected by the 2003 earthquake

(a) Province affected by the earthquake.



(b) County of the epicenter of the earthquake as well as neighboring counties of first and second order.

(Source: Authors' illustration)

Outcome variable

The outcome variable in all of our estimations is the natural logarithm of the sum of nighttime lights using the data provided by Li et al. (2020). Using nighttime light (NTL) data as a proxy for economic activity has at least four advantages for this study. First, the growth in nighttime lights reflects growth in economic activity, but it does not include the possible measurement error of the gross domestic product (GDP) in countries with low-quality regional and national accounts (Elvidge et al. 1997; Chen and Nordhaus 2011; Henderson, Storeygard, and Weil 2012; Felbermayr et al. 2022). Second, official GDP statistics do not account for the informal economy, which is included in NTL and can be large and important in many countries (Ghosh et al. 2009; 2013; Tanaka and Keola 2017; Farzanegan and Hayo 2019; Farzanegan and Fischer 2021). These two aspects can lead to a situation where the true effect of natural disasters on the economy will be underestimated, as shown by several authors (Bertinelli and Strobl 2013; Elliott, Strobl, and Sun 2015; Klomp 2016; Fabian, Lessmann, and Sofke 2019). The third advantage of NTL data is that remote sensing datasets are available for all countries or smaller geographical units, making them comparable across units. This is connected to the fourth advantage because during the period of this study (1992 to 2020), several reforms related to provincial and county borders occurred in Iran. This will make it difficult to compare GDP statistics for all Iranian provinces and counties over longer time periods. Using NTL addresses this problem and provides us with more observations.

This study utilizes version 5 of the harmonized global NTL dataset by Li et al. (2020), which is based on data from the Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS) of the United States Department of Defense. The data range is from 1992 to 2013 and data from Visible Infrared Imaging Radiometer Suite/Day Night Band (VIIRS/DNB) of the Earth Observation Group of the United States National Oceanic and Atmospheric Administration (NOAA) ranges from 2012 to 2020. We extract the NTL data from 2017 (OCHA 2019b), which includes 31 provinces and 429 counties, with provincial and county borders. We calculate the sum of light intensity for each of the provinces and counties over the period of 1992–2020, which leaves us with a province-level panel dataset of 899 observations and a county-level panel dataset of 12,441 observations for the NTL. The values represent the yearly average of the sum of nighttime light intensity in each Iranian province and county. It is the sum of pixels of approximately 1 km² (30 arc seconds) in each geographical unit, where the light intensity ranges from 0 (black) to 63 (white). Based on 489 observations of the province-level data, we calculated Pearson's correlation coefficient of 0.63 for the relationship between the real GDP of Iranian provinces in trillion Iranian Rial (IRR) and its average NTL, which shows a clear positive relationship between the two variables. The provincial GDP data used in the correlation is from the Iranian Ministry of Economic and Financial Affairs (MEFA) and is available from 2004 to 2019 (MEFA 2021).

Predictor variables

In the estimations with the province-level data, we are using several predictor variables based on previous studies. We use every second year of NTL in the pre-disaster period which will help provide a good pre-disaster fit of the affected and synthetic province (Abadie and Gardeazabal 2003; Cavallo et al. 2013; Barone and Mocetti 2014; Abadie, Diamond, and Hainmueller 2015). As discussed by Kaul et al. (2021), we do not use all years of the outcome variable because using all outcome lags as separate predictors renders all other covariates irrelevant and might result in a larger potential bias of the estimated treatment effect. In addition, we use several other predictor variables that are relevant in the case of natural disasters, namely the pre-disaster average of the outcome variable, pre-disaster average of the first difference of the outcome variable, pre-disaster average of the population growth rate, natural logarithm of the population density, and natural logarithm of the natural disaster risk measurement. We calculated the population growth rate in percent and the population density in persons per km². Natural disaster risk is measured by natural disasters per year per 10,000 km² in the period 1990-2019 (OCHA 2019b; EM-DAT 2021).

With the NTL predictors, we cover aspects such as the level of economic development and economic growth and with population growth and density, we cover demographics. The natural disaster risk covers geographic and institutional aspects because disaster risk is usually a consequence of these, including exposure to natural disasters due to geography and man-made factors such as susceptibility, vulnerability, and coping capacities. As the data availability at the county level is more limited, we are using slightly different predictors. The NTL data are from the county level and are extracted and calculated in the same way as the province-level variables, but the remaining data are from the province level, thus we are additionally controlling for the characteristics of the province of the selected donor pool counties. In the case of the county-level estimations, we do not only use donor pool counties from the same province, but from all of Iran, which will provide a larger donor pool.

4. Results and Statistical Inference

First, we applied the SCM with province-level data where Kerman Province is the affected unit and 2003 is the disaster year. According to the results, the synthetic Kerman is best generated by the weighted average of seven provinces (out of 25 provinces in the donor pool), namely Razavi Khorasan (58.6%), North Khorasan (10.3%), Khuzestan (9.5%), Semnan (8.1%), Lorestan (6.9%), Markazi (4.6%), and Kohgiluyeh and Boyerahmad (1.9%). In the following, we refer to the affected Kerman as factual Kerman, which has experienced the disaster event, and the counterfactual Kerman as synthetic Kerman. Table 1 shows the average values of the covariates of factual Kerman and synthetic Kerman before the disaster year 2003. According to the values, synthetic Kerman closely reflects the pre-disaster performance of the NTL covariates of factual Kerman and synthetic Kerman is similar in terms of the other predictor variables, namely the average and growth of NTL, population growth rate, population density, and natural disaster risk. In addition to the values of factual Kerman and synthetic Kerman, we also present in Table 1 an unweighted average of the variables for the seven provinces with weights greater than zero. The predicted outcome in the pre-disaster period is similar between factual and synthetic Kerman with the selected weights. In comparison to the unweighted average of the same seven provinces, the gaps between factual Kerman and synthetic Kerman are smaller for almost all predictors, which highlights again the advantage of the SCM, which chooses the optimal weights, in contrast to simply using the unweighted average.

Table 1: Means of predictors during the pre-disaster period (1992-2002)

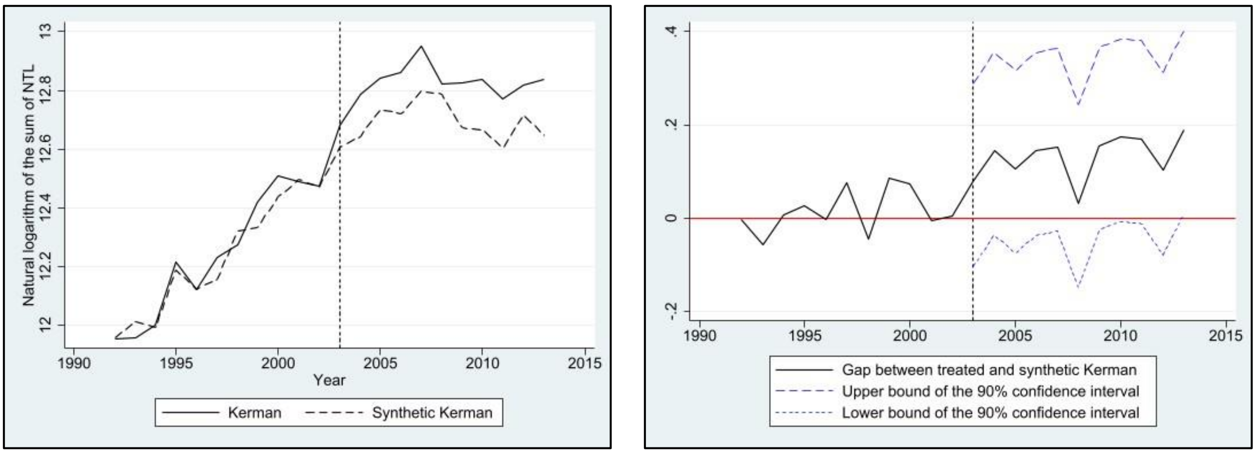
	(1) Factual Kerman	(2) Synthetic Kerman	(3) Unweighted average of variables for provinces with weight > 0	(4) Difference (1-2)	(5) Difference (1-3)
NTL (1992)	11.953	11.956	11.572	-0.002	0.382
NTL (1994)	12.000	11.993	11.601	0.007	0.399
NTL (1996)	12.120	12.122	11.742	-0.003	0.378
NTL (1998)	12.274	12.320	11.864	-0.046	0.410
NTL (2000)	12.509	12.436	11.999	0.073	0.510
NTL (2002)	12.475	12.470	12.003	0.005	0.472
NTL(mean 1992-2002)	12.240	12.226	11.798	0.014	0.442
ΔNTL(mean 1993-2002)	0.052	0.051	0.043	0.001	0.009
Population growth (mean 1992-2002)	1.412	1.408	1.410	0.004	0.002
Population density (mean 1992-2002)	2.696	3.694	3.561	-0.998	-0.866
Natural disaster risk	1.363	1.839	2.083	-0.476	-0.720

Notes: In this table, NTL refers to the natural logarithm of the sum of nighttime lights. Population density and natural disaster risk are also used as natural logarithms.

Figure 2a shows the trajectory of the natural logarithm of the sum of NTL of factual Kerman and its synthetic counterpart during the period between 1992 to 2013. We can see that synthetic Kerman reproduces the development of NTL of factual Kerman in the period before the 2003 earthquake. The estimate of the effect of the earthquake disaster is shown by the difference between the factual and synthetic Kerman. If we compare the trajectories of both cases, we see that both continue to grow until 2007, where they peak before going down again. However, the development of nighttime lights in synthetic Kerman is lower than the development of factual Kerman which suggests that the earthquake disaster had a positive impact on the NTL development in factual Kerman. In addition, we can see that factual Kerman does not return to its pre-disaster development path in the ten years after the event.

However, it is also important to consider the uncertainty of the estimation of the synthetic control, which can be evaluated with several established placebo tests and the confidence bounds developed by Firpo and Possebom (2018) as well as Ferman et al. (2020). The latter proposed a uniform confidence set around the estimated effect of the synthetic control, which is presented as the gap between the factual and counterfactual values of the outcome variable. It contains all functions that are deviations from the estimated treatment effect by an additive and constant factor and are not rejected by the placebo test. Figure 2b presents the estimated gap between factual Kerman and synthetic Kerman with uniform confidence sets at the 90% confidence level. If the confidence sets do not include the zero line, then we are 90% certain about the true effect of the earthquake event on the economic activity in Kerman Province. According to the results, the estimated positive effect of the 2003 earthquake is not significant in the ten years following the event.

Figure 2: Synthetic control analysis of Kerman Province



(a) Factual and synthetic Kerman.

(b) Gap between factual and synthetic Kerman including confidence sets.

The other established placebo tests are presented in Figure A1 in the Appendix. In the context of the SCM, there are several established placebo or falsification tests which can also be described as randomization inference tests (Bertrand, Duflo, and Mullainathan 2004). Following Abadie et al. (2010; 2015), we have applied an in-space placebo test, an in-time placebo test, and the leave-one-out test and calculated a pseudo p-value based on the ratio of the post-disaster root mean square prediction error (RMSPE) to the pre-disaster RMSPE. The ratio is 2.98 in the case of Kerman with a pseudo p-value of 0.23 and Kerman Province ranks sixth of all provinces from the donor pool. The RMSPE measures the lack of fit between the path of the outcome variable for any particular province and its synthetic counterpart. As there are some discrepancies between the predictors of the factual and synthetic Kerman (see Table 1), we also applied the penalized synthetic control. It uses different estimation techniques for bias correction of inexact matching (Abadie and L'Hour 2021; Wiltshire 2022). The results are presented in Figure A2 in the Appendix and show that the bias-corrected gap of NTL between the factual and synthetic Kerman is very similar when using OLS, Ridge, Lasso, and elastic net regressions with the entire donor pool. Estimating the bias-corrected gap using OLS regression with only the positively weighted donor pool units produces a smaller gap, especially after the year 2005. Overall, the placebo tests support previous findings of the confidence sets which suggest a non-significant impact of the 2003 earthquake in Kerman on the province level. Similar results about non-significant impacts on higher aggregated administrative levels can also be observed in other studies (Albala-Bertrand 1993; Cavallo et al. 2013; Fabian, Lessmann, and Sofke 2019; Fischer 2021).

