Political Economy of Natural Disasters

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Erläuterungen zu den Beiträgen der Ko-Autoren

Das dritte Kapitel „Nighttime Light Development after the 2003 Bam Earthquake in Iran: A Synthetic Control Analysis” wurde von Sven Fischer (SF) zusammen mit Mohammad Reza Farzanegan (MRF) verfasst. Die Autoren haben folgende Beiträge geleistet: Konzept und Grundidee: MRF; Methodik: MRF; Softwareanwendung: SF; Analyse und Visualisierung: SF; Literaturrecherche: MRF und SF; Datenbearbeitung: SF; Schreiben des ersten Entwurfs: SF; Überprüfung und Überarbeitung: MRF; Beaufsichtigung und Betreuung: MRF.

Das fünfte Kapitel „Disaster Literacy in Iran: Survey-based Evidence from Tehran” wurde von Sven Fischer (SF) zusammen mit Mohammad Reza Farzanegan (MRF) und Peter Noack (PN) verfasst. Die Autoren haben folgende Beiträge geleistet: Konzept und Grundidee: MRF; Methodik: MRF; Survey Design: MRF, SF und PN; Softwareanwendung: SF; Analyse und Visualisierung: SF; Literaturrecherche: SF und PN; Datenbearbeitung: SF; Schreiben des ersten Entwurfs: SF und PN; Überprüfung und Überarbeitung: MRF; Betreuung und Projektleitung: MRF; Finanzakquise: MRF und PN.

Das sechste Kapitel „The Impact of the COVID-19 Pandemic on Marriage and Fertility Behavior: Survey-based Evidence from Iran” wurde von Sven Fischer (SF) zusammen mit Mohammad Reza Farzanegan (MRF) verfasst. Die Autoren haben folgende Beiträge geleistet: Konzept und Grundidee: MRF; Methodik: MRF; Survey Design: MRF und SF; Softwareanwendung: SF; Analyse und Visualisierung: SF; Literaturrecherche: SF; Datenbearbeitung: SF; Schreiben des ersten Entwurfs: SF; Betreuung und Projektleitung: MRF; Finanzakquise: MRF.

Zusammenfassung

Die vorliegende Arbeit befasst sich in fünf Artikeln mit der politischen Ökonomie von Naturkatastrophen am Beispiel Irans. Innerhalb dieser fünf Kapitel werden die sozialen und wirtschaftlichen Konsequenzen von Naturkatastrophen auf verschiedenen Ebenen untersucht, darunter die Provinzebene, die Bezirksebene, und die individuelle Ebene. Im ersten Artikel (Kapitel 2) wird der Zusammenhang zwischen Naturkatastrophen und Wirtschaftswachstum mithilfe eines *Spatial Durbin Panel Model* im Zeitraum von 2010 bis 2016, unter Berücksichtigung von 29 iranischen Provinzen, untersucht. Die empirischen Ergebnisse zeigen, dass es einen statistisch-signifikanten und positiven Zusammenhang zwischen dem räumlich verschobenen Auftreten von Naturkatastrophen und dem Wirtschaftswachstum, gemessen als Differenz erster Ordnung des natürlichen Logarithmus des BIP pro Kopf, gibt. Das bestätigt die Existenz von räumlichen Übertragungseffekten zu Nachbarprovinzen.

Der zweite Artikel (Kapitel 3) untersucht die Auswirkungen des Bam-Erdbebens im Jahr 2003 in der iranischen Provinz Kerman mithilfe der *Synthetic Control Method* und Nachtlichtdaten aus dem Zeitraum von 1992 bis 2020 unter Berücksichtigung von 31 Provinzen und 429 Bezirken. Die empirischen Ergebnisse zeigen, dass die Provinz Kerman, der Bezirk Bam und die Nachbarbezirke Bams eine Steigerung der Wirtschaftsaktivität infolge des Erdbebens erlebt haben. Das kann durch verschiedene Faktoren erklärt werden, beispielsweise Typ der Katastrophe, Schwere der Zerstörungen, Zusammensetzung der Wirtschaft, betroffene geografische Fläche, und Aufmerksamkeit der internationalen Medien. Mit derselben Methode wurden im dritten Artikel (Kapitel 4) die Auswirkungen der Flutkatastrophe in der Provinz Golestan im Jahr 2001 untersucht. In diesem Fall zeigen die Ergebnisse einen Rückgang der wirtschaftlichen Aktivität aufgrund der Katastrophe.

Im vierten Artikel (Kapitel 5) wird der Zustand der Katastrophenkompetenz in der Stadt Teheran mithilfe einer Umfrage mit 502 Befragten aus dem Jahr 2020/2021 untersucht. Die Ergebnisse der empirischen Untersuchung mithilfe von logistischen Regressionen zeigen, dass das Haushaltseinkommen, das Vertrauen in das iranische Katastrophenmanagement, die Angst vor Naturkatastrophen, die wahrgenommene Häufigkeit von Naturkatastrophen, und die Internetnutzung einen statistisch-signifikanten und positiven Zusammenhang mit den Fragen zur Katastrophenkompetenz aufweisen. Außerdem wird deutlich, dass es räumliche Ungleichheiten in Bezug auf Katastrophenkompetenz innerhalb der Stadt Teheran gibt, und zwar haben die nördlichen Bezirke höhere Werte des selbst entwickelten *Disaster Literacy Index* als die südlichen Bezirke.

Der fünfte Artikel (Kapitel 6) untersucht die Auswirkungen der COVID-19-Pandemie auf die Familienentwicklung im Iran mithilfe einer repräsentativen Umfrage mit 1214 Befragten aus dem Jahr 2022. Die Ergebnisse der empirischen Untersuchung mithilfe von logistischen Regressionen zeigen, dass die Sorge über das Andauern der Pandemie und der Impfstatus einen negativen und statistisch-signifikanten Zusammenhang mit der Geburt eines Kindes während der Pandemie aufweisen. Außerdem zeigt das Erleben eines Todesfalles und der Arbeitsplatzverlust einen positiven Zusammenhang mit dem Nachlassen des Kinderwunsches. Im Gegensatz dazu weist die Zunahme der Familienzeit einen positiven Zusammenhang mit der Zunahme des Kinderwunsches auf, und der Arbeitsplatzverlust aufgrund der Pandemie zeigt einen positiven Zusammenhang mit der Heirat während der Pandemie. Des Weiteren ergibt unsere Analyse, dass heterogene Effekte abhängig von Geschlecht, Raum und sozialer Klasse existieren. Insgesamt zeigen die Ergebnisse, wie die COVID-19-Pandemie die Heirats- und Fruchtbarkeitsdynamiken im Iran, und somit auch die demografische Entwicklung, beeinflusst hat.

