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Article — Published Version

The impact of a large-scale natural disaster on local economic activity: evidence from the 2003 Bam earthquake in Iran

Empirical Economics

Provided in Cooperation with:

Springer Nature

Suggested Citation: Farzanegan, Mohammad Reza; Fischer, Sven (2024): The impact of a large-scale natural disaster on local economic activity: evidence from the 2003 Bam earthquake in Iran, Empirical Economics, ISSN 1435-8921, Springer, Berlin, Heidelberg, Vol. 68, Iss. 3, pp. 1409-1428, https://doi.org/10.1007/s00181-024-02676-y

This Version is available at: https://hdl.handle.net/10419/323192

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The impact of a large-scale natural disaster on local economic activity: evidence from the 2003 Bam earthquake in Iran

Received: 19 January 2024 / Accepted: 19 October 2024 / Published online: 4 November 2024 © The Author(s) 2024

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) to nighttime light (NTL) data from 1992 to 2013 to study the impact of the 2003 Bam earthquake on Bam County in Iran and its neighboring counties. According to the results and statistical inference tests for the SCM, Bam County and its neighboring counties experienced a statistically significant boost in economic activity in the years following the earthquake. Bam's GDP economic activity increases by an accumulated US\$620 million in the post-earthquake period. We find that the average economic gain in Bam following the 2003 earthquake is approximately 5% of Bam's GDP. We also discuss possible contributing factors to the post-disaster economic boom in Bam.

Keywords Natural disaster \cdot Earthquake \cdot Synthetic control \cdot Economic development \cdot Nighttime light \cdot Iran

JEL Classification $H84 \cdot O53 \cdot Q51 \cdot Q54 \cdot R11 \cdot R12$

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,



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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 (Farzanegan et al. 2024). We choose to focus on the 2003 Bam earthquake since it was the largest natural disaster in the period of available nighttime data and because Bam and its cultural landscape are important UNESCO World Heritage Sites. 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).

This study offers two key contributions. One of the main contributions is the creation of a counterfactual Bam County to investigate the development impact of the earthquake. To achieve this, we use the synthetic control method (SCM) to construct a synthetic version of Bam County that has not been affected by the earthquake. The difference between the development path of the affected county, in comparison to its synthetic version, provides the estimations of the impact of the 2003 Bam earthquake. We measure economic activity in Iranian counties using nighttime light (NTL) data from 1992 to 2013 (Li et al. 2020), which has several advantages for our study. The second contribution is that this study is one of the first to use SCM to investigate spatial spillovers into neighboring geographical units.

The main findings are that Bam County and its six neighboring counties experienced a boost in economic activity in the years following the disaster, returning to their pre-disaster development paths within ten years. We identify 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 disaster received. 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

Empirical evidence for various short- and long-term economic impacts of natural disasters 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 (Noy 2009; Loayza et al. 2012; Cavallo et al. 2013; Felbermayr

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).



and Gröschl 2014; Klomp 2016; Noy and duPont IV 2018; Fabian et al. 2019; Onuma et al. 2021; Felbermayr et al. 2022). On the one hand, several of these studies show an increase of economic development or growth following natural disasters under certain conditions, supporting the creative destruction hypothesis and the existence of a recovery processes following the shock (Albala-Bertrand 1993; Skidmore and Toya 2002; Noy 2009; Loayza et al. 2012; Klomp 2016; Onuma et al. 2021; Felbermayr et al. 2022; Porcelli and Trezzi 2019; Brata et al. 2018). On the other hand, there are several studies that highlight the negative impact of natural disasters on growth (Bertinelli and Strobl 2013; Felbermayr and Gröschl 2014; Elliott et al. 2015; Fabian et al. 2019; Joseph 2022). There are also studies which show mixed effects from positive impacts on capital growth and aggregate consumption to negative effects on employment growth, aggregate investment and services sector output (Tanaka 2015; Best and Burke 2019).