A common problem is that even large-scale natural disasters might only affect local economies in a measurable way which might not be reflected on the country or province levels. Therefore, in the second step, we investigate the impact of the Bam earthquake on the county level. An earthquake with a clear epicenter also gives us the possibility to study spatial spillovers into neighboring counties and we assume that the impact of the event becomes weaker in counties further away. We removed all counties from the donor pool that have been affected by large-scale natural disasters or are neighboring counties of first order of the affected counties which might suffer from spillover effects. This leaves us with 63 counties in the donor pool which are presented in Table A1 in the Appendix. We follow the same procedure as in the case of Kerman Province, but now we focus on Bam County and its neighboring counties of first and second order which are shown in Figure 1b. We count six neighboring counties of first order, which are all located in Kerman Province and sixteen neighboring counties of second order, which are in the provinces of Kerman, South Khorasan, as well as Sistan and Baluchestan.

The values used for the SCM analysis of the neighbors are the unweighted averages of the neighboring counties of different orders. For example, the values for the neighboring counties of first order are the unweighted average of six counties and the neighboring counties of second order are the unweighted average of sixteen counties. We also use a modified version of neighboring counties of first order, because according to our results, two of these counties, Kerman and Jiroft, do not show significant gaps in their factual and synthetic versions. This leads to insignificant results when using the confidence sets and is an additional explanation for why the impact of the earthquake is insignificant on the province level. While most counties of Kerman Province were directly or indirectly affected by this large-scale disaster, not every county was affected in a measurable way. Table 2 shows the weights used to create the synthetic Bam County as well as its neighboring counties of different orders. Synthetic Bam is best generated by the weighted average of six counties, namely Bonab (39.6%), Khalkhal (19.5%), Tehran (19.2%), Tarom (10.7%), Shemiranat (7.9%), and Tabriz (3%).

Table 2: County weights of synthetic Bam and its neighbors

	Weights of synthetic Bam	Weights of synthetic Bam's neighbors I	Weights of synthetic Bam's neighbors I (selected)	Weights of synthetic Bam's neighbors II
Bonab	0.396	0.115	0	0.146
Firuzkuh	0	0	0.009	0
Jolfa	0	0.124	0.287	0.096
Khalkhal	0.195	0.295	0.02	0.225
Khorramdarreh	0	0	0.063	0
Qarchak	0	0	0.197	0.219
Shemiranat	0.079	0.242	0.015	0.181
Tabriz	0.03	0.06	0	0
Takab	0	0	0.169	0.074
Tarom	0.107	0	0.239	0.06
Tehran	0.192	0.162	0	0
Remaining 52 counties	0	0	0	0

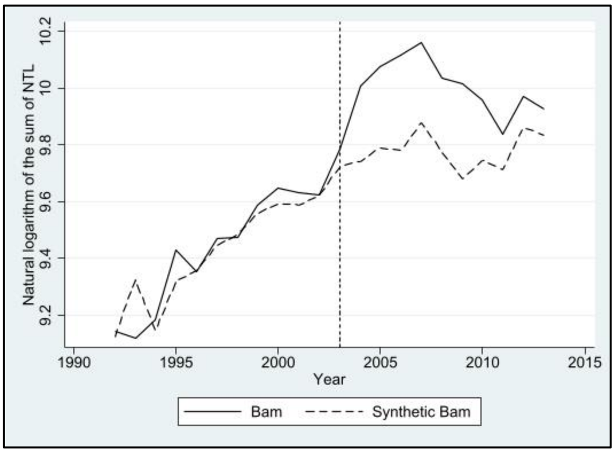
Table 3: Means of predictors during the pre-disaster period (1992-2002)

	(1) Factual Bam	(2) Synthetic Bam	(3) Factual Bam's n. I	(4) Synthetic Bam's n. I	(5) Factual Bam's n. I (selected)	(6) Synthetic Bam's n. I (selected)	(7) Factual Bam's n. II	(8) Synthetic Bam's n. II
NTL (1992)	9.143	9.123	9.176	9.141	8.063	8.024	8.552	8.518
NTL (1994)	9.183	9.146	9.263	9.212	8.150	8.122	8.597	8.585
NTL (1996)	9.354	9.357	9.352	9.351	8.388	8.401	8.712	8.757
NTL (1998)	9.474	9.484	9.500	9.521	8.564	8.584	8.876	8.932
NTL (2000)	9.647	9.594	9.723	9.676	8.757	8.691	9.126	9.066
NTL (2002)	9.623	9.622	9.755	9.734	8.771	8.761	9.102	9.111
NTL(mean 1992-2002)	9.424	9.415	9.481	9.461	8.475	8.468	8.844	8.854
ΔNTL(mean 1993-2002)	0.048	0.050	0.058	0.059	0.071	0.074	0.055	0.059
Population growth (mean 1992-2002)	1.360	1.359	1.360	1.358	1.360	1.360	1.359	1.362
Population density (mean 1992-2002)	6.124	7.728	6.229	7.570	6.519	7.865	6.103	8.211
Natural disaster risk	1.363	2.288	1.363	2.409	1.363	2.223	1.272	2.391

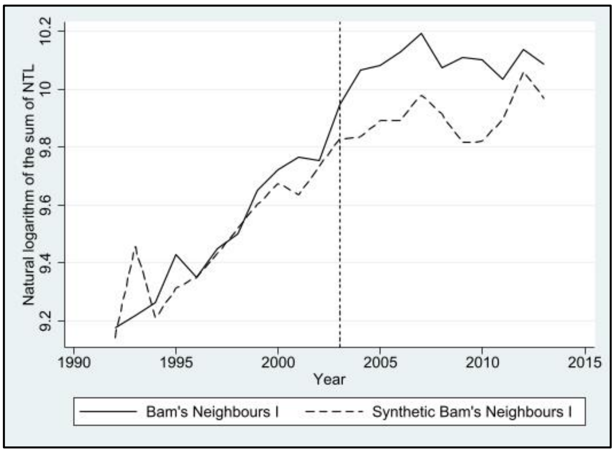
Notes: In this table, NTL refers to the natural logarithm of the sum of nighttime light. Population density and natural disaster risk are also used as natural logarithms.

Table 3 shows the average values of the covariates of factual and synthetic Bam before the disaster year of 2003, as well as the same information for the aggregated neighboring provinces of first and second order. According to the values, the synthetic versions closely reflect the pre-disaster performance of the NTL covariates of the factual counties, and we can also see similarities among the other predictor variables, namely the average of NTL, growth of NTL, population growth rate, natural logarithm of the population density, and natural logarithm of the natural disaster risk indicator. Figure 3 shows the trajectories of the natural logarithm of the sum of NTL of factual and synthetic Bam and its neighbors in the period 1992 to 2013. In all four cases, we can see that the synthetic versions reproduce the development of the NTL of the factual counties in the period before the 2003 earthquake. The difference between the factual and synthetic versions of the counties shows the effect of the earthquake.

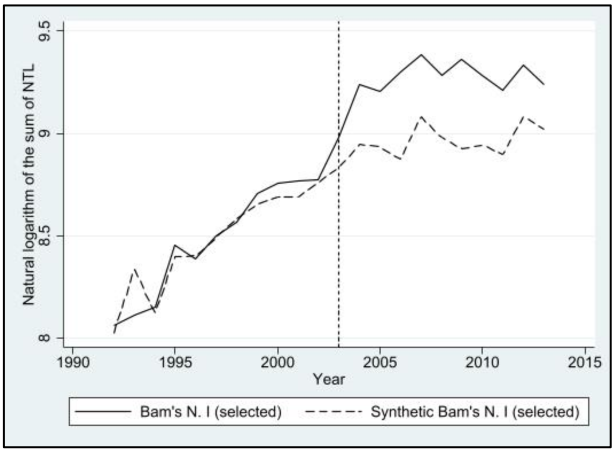
Figure 3: Factual and synthetic trajectories of Bam and its neighbors



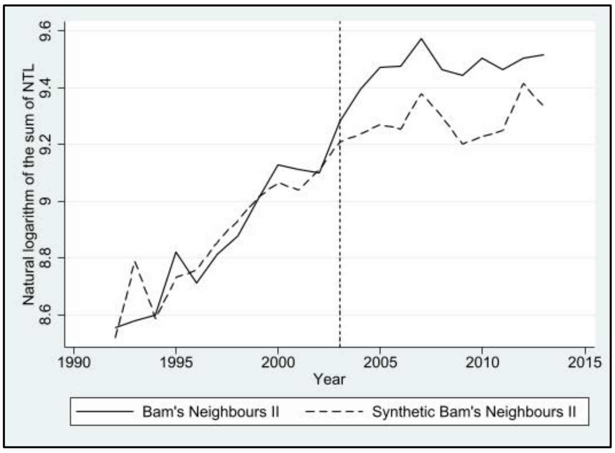
(a) Bam.



(b) Bam's neighboring counties of first order.



(c) Bam's neighboring counties of first order (excluding Kerman and Jiroft counties).

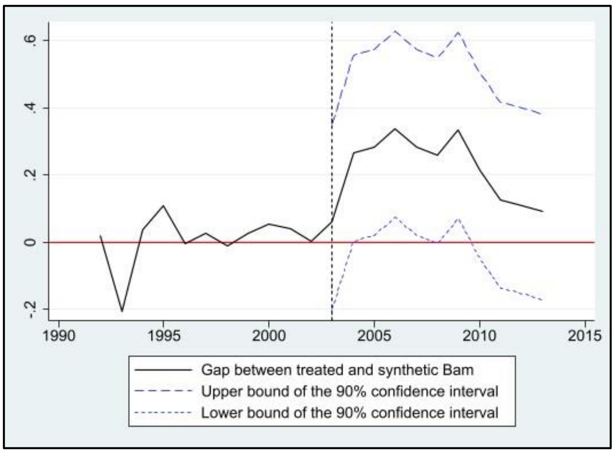


(d) Bam's neighboring counties of second order.

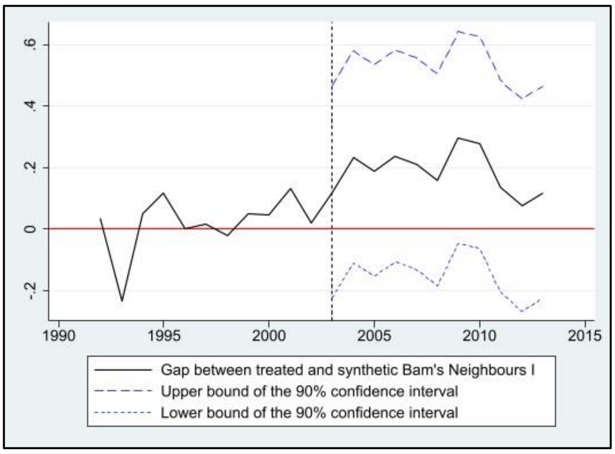
Figure 3a presents the trajectories of the factual and synthetic Bam County and we can see the largest gap between the factual and synthetic versions, compared to the other three gaps. The remaining graphs show the trajectories of Bam’s neighboring counties of first order, first order excluding Kerman and Jiroft counties, and second order. Figure A3a of the Appendix presents the trajectory of Bam’s neighboring counties of third order, which does not have a significant gap. This is plausible because it represents the impact of the earthquake on NTL on the average county of third order and we would expect a smaller impact the further away the county is. The neighboring counties of third order are those counties that border the counties of second order. The latter are highlighted in yellow in Figure 1b. However, it is not the case that closeness to the epicenter of the earthquake automatically means a measurable impact, as we can see when investigating the impact on the neighboring provinces of first order. Figure 3b shows the trajectory of Bam’s neighboring counties of first order, which is the average of six counties, and Figure 3c shows the same neighboring counties excluding Kerman and Jiroft counties. Both show gaps between its trajectories, but the statistical inference tests in Figure 4 and in the Appendix show that the gap of Bam’s neighboring counties of first order is not statistically different from the gaps when treating other counties of the donor pool in the same year. The same applies to Bam’s neighboring counties of second order, of which the results are presented in Figure 3d. These findings tell us that not all neighboring counties of Bam were impacted by the earthquake in a measurable way.