Abstract

This thesis explores in five empirical papers the political economy of natural disasters using the case study of Iran. Within these five chapters, the social and economic consequences of natural disasters are evaluated on different levels, namely province level, county level, and individual level. In the first paper (Chapter 2), I study the relationship between natural disasters and economic growth, using a spatial Durbin panel model and covering the period from 2010 to 2016 and including 29 Iranian provinces. The results of the empirical investigation suggest that there is a statistically significant positive relationship between the spatially lagged occurrence of natural disasters and the change of the first difference of the natural logarithm of GDP per capita. This confirms the existence of spatial spillover effects of natural disasters to neighboring provinces.

The second paper (Chapter 3) examines the impact of the 2003 Bam earthquake in the Iranian Kerman Province, using the synthetic control method (SCM) and nighttime light (NTL) data from 1992 to 2020 for 31 provinces and 429 counties. According to the results, Kerman Province, Bam County, and the neighboring counties experienced a boost in economic activity in the years following the earthquake, which can be explained by the type and severity of the event, the underlying composition of the economy, the total area impacted, and the international media attention. With the same methodology, the third paper (Chapter 4) studies the impact of the 2001 flood in Golestan Province and found a drop of economic activity in the years following the flood disaster.

In the fourth paper (Chapter 5), we have investigated the state of disaster literacy in Tehran City, based on a survey with 502 participants which was conducted in 2020/2021. The results of the empirical investigation using logistic regressions suggest that the household's income level, the trust in Iran's natural disaster management, the fear of natural disasters, the perceived frequency of natural disasters, and internet usage show positive associations with the disaster literacy items. Additionally, we reveal a spatial inequality within Tehran City, where the Northern subsample has significantly higher scores of the self-developed disaster literacy index (DLI) than the Southern subsample.

Finally, the fifth paper (Chapter 6) studies the impact of the COVID-19 pandemic on the family development in Iran with a representative survey of 1214 participants which was conducted in 2022. The results of the empirical investigation using logistic regressions suggest that the concern about the continuation of the pandemic and the respondents' vaccination status show negative associations with childbirth during the pandemic, and the experiences of life loss and job loss are positively associated with a decrease of the respondents' child desires. In contrast, spending more time with the family is positively associated with an increase of the respondents' child desires. The experience of unemployment due to the pandemic is positively associated with marriage during the pandemic. Additionally, we found heterogenous effects depending on the respondents' gender, location, and social class. Overall, the results show how the COVID-19 pandemic affected marriage and fertility dynamics, and thus demographic development, in Iran.

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Sven Fischer January 2023

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1. Introduction

1.1 Background and Research Context

In the context of economic and social challenges due to natural disasters, which can partly be attributed to climate change, the general awareness as well as national and international efforts to promote environmental protection and disaster resilience have intensified in the past decades. However, this cannot prevent disasters from happening. The spread of the coronavirus is only the most recent example of the unintended consequences of the interaction of humans and wildlife, due to economic development and rapid urbanization, which led to a worldwide pandemic. While these are global challenges, the consequences of man-made and natural disasters are not equally distributed among countries. Especially low-income and middle-income countries are more vulnerable to the highest disaster risk (WRR 2017), which makes it important to look closer at this group of countries.

Accordingly, scientific research has also addressed questions related to the political economy of natural disasters. One of the first comprehensive studies is "*The Political Economy of Large Natural Disasters: With Special Reference to Developing Countries"* by Albala-Bertrand (1993) who presented a theoretical framework for the effects of natural disasters on economic output. This was followed by many other authors who developed theoretical models and provided empirical evidence for the relationship between natural disasters and economic growth. They have shown that the impacts of natural disasters on the economic performance depend on the country's characteristics and the characteristics of the disaster events (Noy 2009; Loayza et al. 2012; Cavallo et al. 2013; Felbermayr and Gröschl 2014; Klomp 2016; Noy and duPont IV 2018; Fabian, Lessmann, and Sofke 2019; Onuma, Shin, and Managi 2021; Felbermayr et al. 2022). Some of these country characteristics are economic development (e.g., GDP per capita, trade openness), social development (e.g., literacy rate), institutional development (e.g., natural disaster management, level of corruption), and the geographical location of the country. Among the relevant characteristics of the natural disasters are the type of disaster and the severity of the disaster. In addition, previous empirical evidence has also shown different effects in the short, intermediate, and long term.

However, the gap in the literature is that there are very few systematic empirical studies on the political economy of natural disasters with a focus on the Islamic Republic of Iran (which will be called in the following thesis "Iran"). The case study of Iran is especially interesting given its population size and geography which makes it prone to natural disasters. In addition, the country belongs to the group of lower middle-income countries (WDI 2022). According to EM-

DAT (2021), Iran experienced more than 250 natural disasters over the past century, including floods, earthquakes, droughts, storms, and others, which affected accumulated more than 60 million people, while killing at least 158,350 people, and causing an estimated damage of more than US$53 billion (adjusted for inflation).

Given the importance of the topic of political economy of natural disasters in Iran, this thesis aims to improve the understanding of the social and economic consequences of natural disasters in Iran on both the macro (as in Chapter 2, Chapter 3, and Chapter 4) and micro levels (as in Chapter 5 and Chapter 6). The rationale behind this approach is that an understanding of the dynamics of natural disasters on different levels will be needed to design targeted and effective policies of natural disaster management. Chapter 2 focuses on the impacts of natural disasters, especially earthquakes and floods, on the economic growth of Iranian provinces in the period from 2010 to 2016. The topic contributes to the literature on the short-term effects of natural disaster, and it provides new empirical evidence about the spillover effects of natural disasters. Chapter 3 and Chapter 4 focus on the impact of two individual natural disasters on economic activity in Iranian provinces and counties in the period from 1992 to 2020. The papers contribute to the discussion of intermediate and long-term effects of natural disasters and provide counterfactual evidence for the true impact of these disaster events.