The advantage of using nighttime light data to evaluate the economic impact of natural disasters and the recovery process is discussed in several studies (Bertinelli and Strobl 2013; Elliott et al. 2015; Klomp 2016; Fabian et al. 2019; Nguyen and Noy 2020; Felbermayr et al. 2022; Joseph 2022). The synthetic control method (SCM) has also been used in several studies in the context of natural disasters and environmental degradation, for example in studies on economic growth, employment, population size, tourist arrivals, migration, and government spending (Coffman and Noy 2011; Cavallo et al. 2013; Barone and Mocetti 2014; duPontIV and Noy 2015; Lynham et al. 2017; Pagliacci and Russo 2019; Basile et al. 2023; Porcelli and Trezzi 2019; Best and Burke 2019).

Case studies on Iran, using both quantitative and qualitative methodologies, also exist; for example, studies on the short-term impact of natural disasters on economic growth (Sadeghi and Emamgholipour 2008; Sadeghi, Emamgholi Sefiddasht, and Zarra Nezhad 2009; Yavari and Emamgholipour 2010; Fischer 2021) or the social and economic consequences of different earthquakes in Iran (Hosseini et al. 2013; Yuan et al. 2018). In addition to earthquakes, there is also a discussion in the literature about weather-related disasters such as droughts and floods. Droughts in Iran have already had social and economic consequences, such as inter-province migration (Farzanegan et al. 2023)² and increasing housing and residential land prices (Farzanegan et al. 2021). The effect of floods on economic activities in the case of Iran is also examined by Farzanegan and Fischer (2024).

There have also been discussions about a disaster's impact beyond economic growth, especially related to the topics of disaster response and recovery, and civic engagement. There are several studies that discuss post-disaster aid flows and fiscal policies in the aftermath of natural disasters (Noy and Nualsri 2011; Becerra et al. 2014; 2015). Additionally, Carrero et al. (2019) discuss the role of informal networks for the disaster response and recovery process, which is also relevant in the context of the Bam earthquake, where civil society played a crucial role (Yuan et al. 2018).

² Earthquakes can also change the demographics of the affected cities, because the destruction can cause out-migration and reconstruction can cause in-migration (Collins and Friesen 2022). Further evidence based on cross-country results was presented by Drabo and Mbaye (2015) who show that natural disasters are positively associated with emigration rates.



Overall, there is already 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 (with the exception of Farzanegan and Fischer's (2024) study on the impact of the 2001 flood in Iran). We fill this gap by using the SCM and provide empirical evidence for the impacts of a large-scale earthquake in the short and intermediate term.³

3 Methodology and data

3.1 Methodology

We use the SCM developed by Abadie et al. (2003; 2010; 2015), that can be used to study the effects of a shock on an outcome variable, which in our case is the natural logarithm of the sum of nighttime lights. In the SCM application, the shock is the 2003 Bam earthquake which suggests that the disaster year is 2003 and the affected unit (j = 1) is Bam County. The remaining counties will be used as the donor pool (j = 2 to j = J + I). The advantage of the SCM is that we use the combination of several unaffected counties to approximate the pre-disaster characteristics of the affected county, which is more accurate than using any single unaffected county. We also need a sample that is a balanced panel dataset, where all units are observed at the same time periods t = 1,...,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 $T_0 + 1,...,T$, and the disaster has no effect during the period T_0 . With this approach, we 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 $J \times I$ vector of weights $W = (w_2, ..., w_{J+1})'$, with $0 \le w_j \le I$ for j = 2, ..., J+1 and $w_2 + ... + w_{J+1} = I$. We choose a synthetic control by selecting a particular value for W. It will be selected using Mill's Method of Difference, 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_I , of the affected unit that we aim to match as closely as possible are included in a $k \times I$ 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_I and X_0 may also include pre-disaster values of the outcome variable. The vector X_I - 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,...,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

³ The SCM approach has recently gained popularity in case studies of Iran, focusing on the economic effects of conflict, war, and sanctions (Farzanegan and Batmanghelidj 2023).



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 control of the affected unit (Bam County in our case study) reproduces the values of variables with large predictive power on the outcome variable. 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 $Y_1 = (Y_1 T_0 + 1, \dots, Y_1 T)$. 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 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 $t \ge T_0$), the estimator is given by:

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

Additionally, the corresponding variables X_0 and X_1 are the predictors of the postdisaster 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 predisaster 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 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 consider several requirements that are necessary to apply the SCM. We need a sufficient number of pre-disaster periods to determine the synthetic control and enough years after the event so that we could evaluate the long-term impact. Additionally, we need to find a natural disaster that only affected one or a few counties simultaneously so that we could have enough donor counties that were not affected by the shock. In the analysis, we choose Bam County with the disaster year 2003 and we restrict the donor pool and remove all counties and neighboring counties that experienced one of the large-scale disasters



over the whole period of available data. This leaves us with 63 out of 429 counties. The included counties are presented in Table A1 in the online Appendix.