If we compare the trajectories in Figure 3, we see an increase in economic activity directly after the event in all cases, but only Bam and its neighboring counties of first order clearly return to their pre-disaster development path in the ten-year period after the earthquake. The synthetic development path (without the impact of the disaster event) is reflected by the synthetic control. A further analysis using the uniform confidence sets at the 90% confidence level is presented in Figure 4 and reveals that Bam County, as well as its neighboring counties of first order (excluding Kerman and Jiroft counties), show significant gaps between the factual and synthetic trajectories. According to the results, the gap between the factual and synthetic Bam is significant until about seven years after the earthquake (Figure 4a) and the gap for the selected neighboring counties of first order is significant about nine years after the disaster (Figure 4c). In the other cases, we do not see a significant gap. Therefore, we can say that the affected counties return to their pre-disaster development paths after 7-9 years.

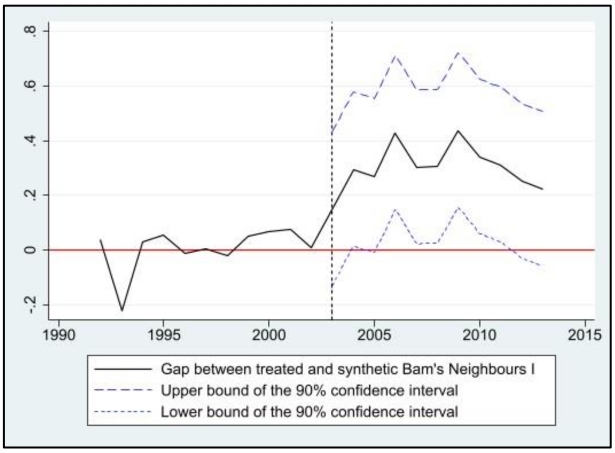
Figure 4: Gap between factual and synthetic counties, including confidence sets



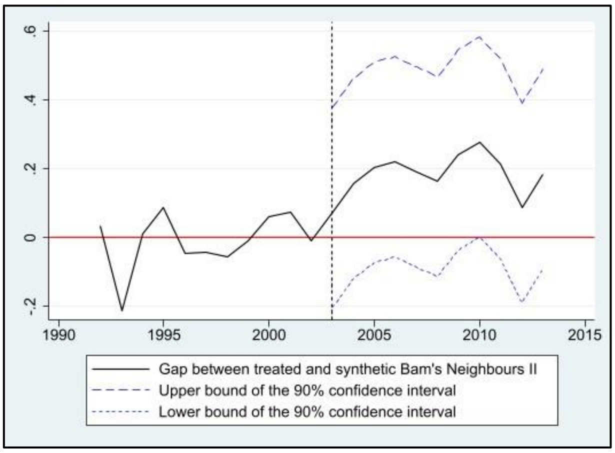
(a) Bam.



(b) Bam's neighboring counties of first order.



(c) Bam's neighboring counties of first order (excluding Kerman and Jiroft counties).



(d) Bam's neighboring counties of second order.

In addition to the confidence intervals, we also applied established placebo tests which are presented in Figures A4 to A7 in the Appendix. The in-space placebo tests show an exceptionally large gap between the factual and synthetic units compared to the gaps of all of other counties in the donor pool in the cases of Bam and its selected neighboring counties of first order, in the years directly after the disaster. Moreover, the post-disaster RMSPE to the pre-disaster RMSPE of the four cases are 3.1 (Bam), 2.1 (Bam's neighbors I), 3.9 (Bam's neighbors I selected), and 2.4 (Bam's neighbors II) and the corresponding pseudo p-values are 0.14 and 0.34 and 0.02 and 0.29, respectively. The RMSPE ratios of three cases are among the highest of the donor pool counties, and the p-values support previously presented significance levels. In addition, the in-time placebo tests show that the disaster year of 2003 produces, in all four cases, a clear gap directly after the event, in comparison to the cases where other years were treated. Finally, the leave-one-out tests show for all four cases that we can create synthetic versions of the counties with similar trajectories when excluding counties from the donor pool with large weights in the original estimations. As an additional sensitivity check of the analysis, we also applied the penalized synthetic control (Abadie and L'Hour 2021; Wiltshire 2022), as previously done in the case of Kerman Province. The results are presented in Figures A8 to A11 in the Appendix and support previous findings, namely, that we can still see a gap in the case of Bam and its selected neighbors of first order after bias correction (Figure A8 and A10). The gaps become smaller than the gaps of the classical synthetic control, but the peaks of the differences between factual and synthetic units stay almost identical. For the other two cases, namely Bam's counties of first and second order, we see that the gaps between factual and synthetic units almost disappear after bias correction (Figure A9 and A11).

In the final step of the analysis, we calculate the costs of the Bam earthquake in US dollars with the help of the estimated gaps and a simple regression of the sum of NTL and the real GDP of Iranian provinces. With the following specification, we can determine the association between a one-unit increase of NTL and the real GDP.

$$GDP_t = \alpha + \beta_1 * NTL_t + \varepsilon_t \tag{3}$$

We will use the sum of NTL data of Kerman Province from Li et al. (2020) and the real GDP in billion Iranian Rial (IRR) of Kerman Province from the Iranian Ministry of Economic and Financial Affairs (MEFA 2021). The latter was calculated with the current GDP in IRR and the consumer price index (CPI). Based on 16 observations and available data from 2004 to 2019, we estimate the slope coefficient $\beta 1$ which is 0.1835 with an R-squared of 0.45. This means that an increase of the sum of NTL by one unit is associated with an increase of GDP by 0.1835 billion IRR. To receive the value in US dollars, we use the official exchange rate from Central Bank of Iran (CBI 2020) for each respective year. Due to regional heterogeneity and to receive a better fit, we only use data from Kerman Province. Our previous investigation of the earthquake has shown that the impact was only statistically significant on the county level, therefore we will focus on these gaps for calculating the monetary value.

Bam County showed a significant gap for seven years and the selected average neighboring counties showed significant gaps of nine years. The calculated values quantify the boost in economic activity of the event, which reflects the economic gains compared to the counterfactual case where the disaster did not happen. According to the results, Bam County's economic activity was boosted by an accumulated US$750 million in the seven years after the earthquake. The selected neighboring counties of first order experienced, on average, a boost of economic activity by an accumulated US$505 million (more details in Table A2 in the Appendix).

5. Discussion of the Possible Contributing Factors to the Post-Disaster Economic Boom in Bam

The results of our empirical analysis have shown that there is a boost in economic activity in Kerman Province, Bam County, and the neighboring counties after the 2003 Bam earthquake. This is supported by the discussed theory (Albala-Bertrand 1993; Skidmore and Toya 2002; Chhibber and Laajaj 2008; Klomp 2016) and previous empirical studies (Noy 2009; Loayza et al. 2012; Barone and Mocetti 2014; Onuma, Shin, and Managi 2021; Felbermayr et al. 2022). To better understand the development of NTL after the Bam earthquake, we follow Noy and duPont IV (2018) and argue that it happened due to the type and severity of the event, the underlying composition of the economy, and the total area impacted. The Bam earthquake was geographically concentrated with the epicenter approximately 10 km southwest of Bam and the direct damage was concentrated in a radius of about 16 km around the city (Fallahi 2007). The aftershock cluster was about 25 km long and 7 km wide with 544 events in the first month after the main shock and the aftershock seismicity was deeper than the main shock. However, after the main earthquake in December 2003, no significant surface ruptures or damage was reported in the area (Tatar et al. 2005). Therefore, disaster response efforts started immediately after the main earthquake and due to the geographical concentration of the damage, the area was more accessible for helpers than, for example, compared to a flood that can last for many days and makes a region inaccessible.

Another factor is the level of economic development and industrialization of the impacted areas. If we compare the population size, economic activity, and human development of Kerman Province with the average Iranian province of the year 2002 (before the earthquake disaster), we see that Kerman had a larger population size with 2.83 million people, compared to the average of 2.36 million people (GDL 2022). Economic activity, measured in the sum of NTL, was also higher in Kerman with a value of 261,638, compared to 184,195 (Li et al. 2020). The same applies at the county level, where Bam County had a higher population than the average Iranian county, with 283,311 people compared to 209,809 people. Economic activity, measured as the sum of NTL units, had a value of 15,115 compared to 13,310. In addition, Kerman, at 0.672, is higher on the Human Development Index, as calculated by Global Data Lab (GDL 2022), compared to the average province at 0.667. The index ranges from 0 to 1 and higher values suggest higher human development, considering health, education, and income.

Related to industrialization, there was also an industrial zone outside of the historical city center of Bam that includes automobile and packaging factories. Reports suggest that there was minor damage to industrial facilities, including cracks in walls and oil spills, which was significantly lower than the damage in residential areas. The industrial facilities who stopped production were not destroyed, but lost access to electricity or other infrastructure such as roads (Eshghi and Razzaghi 2005; Fallahi 2007). Overall, we can see that Kerman Province and Bam County were more economically developed and had more human capital than the average Iranian province and county before the impact of the disasters, which provided them with better coping capacities and conditions for turning disaster relief inflows into economic development.

This leads to other important aspects, namely the size of disaster relief inflows, reconstruction efforts, and media attention, all of which are interlinked. After the impact of the 2003 Bam earthquake, there was US$132.2 million of funding from more than 20 international donors, including the U.S. and U.K. governments (OCHA 2004; AidData 2023). It is worth mentioning that both databases used do not report any international funding related to other large-scale natural disasters in the period of study, except for the 2019 flood that produced an inflow of US$27.2 million from nine different international donors (OCHA 2019a). One factor for the large amount of funding is that the Bam earthquake happened during the reformist government of President Khatami (1997-2005), which was characterized by improvements in international relationships under the agenda of 'dialogue among civilizations'. In this period of openness, Great Britain’s Prince Charles even visited Bam in 2004, during which he met earthquake survivors and spoke with President Khatami (NBC 2004). It was the only time that a member of the British Royal Family visited Iran after the Islamic Revolution of 1979.

In addition, there was immediate response from the Iranian Red Crescent Society (IRCS), government agencies, military forces, and other volunteers. In addition to the national disaster response, there was assistance from more than 100 international organizations and governments. The IRCS was able to mobilize about 8,500 relief volunteers and nearly 12,000 people were airlifted to hospitals in other provinces. In addition, many volunteers from various parts of Iranian society poured into the region to help those affected and others came to start businesses or work in the construction sector. Additionally, over 200 international non-governmental organizations (NGOs) and 1,600 personnel arrived in Bam and the Kerman NGO House established a new regional network of 100 local NGOs in the Kerman Province (Fallahi 2007; Hosseini, Hosseinioon, and Pooyan 2013; Yuan et al. 2018). Yuan et al. (2018) show for several countries, including Iran, how large-scale natural disasters can motivate people to become active in the civil society, and Aldrich (2011) shows the importance of social capital for a community's ability to recover from a disaster. In this context, we can see that the Iranian society showed higher levels of social trust and confidence in the government during the time of the Khatami administration, compared to later periods[4]. This is an additional factor why such massive mobilization of volunteers after the earthquake was possible.

Several camps and temporary shelters for the homeless were constructed and by the end of March 2004, most of the survivors received temporary accommodation consisting of prefabricated units. To support the reconstruction process, the government offered free long-term bank loans to families who lost their homes. The main reconstruction efforts finished in 2007 and the International Federation of Red Cross and Red Crescent Societies ended its mission in February 2007 (OCHA 2007; Ghafory-Ashtiany and Hosseini 2008). Overall, there was an enormous inflow of people and resources into the region which can explain an increase in nighttime lights in the area in the years following the disaster and the drop in NTL after 2007 can be explained by the end of the intensive reconstruction efforts (see Figure 3a). This inflow of people does not only include aid workers, but it also opportunity seekers, such as businessmen and low-skilled construction workers.