Chapter 5 examines the state of disaster literacy in Tehran City, based on a survey with 502 individuals which was conducted in 2020/2021. This paper contributes to the literature of disaster resilience of Iranians in urban areas and provides evidence for spatial inequalities. It also introduces a disaster literacy index (DLI) as a new tool to measure disaster literacy. Chapter 6 focuses on the impact of the COVID-19 pandemic on the family development in Iran with a representative survey of 1214 individuals which was conducted in 2022. This paper contributes to the debate on marriage and fertility behavior during the pandemic, and through which mechanisms the pandemic affected individual marriage and fertility decisions.

1.2 Thesis Outline

This section outlines the structure of the thesis, which consists of two single-authored papers (Chapter 2 and Chapter 4) and three co-authored papers (Chapter 3, Chapter 5, and Chapter 6). The following paragraphs highlight the main research questions of each paper, methodology and data, and the main contributions made.

Chapter 2: Post-disaster Spillovers: Evidence from Iranian Provinces

This chapter's research question is two-fold, because on the one hand, it wants to study the relationship between natural disasters and economic growth in a disaster-prone country using provincial data, and on the other hand, it wants to find out if there are post-disaster spillover effects from neighboring provinces. This study uses a balanced panel of 29 Iranian provinces for the time period 1389 to 1395 according to the Iranian calendar years, which is approximately 2010–2016. As an econometric approach, it uses the spatial Durbin panel model with the maximum likelihood estimation. The contribution of this study is three-fold. First, there has not been a case study of Iran that has systematically studied the effect of natural disasters on the economic performance of the country. Second, previous studies on natural disasters and economic growth have mainly focused on the cross-country level, but this paper uses a case study of Iran with cross-provincial data. Third, spatial aspects have rarely been included in previous regression models of the literature on natural disasters and economic growth.

Chapter 3: Nighttime Light Development after the 2003 Bam Earthquake in Iran: A Synthetic Control Analysis

This chapter ties on the previous chapter in several aspects. First, it focuses on the intermediate and long-term effects of natural disasters, while the previous chapter only focused on the short-term effects. Second, by using the case study of one disaster in one geographical unit, it keeps the characteristics of the natural disaster event and the geographical unit constant. Third, it provides additional evidence for post-disaster spillovers using a different methodology and a different dataset. One of the main contributions of this study is that we are creating a counterfactual case of Kerman Province and Bam County to investigate the impact of the earthquake. 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, and then estimate the economic development of the counterfactual province and county, which reflect the development path, if the impact of the disaster event did not happen. The difference between the development paths of the treated province and county in comparison to its synthetic versions will provide us estimations of the impact of the 2003 Bam earthquake. We are measuring economic activity in the Iranian provinces and counties using nighttime light (NTL) data from 1992 to 2020 which has several advantages for our study. This is the first study on the case of Iran which measures the costs of natural disasters by creating counterfactual cases of the affected province and counties. It has also an advantage over previously used approaches because the estimated synthetic control will reflect the development of the province and counties in absence of the disaster. This is also the first study that uses the SCM to investigate spatial spillovers to neighboring geographical units.

Chapter 4: Nighttime Light Development after the 2001 Flood in Iran: A Synthetic Control Analysis

This chapter ties on the previous chapter by using the same methodology with another case study of a disaster event which has a different disaster type. To evaluate the true economic costs of this flood disaster, the chapter compares the factual development of nighttime light (NTL) with the counterfactual development in the hypothetic absence of the flood. This will provide us an estimation of the costs in terms of economic development that are usually not considered when estimating the direct damage of a disaster event. We will use the synthetic control method (SCM) to construct synthetic versions of Golestan Province and the counties Azadshahr, Galikash, and Minudasht, and then estimate the economic development of the counterfactual province and counties, which reflect the development path, if the impact of the disaster event did not happen. The difference between the development paths of the treated units in comparison to its synthetic versions will provide us estimations of the true impact of the 2001 flood. We are measuring economic activity in the Iranian provinces and counties using NTL data from 1992 to 2020, and we follow the approach of Chapter 3 of this thesis, with the main difference being the disaster type of the studied disaster event. The contribution of this study is that we provide evidence for the impact of a large-scale flood disaster on NTL, and we present an approach to convert NTL to US dollar.

Chapter 5: Disaster Literacy in Iran: Survey-based Evidence from Tehran

While previous chapters have studied the impact of natural disasters on the province and county levels, this chapter goes further down on the micro level and investigates the relationship between natural disasters and individual behavior. In this chapter, we evaluate the state of disaster literacy in Tehran City with a self-developed survey, using computer-assisted telephone interviews (CATI). This provided us a cross-sectional dataset of 502 respondents which were interviewed in December 2020 and January 2021. We are using logistic regression models to determine the association between the experience of natural disaster events, among other characteristics, and several items that measure the respondents' disaster literacy. The research question is the following: *What are the main determinants of disaster literacy within the population of Tehran City?* After identifying the main determinants of disaster literacy, we create a disaster literacy index (DLI), which we used to additionally investigate the determinants of disaster literacy with the method of ordinary least squares (OLS). The contribution of this study is that it provides new empirical evidence for the individual characteristics that shape disaster preparedness and disaster literacy in a disaster-prone country.

Moreover, this is the first time that a disaster literacy index was created for the case of Tehran or Iran, which can also provide some lessons for other urban areas in the country.