3.2 Data: outcome variable and predictors

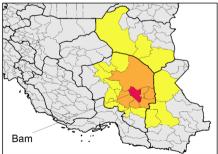
In December 2003, the historic city of Bam experienced an earthquake that measured 6.6 on the Richter scale. The city of Bam is located in Bam County of Kerman Province, which is in southeastern Iran, as presented in Fig. 1. It was one of the deadliest earthquakes in Iranian history, killing 26,796 people, 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 et al. 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 were estimated to be US\$700 million (Ghafory-Ashtiany and Hosseini 2008; EM-DAT 2021). In contrast to residential structures, industrial structures suffered less damage, such as cracks in walls and oil spills (Eshghi and Razzaghi 2005).

3.2.1 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 (Henderson et al. 2012; Pinkovskiy and Sala-i-Martin 2016) 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



(a) Province affected by the earthquake.



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

Fig. 1 Provinces and counties affected by the 2003 earthquake



low-quality regional and national accounts. 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. 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 et al. 2015; Klomp 2016; Fabian et al. 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 2013), several reforms regarding county borders were implemented in Iran. This makes it difficult to compare GDP statistics for all Iranian counties over longer 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). We extract the NTL data using a shapefile with political borders from 2017 (OCHA 2019b), which includes 429 counties. We calculate the sum of light intensity for each of the counties over the period of 1992–2013. The values represent the yearly average of the sum of nighttime light intensity in each Iranian 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).

3.2.2 Predictor variables

In the estimations, we use 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 for the affected and synthetic county. 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 predisaster 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 calculate 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). As data availability at the county level except for NTL data is limited, we use data from the province level. Thus, we additionally control for the characteristics of the province of the selected donor pool counties.

4 Results and statistical inference

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. Figure 1b shows where the epicenter of the earthquake was located and this already suggests a rather regional impact, which we show in this study. Therefore, we investigate the impact of the Bam earthquake on the county level. An earthquake with a



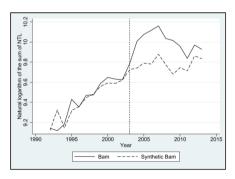
clear epicenter also gives us the possibility to study spatial spillovers into neighboring counties.

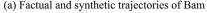
4.1 Bam county

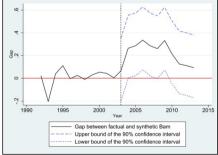
First, we apply the SCM with county-level data where Bam County is the affected unit and 2003 is the disaster year. According to the results, the synthetic Bam is best generated by the weighted average of six counties (out of 63 counties in the donor pool), namely Bonab (39.6%), Khalkhal (19.5%), Tehran (19.2%), Tarom (10.7%), Shemiranat (7.9%), and Tabriz (3%). In the following, we refer to the affected Bam as factual Bam, which has experienced the disaster event, and the counterfactual Bam as synthetic Bam. Table A2 in the online Appendix shows the average values of the covariates of factual Bam and synthetic Bam before the disaster year of 2003. According to the values, synthetic Bam closely reflects the pre-disaster performance of the NTL covariates of factual Bam and we also see similarities among the other predictor variables, namely the average NTL, NTL growth, population growth rate, population density, and natural disaster risk indicator.

Figure 2 shows the trajectories of the natural logarithm of the sum of NTL of factual and synthetic Bam from 1992 to 2013. We see that the synthetic version reproduces the development of the NTL of the factual county in the period before the 2003 earthquake. The difference between the factual and synthetic versions shows the effect of the earthquake. If we compare the trajectories of Bam and synthetic Bam (Fig. 2a), we see that both continue to grow until the peak in 2007. However, the development of nighttime lights in synthetic Bam is lower than the development of factual Bam which suggests that the earthquake disaster had a positive impact on NTL development in the factual Bam.