The significant attention and inflow of financial help also caused temporary migration of poor people from neighboring villages pretending to be survivors and claimed financial support designed for actual victims. Thus, despite the high death toll, several reports suggest that the population of Bam was larger after the earthquake than before. (EERI 2004; Motawef and Asadi 2011). In the first days after the earthquake, there was immediate out-migration, which was followed by an inflow of people into the city, which was studied by Gharazhian et al. (2017). They used data for different districts of Bam from local authorities, which show that the sum of inhabitants in Bam one year after the earthquake was 5,000 more than before the disaster. This suggests an inflow of about 32,000 people into the city, after accounting for the people who lost their lives due to the earthquake.

Compared to other large-scale natural disasters in Iran, the Bam earthquake received a large amount of national and international attention. Some explanations could be the extremely high death count and destruction of a famous city that is a UNESCO World Heritage Site, which can

[4] Iran was included in three out of seven waves of the World Values Survey (WVS), which includes questions about social trust and confidence in government. The surveys took place in 2000, 2005, and 2020. The shares of respondents who answered the question "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?" with "Most people can be trusted" are 65.4%, 10.6%, and 14.8%, respectively, for each year. A similar pattern is visible in confidence in the government. The shares of respondents who answered the question "I am going to name a number of organizations. For each one, could you tell me how much confidence you have in them: is it a great deal of confidence, quite a lot of confidence, not very much confidence or none at all? The Government" with "a great deal" and "quite a lot" are 68.5%, 48.7%, and 52.1%, respectively, for each year (Inglehart et al. 2022). This shows higher social trust and confidence in government in Iran before the year 2005.

cause empathy and emotions in people that helped to mobilize national and international support. Due to these reasons, the Bam earthquake also gained more media attention than previous disasters, which increased post-disaster aid flows. This phenomenon has already been studied by several authors (Strömberg 2007; Becerra, Cavallo, and Noy 2014). Among the examples for the media attention and international interest are the visit of Prince Charles to Bam in 2004 (NBC 2004) and the charity football match between the German and Iranian national teams in Tehran in 2004 (Spiegel 2004), which were both unique events.

After discussing the disaster response and reconstruction process, we can gain a better understanding of what the changes in nighttime lights actually indicate. It is worth noting that this boost in economic activity was driven by an influx of financial and human capital that lasted for approximately seven years. These resources were not present in other parts of the country, which helps explain the significant impact of the disaster on the region's economy.

6. Conclusion

We use sub-regional data and a counterfactual analysis to measure the economic impact of a large natural disaster event in Iran. With our empirical investigation, we closely looked at the 2003 Bam earthquake. By applying the synthetic control method (SCM) and nighttime lights (NTL) data, we estimate the development of economic activity in the hypothetical scenario of absence of the disaster. The first finding is that the estimated synthetic controls on the province level are not robust to the established placebo tests and confidence sets developed by Firpo and Possebom (2018) and Ferman et al. (2020). This is supported by previous studies that have shown that even large-scale natural disasters do not show statistically significant impacts at the country level and suggest studying the impact of natural disasters on lower administrative levels (Cavallo et al. 2013; Fabian, Lessmann, and Sofke 2019; Fischer 2021).

The second result is that Bam County experienced a boost in economic activity following the earthquake, which is shown in the difference between the factual affected and synthetic province and county. We suggest that this development took place due to the type and severity of the event (comparably minor damage to economic structures), underlying composition of the economy (above average economic activity and human capital), and total area impacted (concentrated in one county). In addition, its high death count and cultural importance as a UNESCO World Heritage Site helped to gain media attention and mobilize national and international support. We also highlight the importance of the quality of informal and formal institutions at the time of this disaster in Iran, which was internationally well-respected under the reformist government of Mohammad Khatami. Social trust and confidence in government indicators based on the World Values Survey was higher in 2000 compared to the subsequent waves of the survey in Iran. Also, democratic institutional quality improved during the government of Khatami. Such positive developments were important factors in the mobilization of economic support in the flow of international aid to the affected region. However, this boost in economic activity in Bam County can also be interpreted as a loss in other provinces and counties, except for some neighboring counties, because of the intensive flow of financial and human capital to the affected region. While the inflow of international financial resources into the country is a financial gain to the national economy, the inflow of domestic official disaster aid to the affected region will be a burden to the government and other provincial budgets.

As a third finding, we showed how to estimate spatial spillover effects of natural disasters into neighboring geographical units using the SCM in the example of Bam County and its neighbors. We estimated synthetic controls for the average neighboring counties of first, second, and third orders, and found that the average impact of the earthquake on NTL was smaller the further away the counties are located from the earthquake's epicenter. When using the established placebo tests and confidence bounds, the effect is only statistically significant for the average neighboring counties of first order (when excluding the counties Jiroft and Kerman). Like in the case of Bam County, the gaps between the indirectly affected neighboring counties and their synthetic counterparts show a boost in economic activity due to the earthquake. This suggests positive spillover effects from the reconstruction activities in Bam into neighboring counties, supporting the findings of Fischer (2021).

The fourth result is that we did not find a long-term impact of the 2003 Bam earthquake on economic activity. According to our results, Bam County returned to its pre-disaster development paths, measured by the synthetic control method, within ten years. Therefore, we found effects in the short (0-5 years) and intermediate (6-10 years) terms that were also found by Onuma et al. (2021) in the category of all natural disasters. Other studies also found weak or no evidence for the long-term impact of natural disasters (Felbermayr and Gröschl 2014; Klomp 2016; Fabian, Lessmann, and Sofke 2019).

Finally, we have shown how to use the SCM and NTL to evaluate the true economic costs of natural disasters using a counterfactual which can be applied for other countries. By using NTL, we overcome the problems of data availability that we usually have in low-level administrative units, such as counties, and issues with border reforms that make it difficult to track developments over time with official data. In addition, we showed how to utilize the SCM to investigate spatial spillover effects, which was not done before.

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Appendix

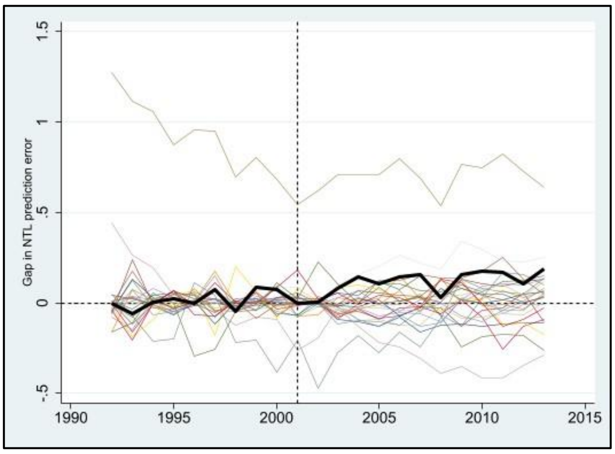
Table A1: Counties in the donor pool after excluding disaster-affected counties

Number	County	Number	County	Number	County
1	Abyek	22	Kangavar	43	Qazvin
2	Ahar	23	Karaj	44	Ravansar
3	Alborz	24	Khalkhal	45	Sahneh
4	Baharestan	25	Khodaafarin	46	Salmas
5	Bilasavar	26	Khorramdarreh	47	Sardasht
6	Bonab	27	Khoy	48	Savojbolagh
7	Bukan	28	Mahneshan	49	Shabestar
8	Chaldoran	29	Malard	50	Shahindej
9	Charuymaq	30	Malekan	51	Shahr-e Qods
10	Chaypareh	31	Maragheh	52	Shahriar
11	Eejrud	32	Marand	53	Shemiranat
12	Eshtehard	33	Meshginshahr	54	Showt
13	Fardis	34	Namin	55	Soltanieh
14	Firuzkuh	35	Naqadeh	56	Sonqor
15	Germi	36	Nazarabad	57	Tabriz
16	Heris	37	Oshnaviyeh	58	Takab
17	Islamabad-e-Gharb	38	Parsabad	59	Takestan
18	Islamshahr	39	Paveh	60	Taleghan
19	Javanrud	40	Piranshahr	61	Tarom
20	Jolfa	41	Poldasht	62	Tehran
21	Kalibar	42	Qarchak	63	Zanjan

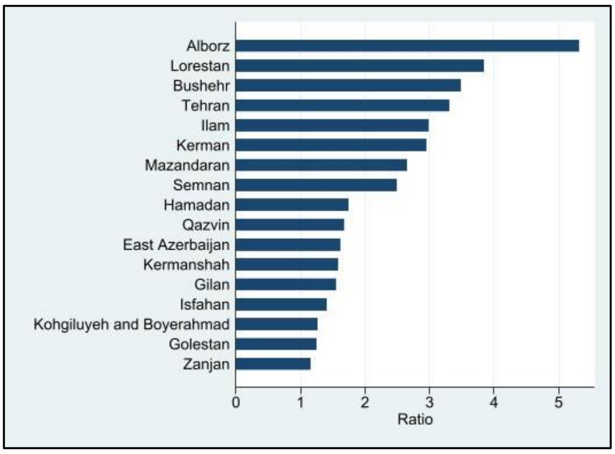
Table A2: Estimated monetary gains due to the Bam earthquake

	Bam County		Bam's neighbors of first order (selected)	
Year	IRR (billion)	US$ (million)	IRR (billion)	US$ (million)
2003	198.19	24.34	201.56	24.75
2004	950.96	111.75	482.46	56.69
2005	1078.98	121.55	432.73	48.75
2006	1299.87	142.14	701.85	76.75
2007	1175.93	127.22	570.39	61.71
2008	958.28	105.65	519.38	57.26
2009	1164.56	117.35	756.12	76.19
2010			568.88	56.82
2011			489.20	47.04
Sum	**6,826.77**	**749.99**	**4,722.58**	**505.96**

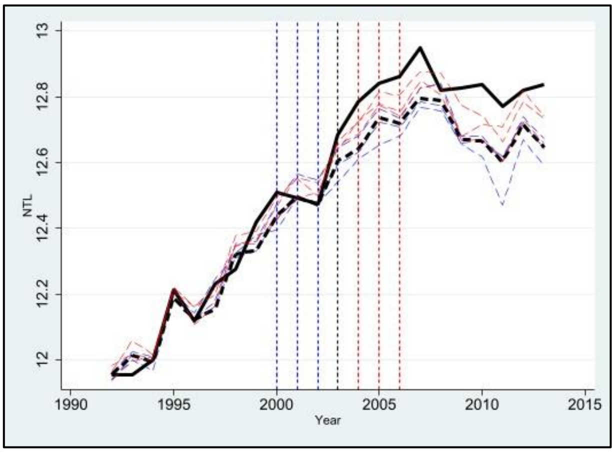
Figure A1: Placebo tests for the SCM analysis of Kerman Province



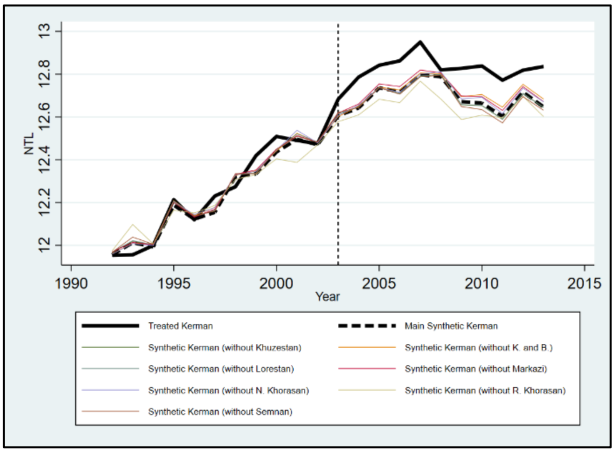
(a) In-space placebo test.



(b) Ratio of post-disaster RMSPE to pre-disaster RMSPE.

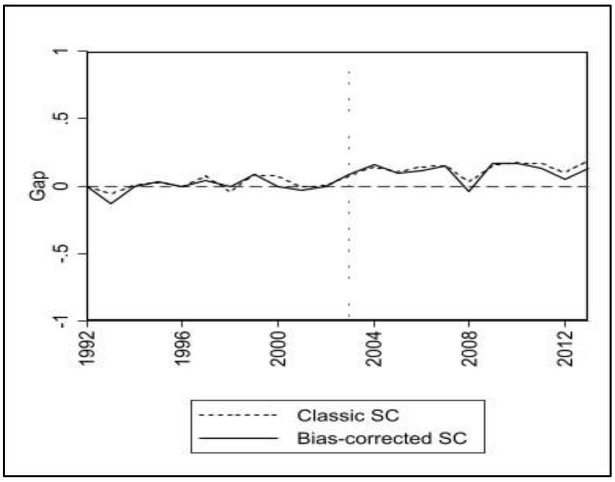


(c) In-time placebo test.