Chapter 6: The Impact of the COVID-19 Pandemic on Marriage and Fertility Behavior: Survey-based Evidence from Iran

This chapter also studies the consequences of a disaster event on the individual level. It investigates the impact of the COVID-19 pandemic and the related change of social life on the family planning behavior of Iranian citizens. We conducted a representative survey in Iran, using computer-assisted telephone interviews (CATI) which provided us a cross-sectional dataset of 1214 respondents which were interviewed in January and February 2022, during the sixth wave of the pandemic. We are using logistic regression models to determine the association between the experience of the pandemic, measured by eight different questions, covering the direct and indirect effects of the pandemic, and the family development, measured by four different questions, which refer to childbirth desires, actual childbirth, and marriage during the pandemic. Additionally, we investigated heterogeneity of responses across genders, locations, and five social classes. The research question is the following: *Did the COVID-19 pandemic affect family development in Iran?* With the sub question: *Did respondents from various genders, locations, and social classes show a different behavior?* The contribution of this study is that it provides new empirical evidence on the social impact of the COVID-19 pandemic in Iran. The studied outcome variables also have implications for the fertility rate in Iran, and therefore not just on the social development, but also on the economic development. The highlight of our study is that we are interested in the impact of the COVID-19 pandemic and the related change of social life on marriage and fertility intentions of both women and men in Iran, which has not been studied yet. Moreover, it is the first study that systematically investigates the heterogeneity across genders, locations (rural versus urban), and social classes, while other studies have only briefly touched this topic. Finally, it is also the first comprehensive study on the case of Iran, and the first study on this scale from a lower-middle income country.

2. Post-disaster Spillovers: Evidence from Iranian Provinces[1]

Abstract

This chapter studies the relationship between natural disasters and economic growth in the disaster-prone country of Iran, using a spatial Durbin panel model and covering the period from 2010 to 2016 and including 29 provinces. The results of the empirical investigation suggest that there is a statistically significant positive relationship between the spatially lagged occurrence of natural disasters and the change of the first difference of the natural logarithm of GDP per capita. Moreover, the estimations support the findings of previous cross-country studies, namely that we cannot find empirical evidence for a statistically significant direct effect of natural disasters on economic growth in the short term. When including time-lags, we can see a statistically significant positive effect of natural disasters on economic growth after two years. When taking into account the disaster type, which is mainly earthquake and flood in the case of Iran, the results suggest that the positive spillover effects are, rather, driven by earthquakes, and that there is a direct positive effect of floods in the short run. These findings extend existing literature and add new insights that are not just relevant for the case of Iran. The novelty of this study is that established and innovative approaches are used to study natural disasters on the provincial level, instead of the country level, and take into account spatial spillover effects after disaster events that have been rarely discussed in literature.

JEL Codes:

C33, H84, O11, O44, Q54, R12

Keywords:

Natural disaster; natural hazard; spatial spillover; spatial panel model; earthquake; flood; economic development; economic growth

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2.1 Introduction

Extreme weather phenomena and other natural disasters, which have been attributed to climate change, are dominating the political and public discourse recently again. However, the devastating impact of natural disasters is more likely to afflict people in developing countries, with those in low-income and middle-income countries more vulnerable to the highest disaster risk (WRR 2017). Therefore, we will focus on the case of Iran, as it is an interesting case study in this context. The country is located in the Middle East and North Africa (MENA) region which has experienced many natural disasters over the past thirty years, affecting more than 40 million people and costing their economies about US$20 billion (World Bank 2014). Main disaster events in the region are floods, earthquakes, storms, and droughts, with Iran being the most affected country. In April 2019, Iran experienced the most severe flood ever recorded in the MENA region, affecting more than 10 million people, and causing damage of more than US$2.5 billion. Furthermore, over the past 30 years two of the most-deadly earthquakes of modern times hit Iran which killed combined more than 65,000 people and caused damage of almost US$9 billion (EM-DAT 2020).

This chapter's research question is two-fold, because on the one hand, we want to study the relationship between natural disasters and economic growth in a disaster-prone country using provincial data, and on the other hand, we want to find out if there are post-disaster spillover effects from neighboring provinces. This study uses a balanced panel of 29 Iranian provinces for the time period 1389 to 1395 according to the Iranian calendar years, which is approximately 2010–2016. As an econometric approach, it uses the spatial Durbin panel model with the maximum likelihood estimation. The contribution of this study is three-fold. First, there has not been a case study of Iran that has systematically studied the effect of natural disasters on the economic performance of the country. Second, previous studies on natural disasters and economic growth have mainly focused on the cross-country level, but here we will use a case study of Iran with cross-provincial data. Third, spatial aspects have rarely been included in previous regression models of the literature on natural disasters and economic growth. Furthermore, this study ties on the first comprehensive study on the political economy of natural disasters (Albala-Bertrand 1993), while using an innovative methodology and latest available data. Finally, this chapter is structured in the following way. In Section 2.2 is the literature review, followed by the description of data and the methodology in Section 2.3. After the empirical analysis and discussion of results in Section 2.4, the chapter will be concluded in Section 2.5.

2.2 Literature Review

In the natural disaster literature, we can find several approaches that try to uncover the link between natural disasters and economic development with inconclusive results. There are different hypotheses and theories on how an economy reacts in the short and long run after the impact of a natural disaster event. On the one hand, when a natural event turns into a disaster, it might cause the loss of human life and destroy infrastructure, which means a loss of human and physical capital. This might affect economic performance in a negative way. On the other hand, several authors find support for the creative destruction argument which means that after the destruction, there is the opportunity to replace old infrastructure and technology with newer versions.