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) and Ferman et al. (2020). The







(b) Gap between factual and synthetic trajectories of Bam, including confidence sets

Fig. 2 Factual and synthetic trajectories of Bam and gap with confidence sets



latter propose 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 Bam and synthetic Bam with uniform confidence sets at the 90% confidence level. If the confidence sets do not include the zero line, then there is 90% certainty that the effect of the earthquake event on the economic activity in Bam County is different to zero.⁴

According to the results, the estimated positive effect of the 2003 earthquake is statistically significant in the seven years following the disaster. Additional placebo tests for the analysis of Bam County are presented in Figure A1 in the online Appendix, namely an in-space placebo test, an in-time placebo test, and the leave-one-out test. In the leave-one-out test, for example, Tehran County is dropped from the donor pool of the analysis which tests if synthetic Bam and the estimated gap is sensitive to the exclusion of certain donors. The results suggest that a similar gap can be reproduced, even when excluding Tehran County or other counties from the donor pool. As there are some discrepancies between the predictors of the factual and synthetic Bam, we also apply 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 A1e in the online Appendix. Overall, the placebo tests support the previous findings of the confidence sets.

4.2 Bam's neighboring counties

For the six neighboring counties (Anbarabad, Fahraj, Jiroft, Kerman, Normashir, and Rigan), all of which are located in Kerman Province, we follow the same procedure as in the case of Bam County. Table 1 shows the weights used to create the synthetic neighboring counties and Table A2 and Table A3 in the online Appendix show the average values of the covariates of the neighboring counties. It is worth noting that in some cases, the weights of the synthetic versions of the six counties consist of the same counties from the donor pool. To show that the selection of these counties is not driving the results, e.g., Tarom County, which is included in five synthetic counties, we use the leave-one-out test which is presented in Figure A4 in the online Appendix.

Figure 3 shows the trajectories of the natural logarithm of the sum of NTL of the factual and synthetic versions of Bam's neighboring counties. In all six cases, we 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 neighboring counties shows the spillover effects of the earthquake. All neighboring counties show a gap between the factual and synthetic versions. However, we also need to consider the uncertainty of the estimation of the synthetic control, which can be evaluated with confidence bounds, as presented in Fig. 4, and several established placebo tests which are presented in Figures A2, A3, A4, A5, and A6 in the online Appendix.

⁴ A similar approach was used by Farzanegan (2022) for the case of the economic impacts of revolution and war in Iran.



Table 1	County	weights	of Bam's	synthetic	neighboring	counties

	Weights of synthetic Bam (%)	Weights of synthetic Anbarabad (%)	Weights of synthetic Fahraj (%)	Weights of synthetic Jiroft (%)	Weights of synthetic Kerman (%)	Weights of synthetic Normashir (%)	Weights of synthetic Rigan (%)
Baharestan	0	17.3	0	0	0	0	14.2
Bonab	39.6	0	0	0	0	53.7	0
Firuzkuh	0	6.9	5.1	0	0	0	3.4
Jolfa	0	0	0.5	0	0	7.2	0
Khalkhal	19.5	17.2	0	20.4	0	0	0
Khoy	0	0	0	0	0	13.3	0
Oshnaviyeh	0	0	4.3	0	0	0	5.3
Paveh	0	11.8	24.3	0	0	0	41.5
Qarchak	0	6.9	28.3	11.6	0	0	0
Qazvin	0	0	0	0	47.6	0	0
Shemiranat	7.9	0	0	58.8	0	0	0
Soltanieh	0	0	0	0	0	10.1	0
Tabriz	3	0	0	0	0	0	0
Takab	0	33.8	2.2	0	0	0	0
Tarom	10.7	6.1	35.3	0	0	15.8	35.5
Tehran	19.2	0	0	9.2	52.4	0	0
Remaining 47 counties	0	0	0	0	0	0	0

According to Fig. 4, the Fahraj and Rigan counties experienced a statistically significant positive shock for ten years after the earthquake. The remaining four counties show shorter significant impacts of the disaster, for example, Anbarabad (five years), Kerman (four years), Normashir (three years), and Jiroft (two years). Overall, the results suggest that not every neighboring county was affected by the spillover effects in a statistically meaningful way for the same length. If we compare the trajectories in Fig. 4, we see an increase in economic activity directly after the disaster in all cases and the counties almost return to their pre-disaster development path within the ten-year period after the earthquake.