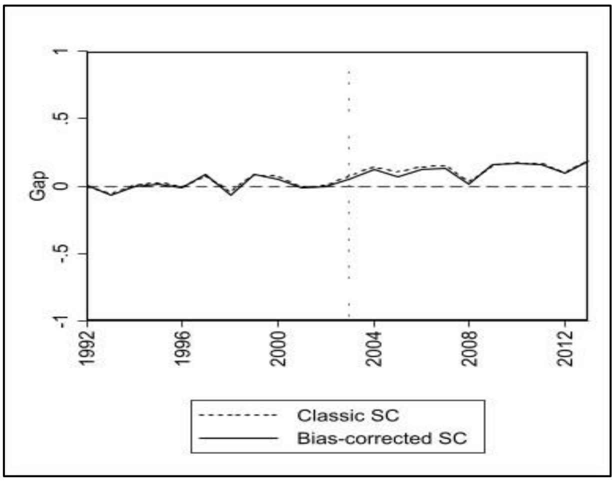


(d) Leave-one-out test.

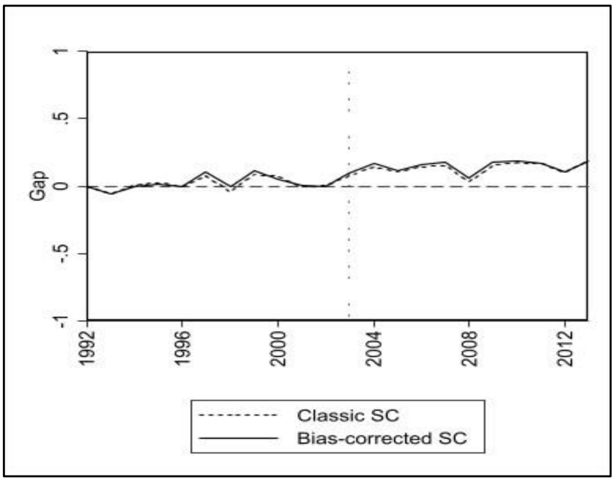
Figure A2: Comparison of gaps in the classic and bias-corrected synthetic controls for the analysis of Kerman Province



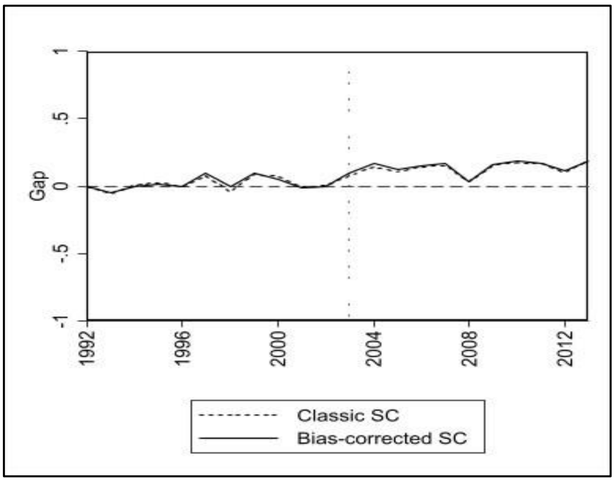
(a) Bias-corrected synthetic control (SC) based on OLS regression.



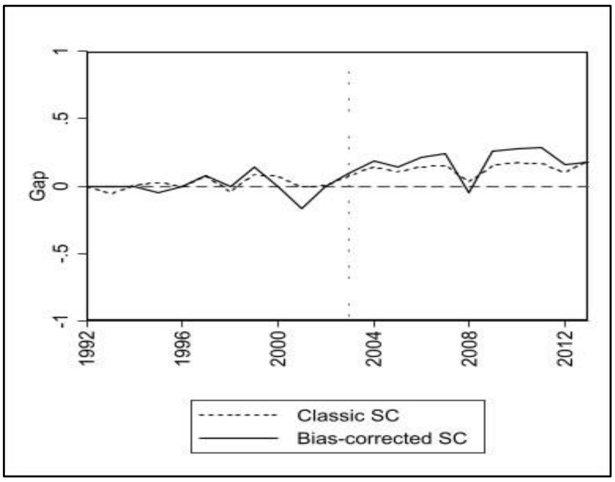
(b) Bias-corrected synthetic control (SC) based on Ridge regression.



(c) Bias-corrected synthetic control (SC) based on Lasso regression.

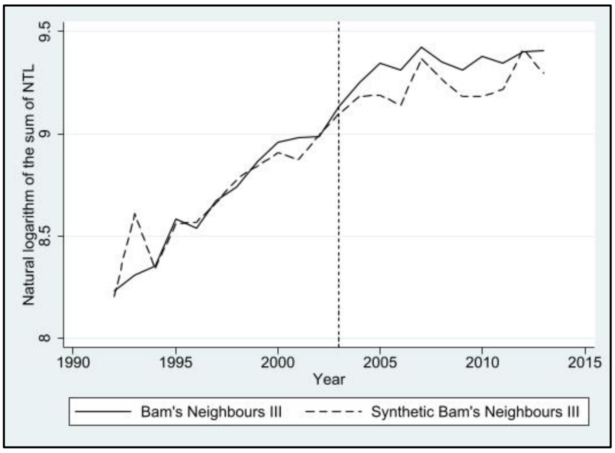


(d) Bias-corrected synthetic control (SC) based on elastic net regression.

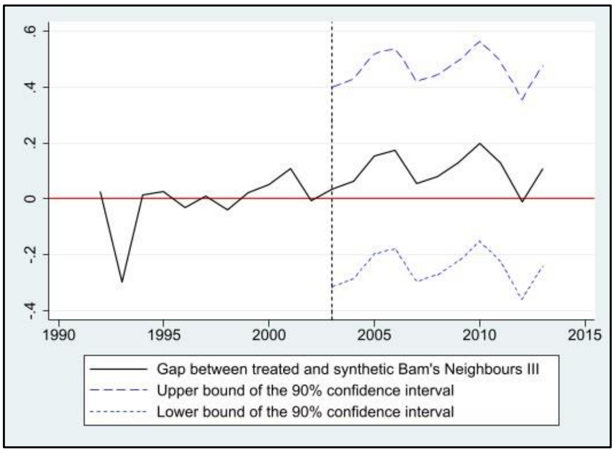


(e) Bias-corrected synthetic control (SC) based on OLS regression with only those donor pool units for which the synthetic-control-estimated weights are strictly positive.

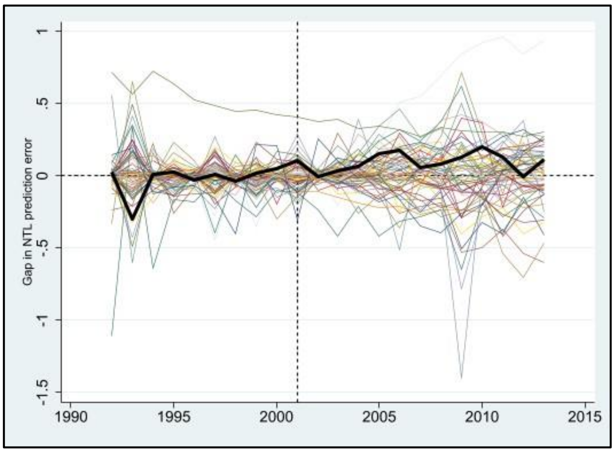
Figure A3: SCM analysis and placebo tests for Bam County’s neighbors of third order



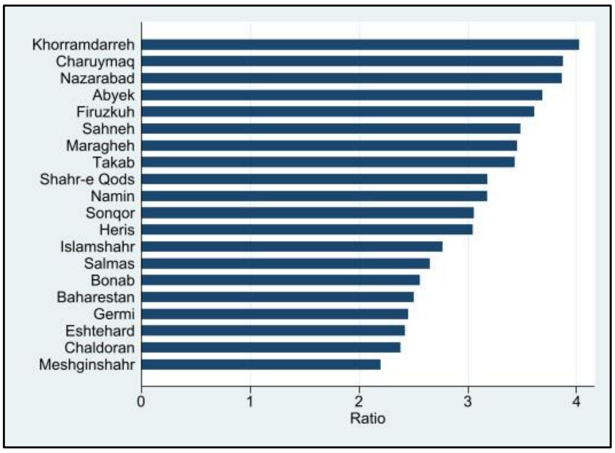
(a) Trajectories of factual and synthetic Bam’s neighbors of third order.



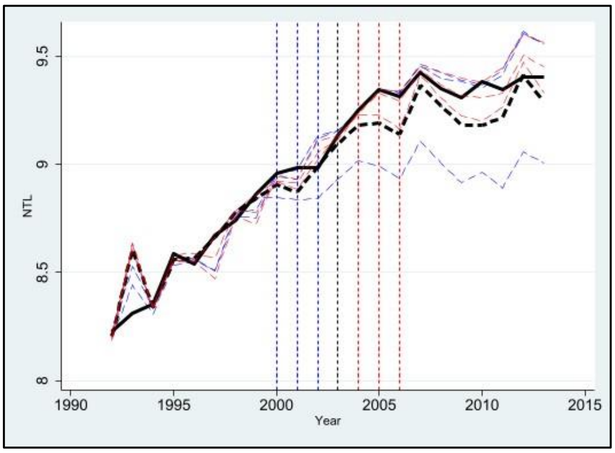
(b) Gap of factual and synthetic Bam’s neighbors of third order including confidence sets.



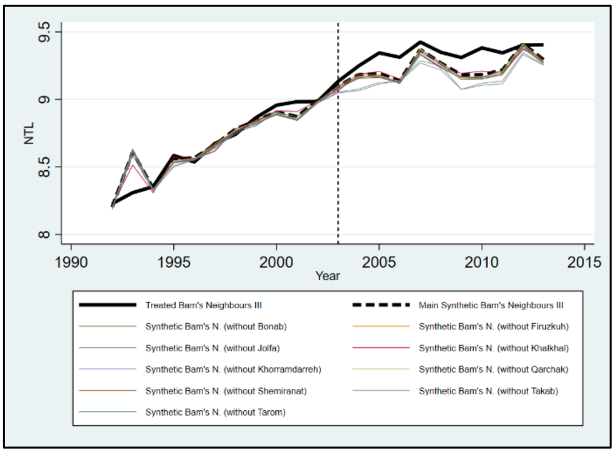
(c) In-space placebo test.



(d) Ratio of post-disaster RMSPE to pre-disaster RMSPE.

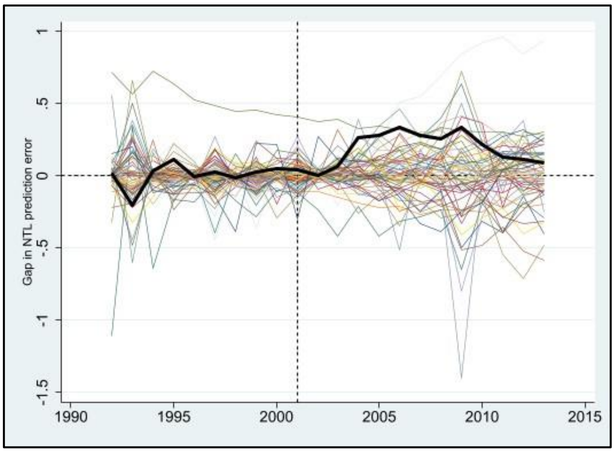


(e) In-time placebo test.