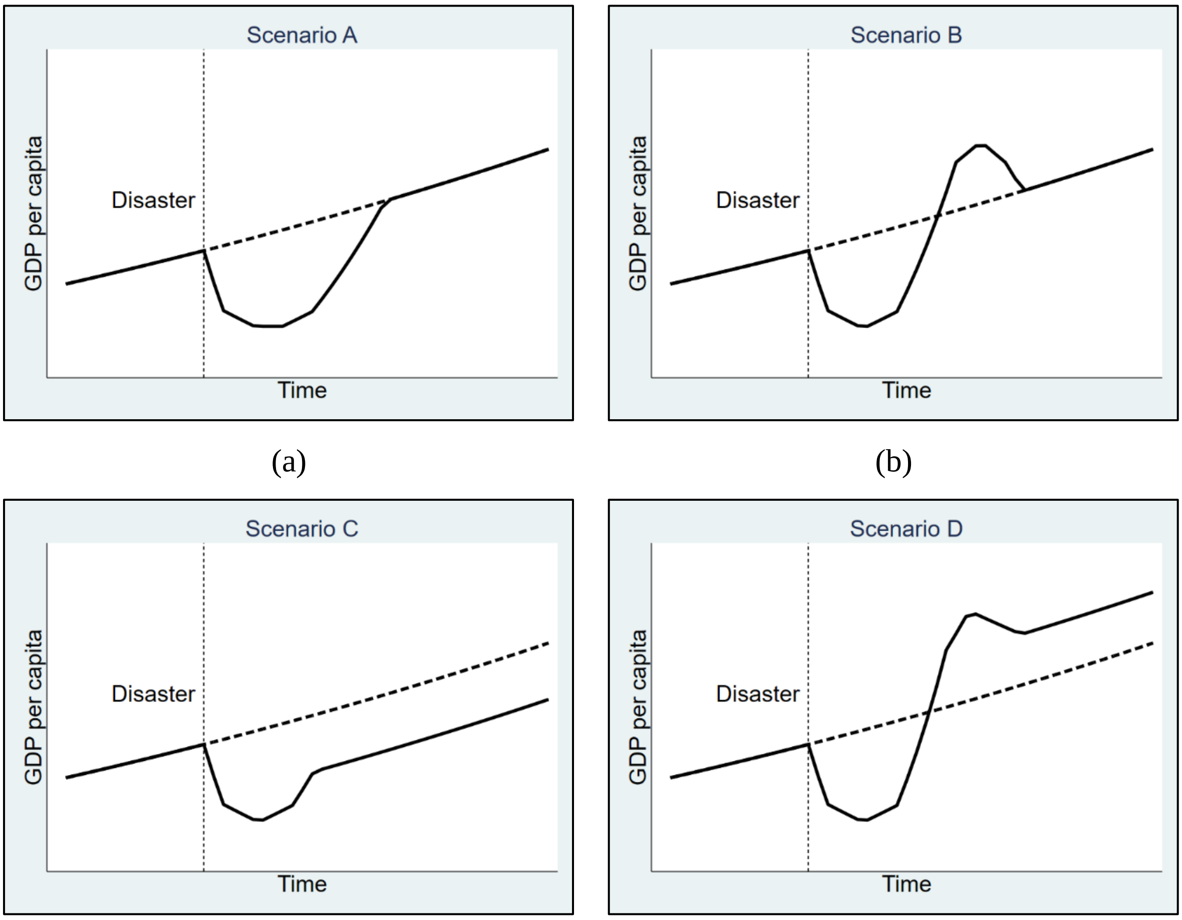
2.2.1 Theoretical Literature

One of the first comprehensive studies on the political economy of natural disasters comes from Albala-Bertrand (1993) who introduces an analytical framework and a macroeconomic model which shows the disaster's effects on output. Moreover, he empirically analyses the relationship between natural disasters and several macroeconomic variables of 28 developing countries. His results suggest that the average growth rates increased in all cases after the disaster and the effects disappear in the long run. In addition, Skidmore and Toya (2002) show with the help of the Cobb–Douglas production function that GDP does not account for damage to capital and durable goods in the short run, but the addition of new capital in the immediate term may increase GDP. 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 to human capital relative to investment capital and increase total factor productivity through the adoption of newer and more productive technologies.

Furthermore, Klomp (2016) summarizes more traditional neo-classical growth models, like the Solow model and Schumpeter's creative destruction theory. The former predicts that the reduction of the capital–labor ratio drives countries temporarily away from their long-run growth path, while the endogenous growth models provide fewer precise predictions. The latter may even predict higher growth rates as a result of natural disasters since these shocks can work as an accelerator for upgrading the destroyed capital stock. In contrast, Kellenberg and Mobarak (2008; 2011) argue that the benefits of investing in more technologically advanced capital are offset by the short-run productivity losses of a disaster because extra time is required to train workers and to fully incorporate new technology.

Based on the discussed theory, Chhibber and Laajaj (2008) and Klomp (2016) show that there are four scenarios of economic recovery after the disaster shock. Two of these scenarios assume an increase of GDP per capita in the intermediate and long run (scenarios B and D), and the two other scenarios assume a decrease of GDP per capita in the same time period (scenarios A and C). Following Figure 1 illustrates the four possible development paths.

Figure 1: The possible long-run impact of a natural disaster event on the GDP per capita



(c) (d)

(Source: Authors' illustration based on Chhibber and Laajaj (2008))

Scenario A predicts a drop of economic growth directly after the disaster event, followed by a retrace to the pre-disaster development path. The mechanism in the intermediate run is an increase in the return on capital, partly with foreign disaster assistance, that stimulates investments and thereby increasing the production capacities. This will lead in the long run to a return to the original balance growth path, as the capital ratio is restored. Scenario B foretells a drop of economic growth directly after the disaster event, followed by a temporary increase, and a return to the pre-disaster development path. The mechanism in the intermediate run is an

increase in return of capital that stimulates overinvestments, and a temporary aid inflow. However, in the long run, the replacement investments cannot take up with the speed of capital depreciation. Therefore, the initial capital-labor ratio is restored and GDP per capita is returning to its original growth path. Scenario C anticipates a drop of economic growth directly after the disaster event and then a slight increase to a new long-term growth path that is hypothetically lower than without the disaster event happening. The mechanism in the intermediate run is that the financial constraints faced by households and firms due to a lack of savings or access to credit causing the recovery to stagger. This will lead in the long run to a lower balanced growth path, as the private sector cannot invest in recovery expenses. Scenario D prognosticates a drop of economic growth directly after the disaster event, followed by a temporary increase, and then a drop to a lower development path that is still higher than the pre-disaster development path. The mechanism in the intermediate run is that the return on capital stimulates investments and increases the production capacities. Moreover, foreign disaster aid inflow supplies additional capital, and the destroyed capital is replaced by new and more productive capital. That means in the long run a higher balanced growth path, as the technology level has increased.
However, some authors such as Kellenberg and Mobarak (2008; 2011) argue in favor of an inverted u-shape relationship between natural disaster damage (measured by deaths) and the level of economic development, meaning that in the early stages of economic development, countries will not put high priority in disaster prevention, but instead will use production methods that increase the vulnerability to disasters. Therefore, there is a positive relationship between economic growth and disaster deaths until a turning point. After this peak, the awareness for disasters becomes higher and the potential capital loss will be higher, so it becomes more attractive to invest in disaster prevention and disaster-proof infrastructure. This will lower the death rates. Another study by Schumacher and Strobl (2011) argues that the relationship depends on the risk level of the geographical region. More precisely, they expect that low-risk countries have an inverted u-shaped relationship and high-risk countries have a u-shaped relationship.