In the final step of the analysis, we calculate the economic boost following the Bam earthquake in US dollars with the help of the estimated gaps, using GDP data from Iranian Ministry of Economic and Financial Affairs (MEFA 2021) and official exchange rate data from Central Bank of Iran (CBI 2020). According to the results, Bam County's economic activity increases by an accumulated US\$620 million in the post-earthquake period. To calculate this accumulated economic gain, we consider only the years in which the estimated gap between Bam County and its synthetic counterpart is statistically significant (i.e., the years 2004–2007 and 2009). The six neighboring first-order counties (i.e., Anbarabad, Fahraj, Jiroft, Kerman, Normashir, and Rigan)



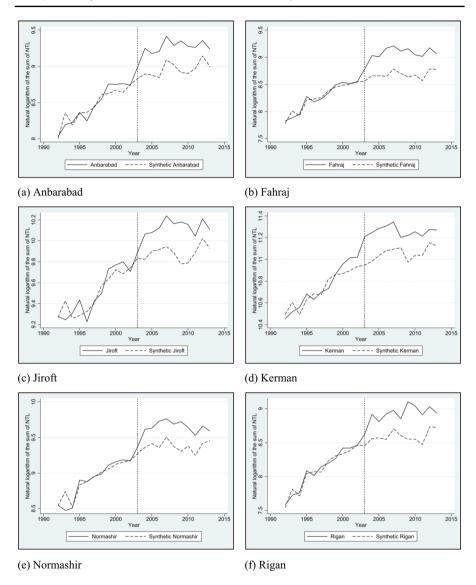


Fig. 3 Factual and synthetic trajectories of Bam's neighboring counties

experience a boost in economic activity amounting to an accumulated US\$3.36 billion. This figure represents the total economic gain in all six counties during the post-Bam earthquake years in which the estimated gap between these counties and their synthetic counterparts is statistically significant (more details in Tables A4 and A5 in the online Appendix). This translates to an average accumulated economic gain of US\$560 million per neighboring first-order counties during the post-Bam earthquake period. As a comparison, the real GDP of Kerman Province was 255.25 trillion rial



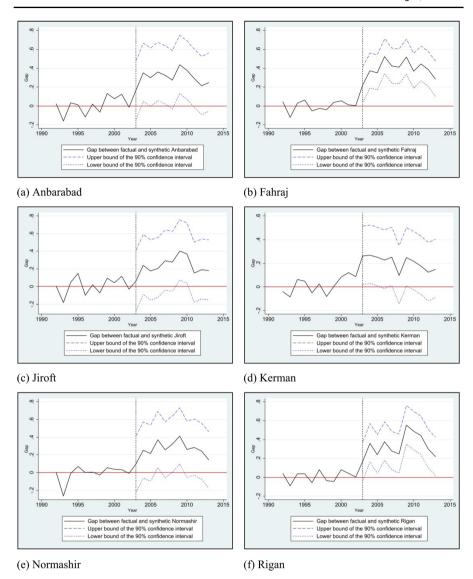


Fig. 4 Gaps between factual and synthetic trajectories of Bam's neighboring counties, including confidence sets

in 2004 which is approximately US\$30 billion using the official exchange rate of the same year.

When considering the values for the calculated real GDP of studied counties (which are presented in Table A6 in the online Appendix), the ratio of the monetary gains compared to the size of calculated GDP can be shown (more details in Tables A7 in the online Appendix). According to the results, the annual average economic gain for Bam County from 2004 to 2007 and in 2009 is estimated at US\$124 million. Additionally,



the annual average calculated GDP of Bam County during these post-earthquake years is US\$2.3 billion. By dividing these two figures, we find that the average economic gain in Bam following the 2003 earthquake is approximately 5% of the Bam's GDP. Similarly, the average share of economic gain for the other six counties relative to their respective estimated GDPs in years following the 2003 earthquake is also around 5%.

5 Discussion of possible contributing factors to the post-disaster economic boom in bam

The results of our empirical analysis show that there is a boost in economic activity in Bam County and four neighboring counties after the 2003 Bam earthquake. This is supported by theory (Albala-Bertrand 1993; Skidmore and Toya 2002; Klomp 2016) and previous empirical studies (Noy 2009; Loayza et al. 2012; Barone and Mocetti 2014; Onuma et al. 2021; Felbermayr et al. 2022; Porcelli and Trezzi 2019; Brata et al. 2018).