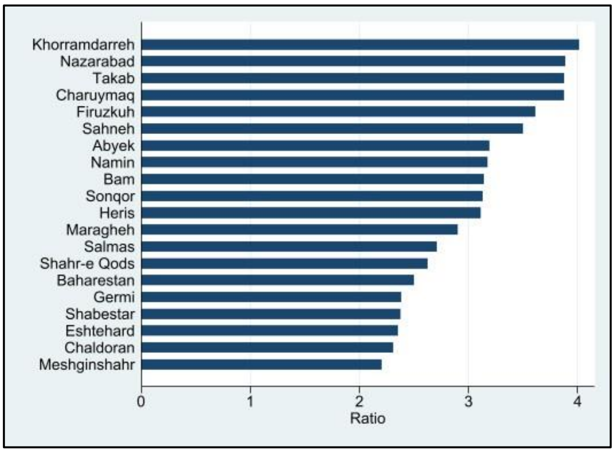


(f) Leave-one-out test.

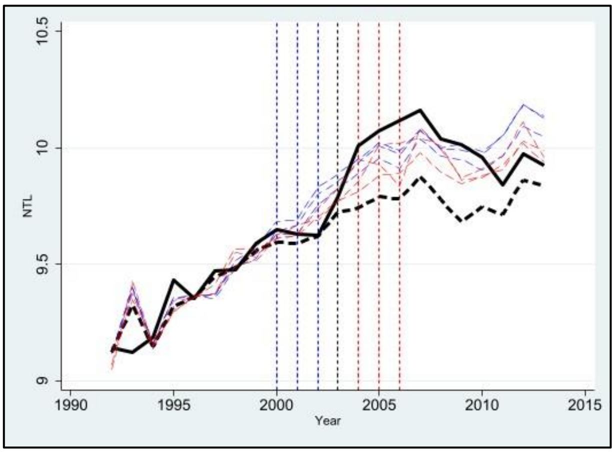
Figure A4: Placebo tests for the SCM analysis of Bam County



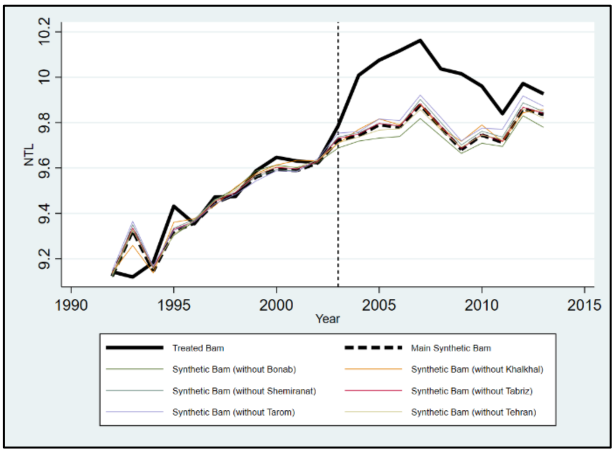
(a) In-space placebo test.



(b) Ratio of post-disaster RMSPE to pre-disaster RMSPE.

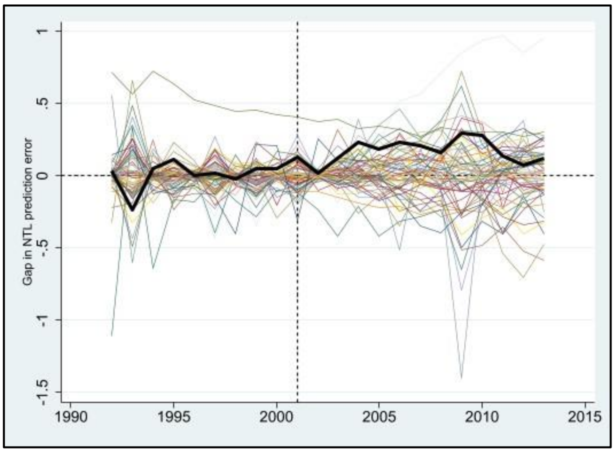


(c) In-time placebo test.

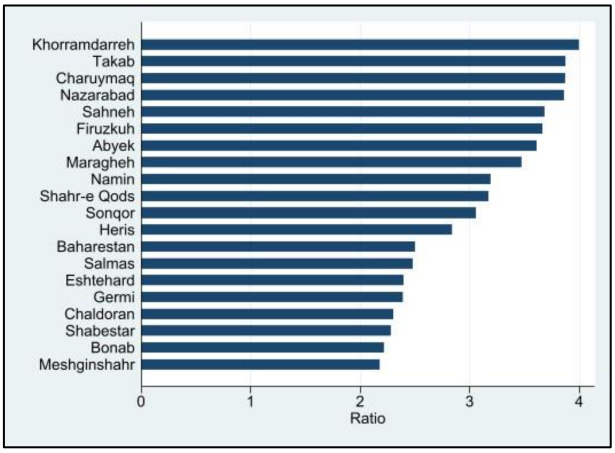


(d) Leave-one-out test.

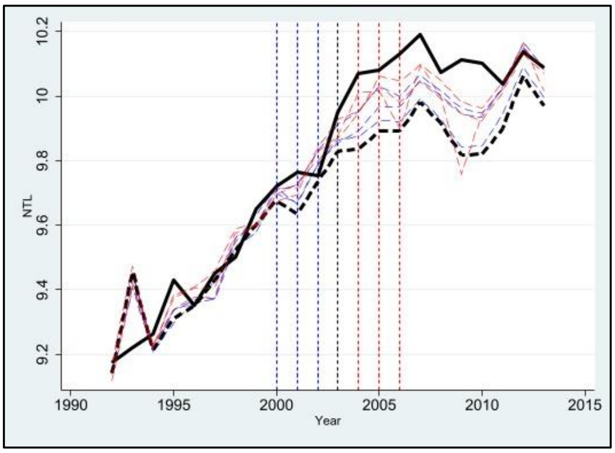
Figure A5: Placebo tests for the SCM analysis of Bam County's neighbors of first order



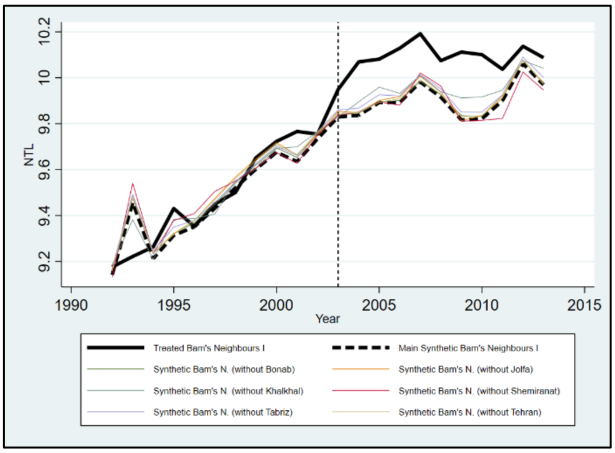
(a) In-space placebo test.



(b) Ratio of post-disaster RMSPE to pre-disaster RMSPE.

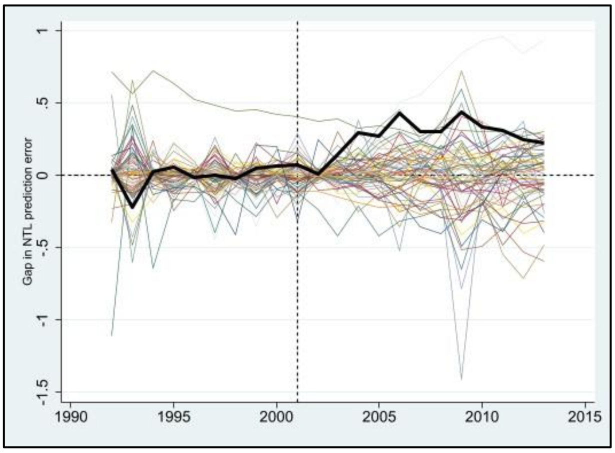


(c) In-time placebo test.

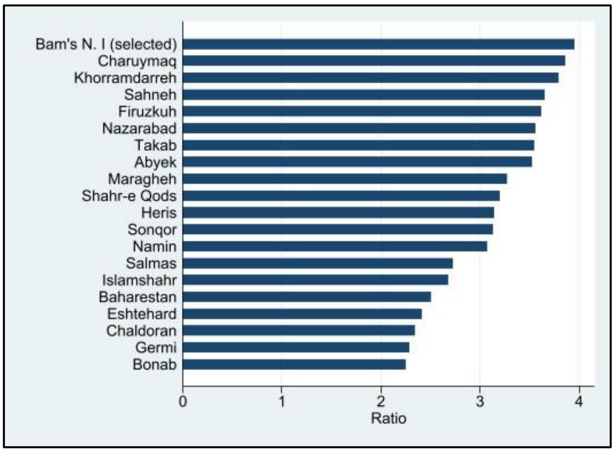


(d) Leave-one-out test.

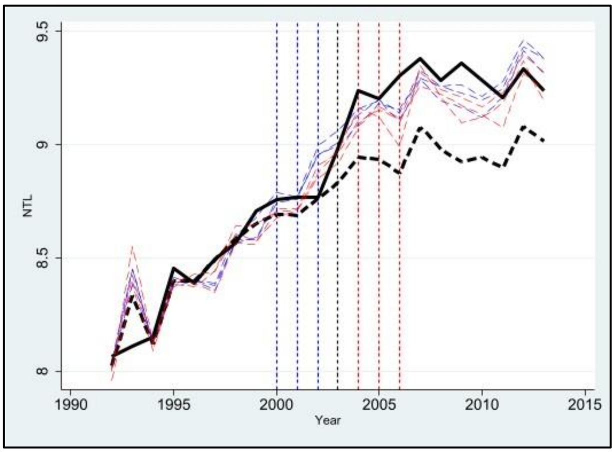
Figure A6: Placebo tests for the SCM analysis of Bam County's selected neighbors of first order (excluding Kerman and Jiroft counties)



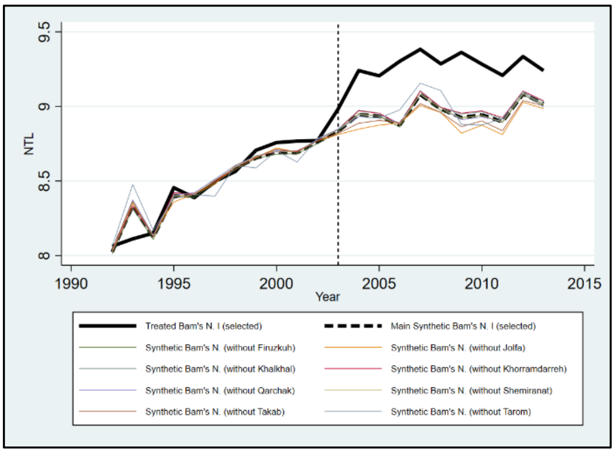
(a) In-space placebo test.



(b) Ratio of post-disaster RMSPE to pre-disaster RMSPE.

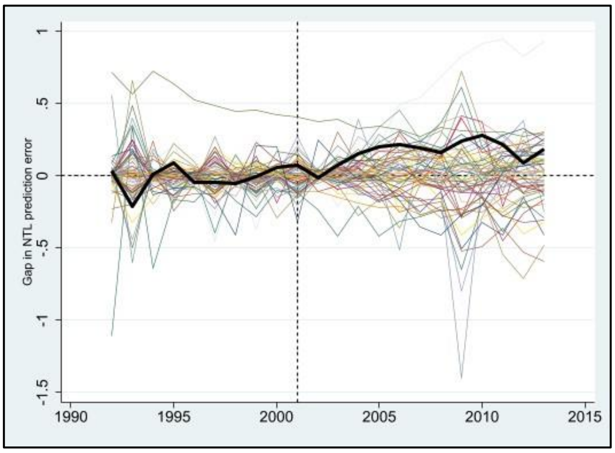


(c) In-time placebo test.

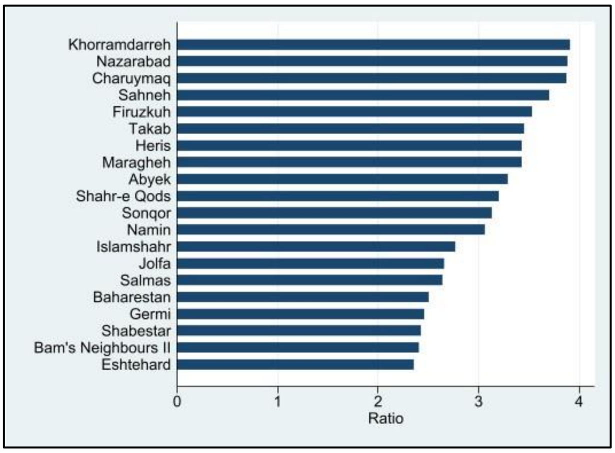


(d) Leave-one-out test.