2.2.2 Empirical Literature

There have been many studies on the effect of natural disasters, which have mainly focused on the impact over time and possible moderating factors: first, Barone and Mocetti (2014) show different effects in the short and long run in different regions, depending on the quality of institutions. Second, Felbermayr and Gröschl (2014) show negative effects of disasters on growth, while trade openness and institutions are moderating factors. Further evidence of negative effects is provided by Klomp (2016) who additionally look into the long-term effects of different kinds of disasters and finds that the significant negative effect of natural disasters disappear after two years for all types, except for geophysical disasters. A study by Noy (2009) focuses on the short-term effects of natural hazards on the macroeconomy. He shows that countries with a higher literacy rate, better institutions, higher per capita income, higher degree of openness to trade, and higher levels of government spending are better able to withstand the initial disaster shock and prevent further spillovers into the macroeconomy.

Overall, previous research shows that positive or negative effects of natural disasters depend on the institutional development, the disaster type, and the geographical region where the disaster event happened (Kellenberg and Mobarak 2008; Loayza et al. 2012; Klomp 2016). However, there is also a path of literature that does not find direct statistically significant effects of natural disasters on economic growth. One of these studies comes from Cavallo et al. (2013) who use the synthetic control method to examine the average causal impact of catastrophic natural disasters on economic growth. They find that only two extremely large disasters have a negative effect on output in both the short and the long runs, but these cases were followed by radical political revolutions. After controlling for these, even extremely large disasters do not display any significant effect on economic growth. One of these examples is the Iranian Islamic Revolution which occurred right after the 1978 Tabas earthquake.

The role of natural disasters in the MENA region or specifically Iran has not been intensively studied from the perspective of social sciences and economics. The majority of studies on the case of Iran are related to health aspects, geography, engineering, and natural disaster management. The first empirical studies on natural disasters and its effects on GDP per capita, savings, and investments in Iran come from Sadeghi and Emamgholipour (2008), Sadeghi et al. (2009), and Yavari and Emamgholipour (2010). Using time-series data over the period 1959–2004, the former found a negative impact of natural disasters on Iran's GDP in the short and long run. In another study, Sadeghi et al. (2009) show similar results for the period 1978–2004, namely negative effects of natural disasters on per capita investment and per capita GDP in the short and long run. Finally, Yavari and Emamgholipour (2010) focus on the impact of natural disasters on total savings in the time period 1973–2006. Their results suggest that natural disasters raise the average propensity to savings in Iran.

A study by Hosseini et al. (2013) investigates the socioeconomic aspects of two major earthquakes in Iran, namely the 1990 Manjil-Rudbar earthquake and the 2003 Bam earthquake. The authors analyze different laws and policies related to disaster management as well as the social situation in the affected areas, the destruction in the affected areas, and the psychological effects of the earthquakes. Overall, they show the huge destruction and the variety of negative effects on the social and regional level. 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 event, but after several months most of the helpers disappear. The study also discusses the reactions of the governments and challenges in coordination between involved agents.

Ainehvand et al. (2019) also focus on disaster management aspects and study the challenges related to food security using semi-structured interviews of 29 experts. According to these, natural disasters have negative impacts on various dimensions of food security such as food availability, food access, food utilization, and sustainability of each of these components. The authors identified several challenges for food supply in the context of disaster relief such as geographic and weather conditions, climate change, vulnerability of people, structure and inefficiencies of disaster management, passive responses, compensation mechanisms, ineligible distribution of food assistance, organization-based responses, unsolicited donations, as well as nutrition and health considerations.

In the wider sense, there are also a couple of studies on natural and man-made hazards such environmental degradation or climate change. Farzanegan and Markwardt (2018) as well as Gholipour and Farzanegan (2018) focus on the role of institutional quality related to air pollution and environmental protection in the Middle East. The former find evidence that improvements in the democratic development of the MENA countries help to mitigate environmental problems, while the latter show that government expenditures on environmental protection alone do not play a significant role in contributing to better environmental quality. However, improvements in quality of governance are shaping the final environmental effects of government expenditures on environmental protection in the MENA region.

An overview about effects of climate change in Iran and five projections of possible future developments are presented by Ashraf Vaghefi et al. (2019) who found that compared to the period of 1980–2004, in the period of 2025–2049 Iran is likely to experience more extended periods of extreme maximum temperatures in the southern part of the country, more extended periods of extreme weather events, including dry and wet conditions. Overall, their projections show a climate of extended dry periods interrupted by intermittent heavy rainfalls, which is a recipe for increasing the chances of floods. Climate change in Iran has already had social and economic consequences such as inter-province migration (Shiva and Molana 2018; Farzanegan, Gholipour, and Javadian 2022) and increasing housing and residential land prices (Farzanegan, Feizi, and Gholipour 2021).

Shiva and Molana (2018) study climate change-induced inter-province migration in Iran from 1996–2011 and found that a rise in temperature and a drop in precipitation act as significant push factors for migration. In addition, Farzanegan et al. (2022) show that higher levels of air pollution have a positive and significant impact on net outmigration in Iranian provinces between 2011 and 2016. Moreover, Farzanegan et al. (2021) examined the effect of drought on housing and residential land prices in Iran, using panel data from 2006–2015 on the province level. According to their results, an increase in the balance of water (reducing the severity of drought) within provinces has a positive effect on property prices.

Last but not least, there has been a focus on the spatial spillover effects of natural disasters in recent years. First, Felbermayr et al. (2018; 2022) use spatial econometric panel methods and data from 1992–2013 to study the spillover effects after natural disasters that are affecting economic activities. They find, in particular, evidence for weather shocks, and substantial heterogeneity across income groups and regions. Second, Lenzen et al. (2019) analyze the economic damage and spillovers from a tropical cyclone using the case study of Australia. Their results show how industries and regions that were not directly affected by storm and flood damage suffered significant job and income losses throughout upstream supply chains. Third, Barbosa and Lima (2019) study the case of flash floods in Brazil using a difference-in-differences model and show that municipalities directly affected by a flood suffered an 8.47% decrease in GDP per capita on the year of the disaster, and that there are significant spillovers to neighboring regions.