To better understand the development of NTL after the Bam earthquake, we follow Noy and duPont IV (2018) and argue that this is due to the type and severity of the event, underlying composition of the economy, and 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 to helpers than compared to a flood, for example, which 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 Bam County with the average Iranian county of the year 2002 (before the earthquake disaster), we see that Bam County had a higher population than the average Iranian county, with 283,311 people compared to 209,809 people (GDL 2022). Economic activity, measured as the sum of NTL units, had a value of 15,115 compared to 13,310 (Li et al. 2020). Regarding 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 see that Bam County was more economically developed and had more human capital than the average Iranian 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, the United Kingdom'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 were immediate responses from the Iranian Red Crescent Society (IRCS), government agencies, military forces, and other volunteers, and 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. Over 200 international nongovernmental 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 et al. 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 civil society and Aldrich (2011) and Carrero et al. (2019) show the importance of social capital and civic engagement for a community's ability to recover from a disaster. In this context, we 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. This is an additional factor for 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

⁵ 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 the government in Iran before the year 2005.



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 Fig. 2a). This inflow of people did not only include aid workers, but also opportunity seekers, such as entrepreneurs and low-skilled construction workers.

The significant attention and inflow of financial help also caused the temporary migration of poor people from neighboring villages pretending to be survivors and claiming financial support designated for actual victims. Thus, despite the high death toll, several reports suggest that the population of Bam was larger after the earthquake. (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. The inflow of migrants after earthquakes and their role in reconstruction is also discussed for earthquakes in New Zealand (Collins and Friesen 2022).

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 UNESCO World Heritage Site, which can cause empathy and emotions in people that helped to mobilize domestic and foreign 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 et al. 2014). Some examples of the media attention and international interest are Prince Charles' 2004 visit to Bam (NBC 2004) and the charity football match between the German and Iranian national teams in Tehran in 2004 (Spiegel 2004), both of which were unique events.

After discussing the disaster response and reconstruction process, we 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. It should also be mentioned that the reconstruction process, as measured by nighttime lights, has outpaced the initial destruction of electricity infrastructure, so that we do not observe a decrease in NTL directly after the earthquake using yearly-aggregated data.



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 look at the 2003 Bam earthquake. The first finding is that Bam County experienced a boost in economic activity following the earthquake, which is shown in the difference between the studied factual and synthetic units. We argue 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.

However, this boost in economic activity in Bam County can also be interpreted as a loss in other 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 provincial budgets. It is a burden to the central and provincial governments, because they now need to allocate budget to the region that could have been used for other purposes, such as spending on health or education. As a second result, we show 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. Our results suggest positive spillover effects from the reconstruction activities in Bam into neighboring counties, supporting the findings of Fischer (2021). The third finding is that we do 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 et al. 2019).

There are several limitations to this study. First, the precision of nighttime light data has been criticized, particularly regarding its difficulty in distinguishing lower levels of light intensity from background noise, which often results in smaller settlements being excluded from the data (Määttä and Lessmann 2019). Additionally, higher levels of light intensity cannot be measured beyond a certain level, which makes it impossible to see small changes in light once the maximum value for measuring light is reached. Second, the study relies on county-level data, which restricts the inclusion of certain covariates in the analysis. For instance, it is difficult to obtain county-level data on human capital, investments, trade, and other drivers of economic activity. Third, other large-scale events could have potentially influenced the outcome variable in Bam County or the donor pool counties, which might bias the results. To mitigate this, the study excluded all counties from the donor pool that experienced natural disasters



during the study period. Bam County did not suffer any major natural disasters after the 2003 earthquake, apart from minor aftershocks (Tatar et al. 2005).

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s00181-024-02676-y.

Acknowledgements We appreciate the helpful comments and suggestions of the editor (Robert M. Kunst), an anonymous reviewer, Annemiek Schilpzand and the participants at the European Public Choice Conference (2023, Hannover). We acknowledge the research assistance of Jhoana Ocampo.

Funding Open Access funding enabled and organized by Projekt DEAL.

Declarations

Conflict of interests The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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