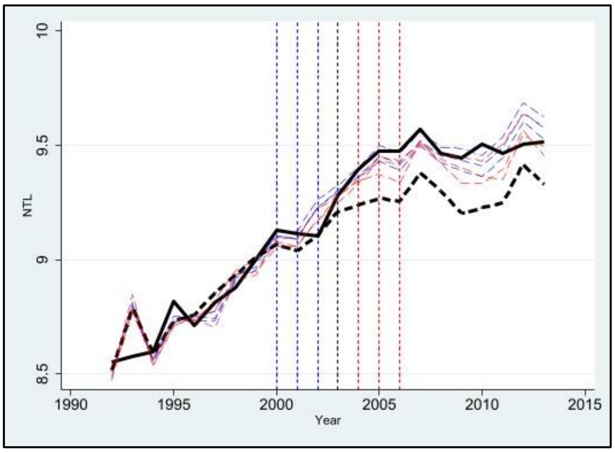
Figure A7: Placebo tests for the SCM analysis of Bam County's neighbors of second order



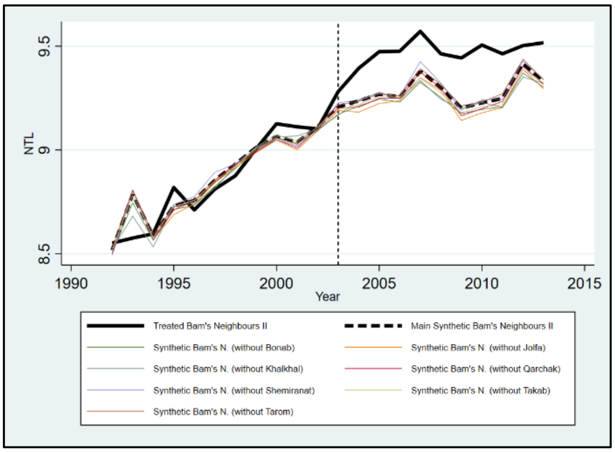
(a) In-space placebo test.



(b) Ratio of post-disaster RMSPE to pre-disaster RMSPE.

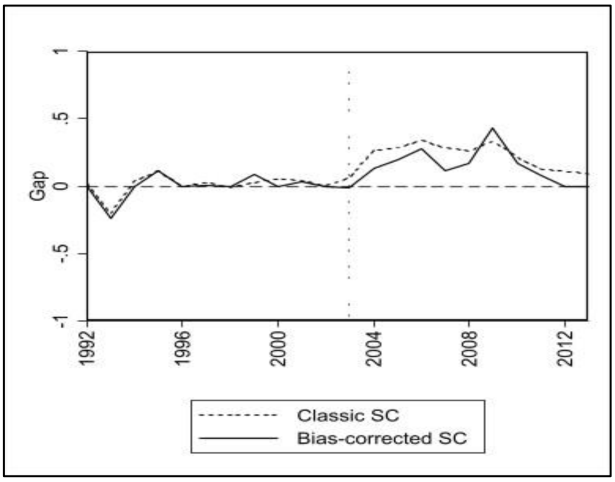


(c) In-time placebo test.

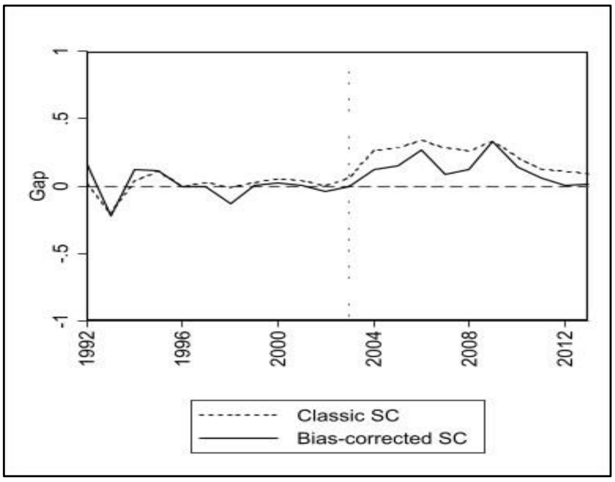


(d) Leave-one-out test

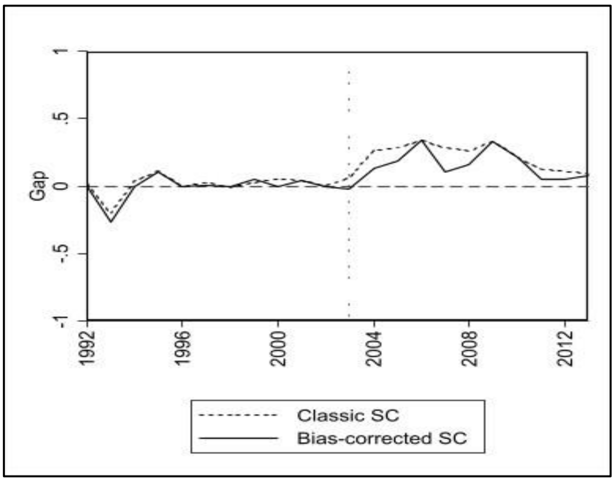
Figure A8: Comparison of gaps in the classic and bias-corrected synthetic controls for the analysis of Bam County



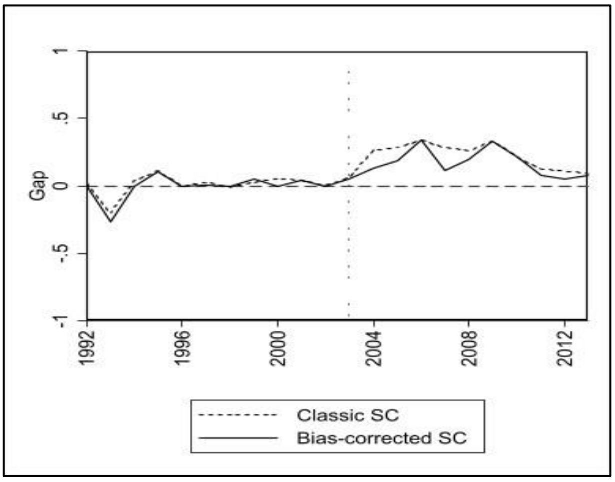
(a) Bias-corrected synthetic control (SC) based on OLS regression.



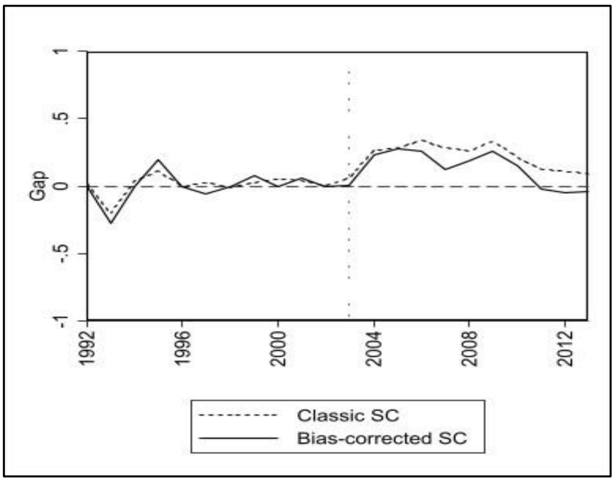
(b) Bias-corrected synthetic control (SC) based on Ridge regression.



(c) Bias-corrected synthetic control (SC) based on Lasso regression.

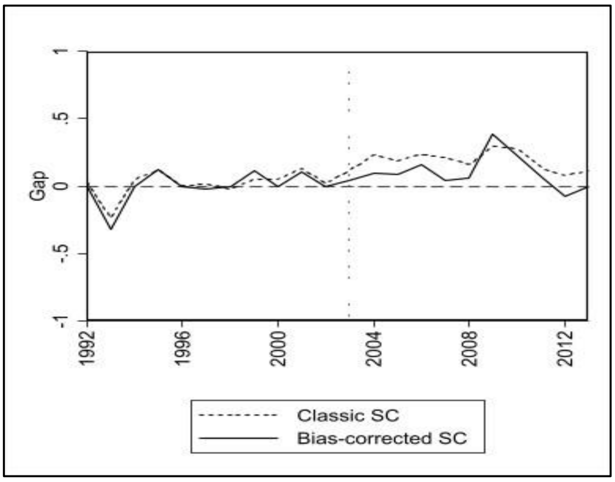


(d) Bias-corrected synthetic control (SC) based on elastic net regression.

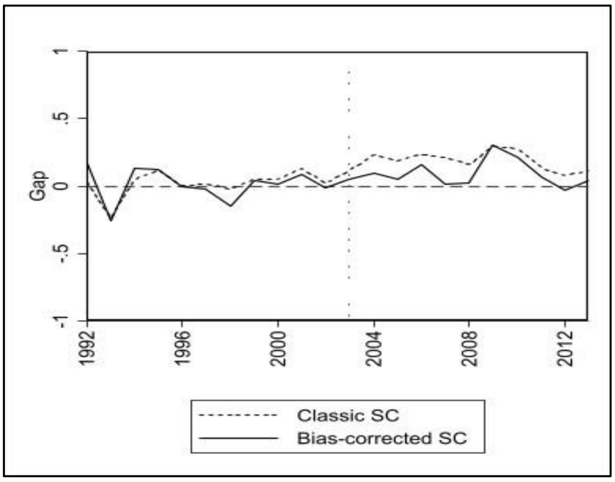


(e) Bias-corrected synthetic control (SC) based on OLS regression with only those donor pool units for which the synthetic-control-estimated weights are strictly positive.

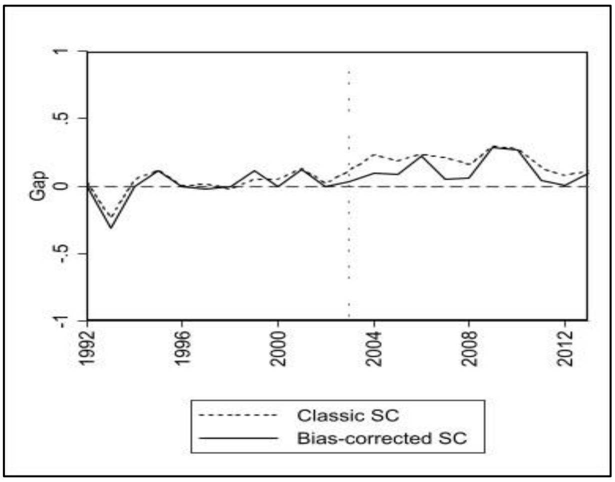
Figure A9: Comparison of gaps in the classic and bias-corrected synthetic controls for the analysis of Bam County's neighbors of first order



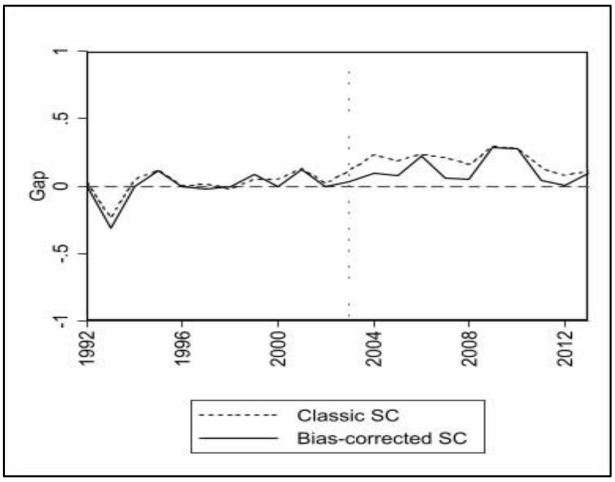
(a) Bias-corrected synthetic control (SC) based on OLS regression.