Moreover, a case study from Thailand comes from Noy et al. (2021) who use a difference-in-difference approach with panel data of repeated waves of the Thai Household Socio-Economic Survey and satellite data to analyze the impacts of the 2011 flood across different socioeconomic groups. From the survey, they identified those who experienced the flood and those who did not. Thus, the authors could measure the direct and indirect impacts of the disaster on income, expenditures, assets, debt, and savings levels for spillover households. Their results show that business income drove the negative impacts on flooded households relative to the control group. Moreover, they found spillover effects on households that were not directly affected by the flood but are almost as large as the loss experienced by directly impacted households. Their results suggest that these spillover effects are mainly driven by declines in business income, but also by declines in wage income. This decline in business income is mostly associated with higher-wealth households, while lower-wealth households did experience a significant decline in agricultural income.

2.3 Data and Methodology

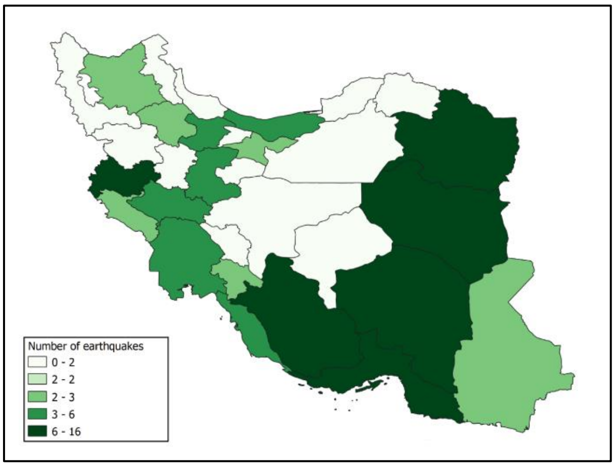
Unlike previous studies, this contribution will focus on natural disasters in Iran using several spatial panel models and data at the provincial level. The main argument for this approach is that the effect on the country level might be small, except for very small countries or island states, as Albala-Bertrand (1993) and other authors show for the effect of natural disasters on GDP. In the case of Iran, we would expect that even large-scale natural disasters that affect only one province or a low densely populated province will hardly be measurable in the national GDP of Iran. Therefore, we need to study the effect of natural disasters on the provincial levels. This gives us also the possibility to keep factors constant that affected all Iranian provinces at the same time and affected the national GDP, for example the Iran-Iraq War, the Islamic Revolution, and the recent economic sanctions. Within the time period of this study, the United States of America (USA) and the European Union (EU) introduced extended sanctions against the Iranian oil trade and financial sector in 2011/2012, which affected the Iranian economy heavily in the following years. In a cross-country or time-series comparison, we will not know if the effects on GDP come from a natural disaster or from one of these major events. This problem became visible in the study of Cavallo et al. (2013).

Data for many macro-economic indicators for 31 Iranian provinces are available for the time period from 1379 to 1398 at the Ministry of Economic and Financial Affairs (MEFA 2020). However, not all data series are available for the whole time period. Additionally, there have been several reforms related to provincial borders, for example the province Alborz that was created in 1389 and was previously part of the province of Tehran. Another example is the former province of Khorasan which was split into the three provinces North Khorasan, Razavi Khorasan, and South Khorasan in 1383. With regard to the balanced panel dataset required, the number of years and provinces in the dataset will be reduced. This leaves us with the time period 1389–1395 and 29 provinces with 203 observations. In comparison, using all 31 provinces will only provide us with a balanced panel dataset from 1391–1394 with 124 observations. As the data sources are several Iranian organizations, such as the Central Bank of Iran (CBI 2020), Ministry of Economic and Financial Affairs (MEFA 2020), and Statistical Center of Iran (SCI 2020), this study will use Iranian years. The Iranian calendar has 12 months and starts in the year 622 CE of the Gregorian calendar, with the new year occurring at the beginning of spring, which is around 21 March. That means the used time period in this study is 21 March 2010 to 20 March 2017, or approximately 2010 to 2016.

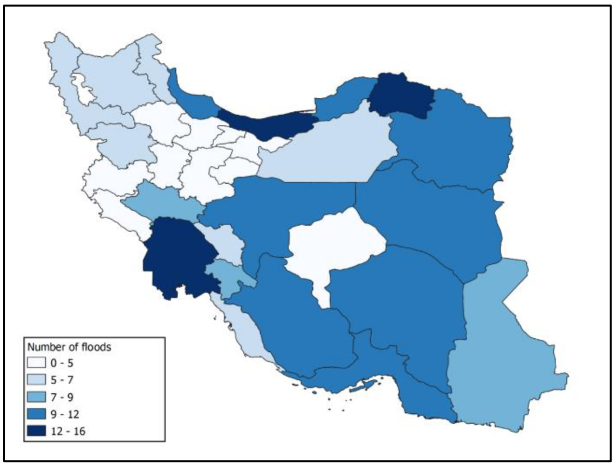
Natural disaster data comes from the International Disaster Database (EM-DAT 2020) of the Centre for Research on the Epidemiology of Disasters (CRED) at the Université catholique de

Louvain. It includes a list of 234 natural disasters that took place in Iran between 1900 and 2019, causing more than 160,000 deaths and an estimated damage of more than US$27 billion. The majority of events were earthquakes and floods. The database counts 126 disastrous earthquakes with more than 150,000 deaths and an estimated damage of US$12.6 billion, and 84 disastrous floods with more than 8000 deaths and an estimated damage of US$11.5 billion. These are not all floods or earthquakes that happened in Iran during the time period, but only those classified as natural disasters by EM-DAT. In a formal definition, the database defines disasters as “a situation or event which overwhelms local capacity, necessitating a request to the national or international level for external assistance, or is recognised as such by a multilateral agency or by at least two sources, such as national, regional or international assistance groups and the media” (Below 2006). An event must fulfill following requirements to be included in the database: 10 or more people reported killed and/or 100 or more people reported affected and/or call for international assistance/declaration of a state of emergency. Figure 2 gives an overview of the spatial distribution of the occurrence of natural disasters in Iran.