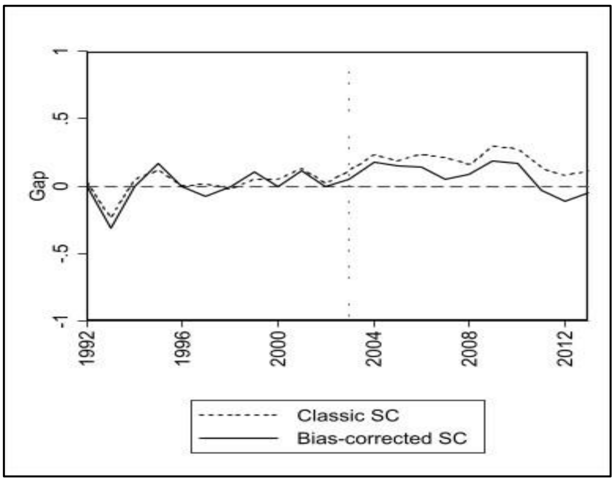
(b) Bias-corrected synthetic control (SC) based on Ridge regression.



(c) Bias-corrected synthetic control (SC) based on Lasso regression.

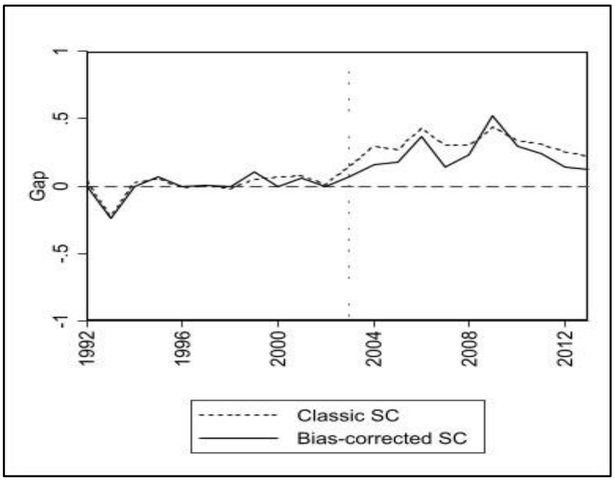


(d) Bias-corrected synthetic control (SC) based on elastic net regression.

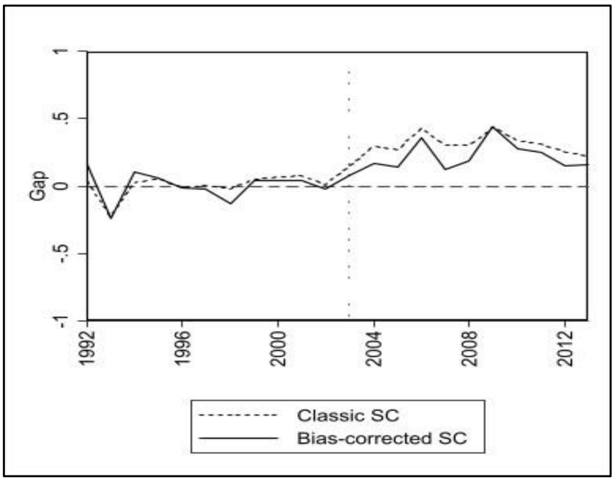


(e) Bias-corrected synthetic control (SC) based on OLS regression with only those donor pool units for which the synthetic-control-estimated weights are strictly positive.

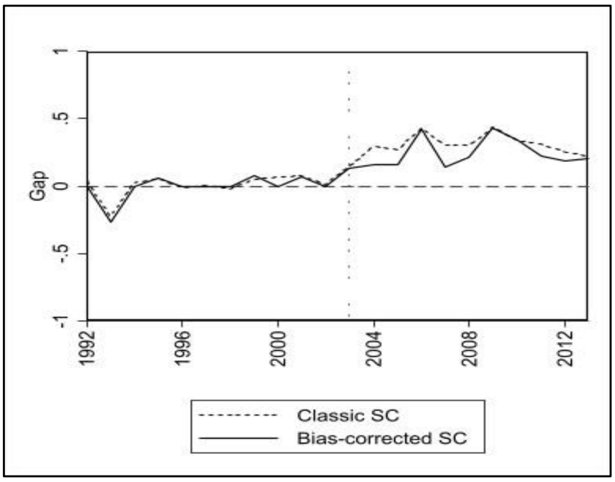
Figure A10: Comparison of gaps in the classic and bias-corrected synthetic controls for the analysis of Bam County's selected neighbors of first order (excluding Jiroft and Kerman)



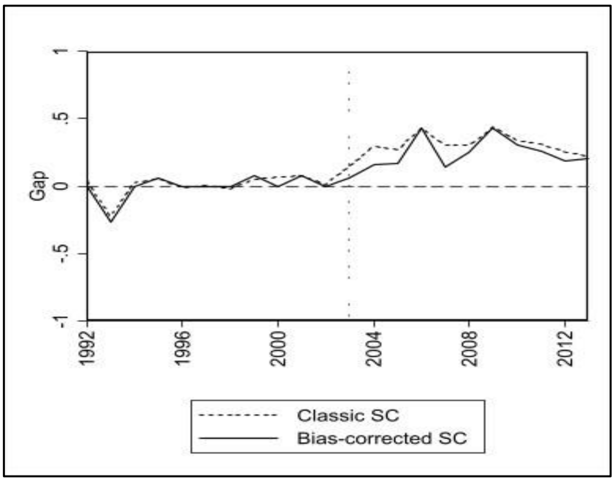
(a) Bias-corrected synthetic control (SC) based on OLS regression.



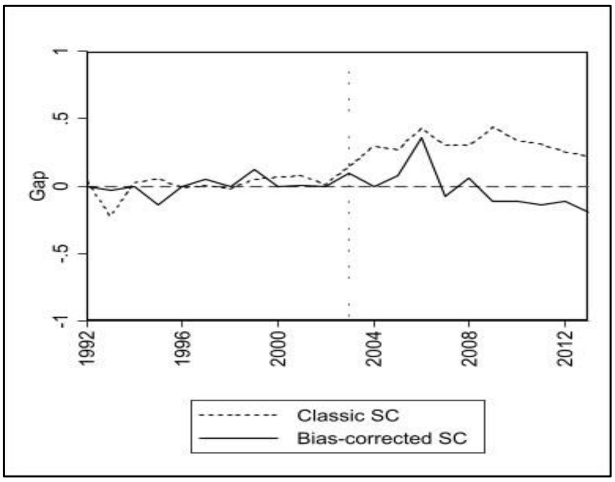
(b) Bias-corrected synthetic control (SC) based on Ridge regression.



(c) Bias-corrected synthetic control (SC) based on Lasso regression.

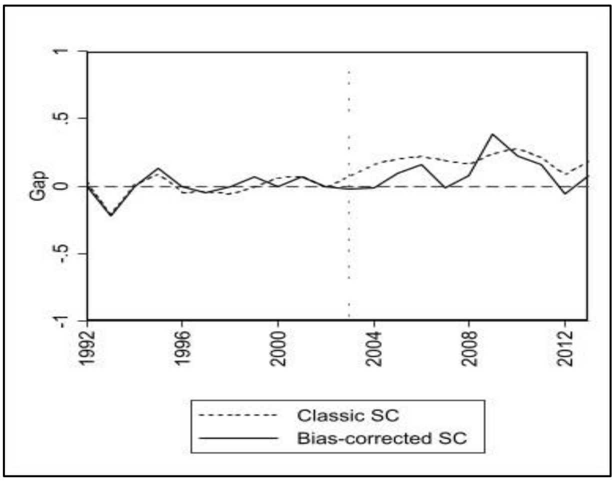


(d) Bias-corrected synthetic control (SC) based on elastic net regression.

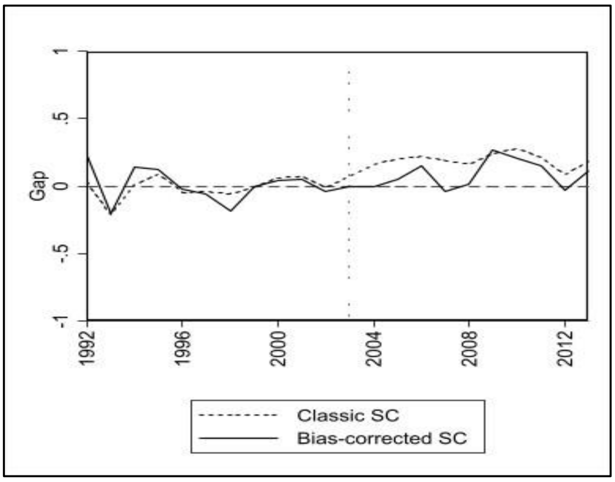


(e) Bias-corrected synthetic control (SC) based on OLS regression with only those donor pool units for which the synthetic-control-estimated weights are strictly positive.

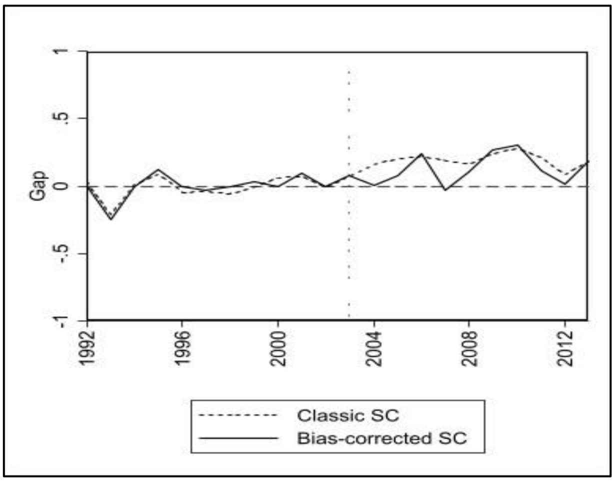
Figure A11: Comparison of gaps in the classic and bias-corrected synthetic controls for the analysis of Bam County's neighbors of second order



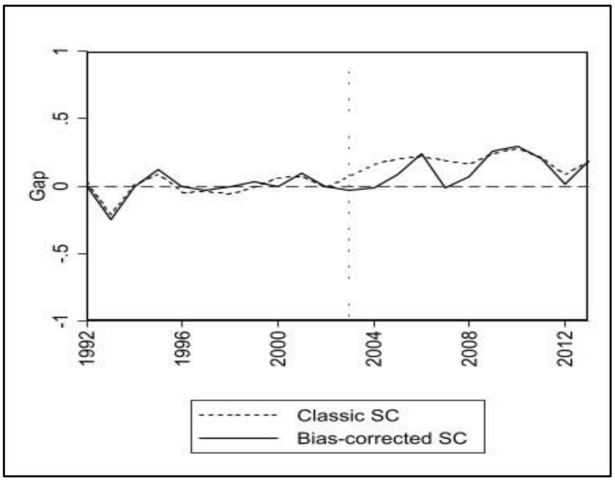
(a) Bias-corrected synthetic control (SC) based on OLS regression.



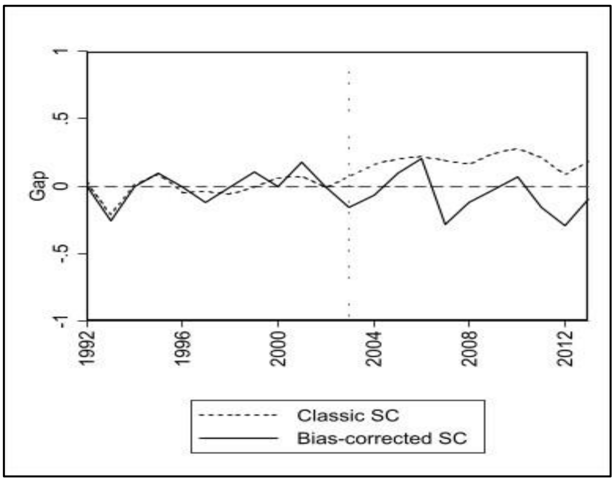
(b) Bias-corrected synthetic control (SC) based on Ridge regression.



(c) Bias-corrected synthetic control (SC) based on Lasso regression.



(d) Bias-corrected synthetic control (SC) based on elastic net regression.



(e) Bias-corrected synthetic control (SC) based on OLS regression with only those donor pool units for which the synthetic-control-estimated weights are strictly positive.