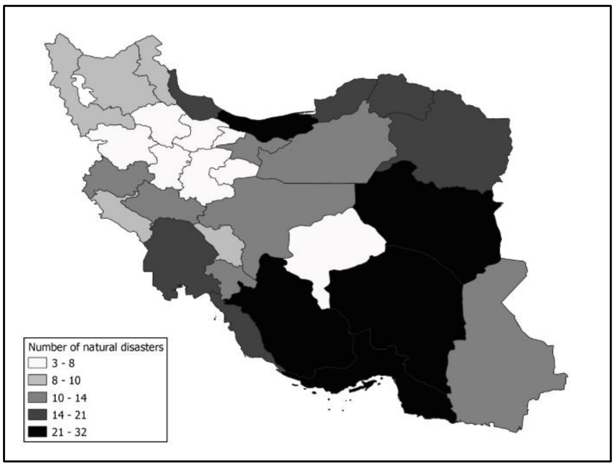
Figure 2: Spatial distribution of the occurrence of natural disasters in Iran



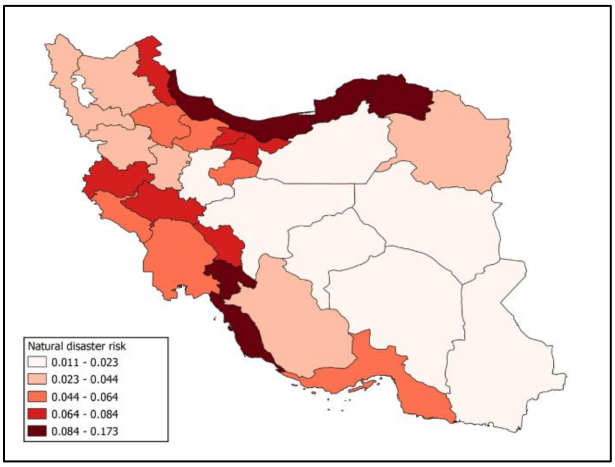
(a) Number of disastrous earthquakes per Iranian province, 1950–2019.



(b) Number of disastrous floods per Iranian province, 1950–2019.



(c) Number of natural disasters per Iranian province, 1950–2019.



(d) Natural disasters per year per 10,000 km² (based on the years 1950–2019).

(Source: Author’s illustration with data from EM-DAT)

Since the database also includes information about the location (coordinates or names of affected cities) and the exact date of each disaster event, it is possible to create a panel for Iranian provinces using Iranian years. Two problems arise in this context. First, it is difficult to calculate the number of deaths, the number of affected people or the amount of damage for each province, if several provinces were affected by the same disasters. This issue is solved by using dummy variables as a measurement of the disasters. Second, there might be no effect of the disaster reflected in the outcome variable if a disaster happened at the end of a year. To solve this issue, the natural disaster dummy variable is 1 when a disaster happened six months before and 0 if no disaster happened six months ago. The models were also estimated without the six months delayed dummy variables and it did not affect the results. According to the available data, there were 21 disaster events (13 earthquakes, 7 floods, and a storm) in the time period 1389–1395, affecting 18 of the 29 provinces. The deadliest event was the 1391 earthquake in the province of East Azerbaijan, killing 306 people and affecting more than 60,000 people. The most severe flood during this time period happened in 1393 in the northeast of Iran, killing 37 people and affecting approximately 440,000 people in six provinces.

The following Table 1 gives an overview of the variables that are used in the estimations. A detailed list of variable definitions can be found in Table A 1 of Appendix A. In addition, all variables have been tested for unit roots, and the results of several tests are also reported in Appendix A, namely in Table A 2.

Table 1: Summary statistics of used variables

Variables	**N**	**Mean**	**St. Dev.**	**Min.**	**Max.**
Iranian Year	203			1389	1395
Disaster dummy (6 months earlier)	203			0	1
Ln(GDP per capita)	203	18.38	0.667	16.99	20.44
ΔLn(GDP per capita)	203	0.187	0.146	−0.366	0.839
Ln(Population)	203	14.36	0.657	13.23	15.68
Consumer Price Index	203	67.00	24.40	30.50	100
Expenditures (% of GDP)	203	1.558	1.285	0.0964	7.345
Trade (% of GDP)	203	20.10	50.56	0.0299	358.1
FDI inflows (% of GDP)	203	0.331	1.139	0	10.84

Using the described data, this study applies the spatial Durbin panel model (SDM) which is a further development of the spatial Durbin model using cross-sectional data introduced by Anselin (1988). It has the following structure, as presented by Elhorst (2014, 7–10):

$$Y = \delta WY + \alpha + X\beta + WX\theta + \varepsilon \tag{1}$$

where Y denotes an N × 1 vector consisting of one observation on the dependent variable for every unit in the sample, α is the constant term, X denotes an N × K matrix of exogenous explanatory variables, β is an associated K × 1 vector with unknown parameters to be estimated, and ε is a vector of disturbance terms. Moreover, δ is called the spatial autoregressive coefficient, while θ, just as β, represents a K × 1 vector of fixed but unknown parameters to be estimated. W is a non-negative N × N matrix describing the spatial configuration or arrangement of the units in the sample. This model includes a spatial lag of the dependent variable WY and a spatial lag of the explanatory variable WX, therefore it combines the spatial autoregressive (SAR) model and the spatial lag of X (SLX) model.

LeSage and Pace (2009, 25–31) summarize several motivations for including spatial autoregressive processes in the regression models. First, the authors refer to the time-dependence motivation which means in the case of this study that the development in an Iranian province might depend on the development of neighboring provinces in previous time periods, for example when determining tax rates or other local policies which might be based on the experience of neighboring provinces. Although the tax rates were set over time by the cross-section of provinces representing our sample, the observed cross-sectional tax rates would exhibit a pattern of spatial dependence. This situation would suggest using a SAR model. Second, the authors argue for an omitted variable motivation which means that our model might not include important explanatory variables related to geographical location that may exert an influence on our dependent variable. They mention examples such as unobservable factors including location amenities, highway accessibility, or neighborhood prestige, and argue that it is unlikely that explanatory variables are readily available to capture these types of latent influence. Here, we should use the SAR, SLX or SDM models, because they capture such influences from neighboring provinces. The third motivation mentioned by the authors is the spatial heterogeneity motivation which assumes that in our panel dataset the intercept for each province can be treated as a spatially structured random effect vector. Making an assumption that observational units in close proximity should exhibit effects that are similar to those from neighboring provinces provides one way of modeling spatial heterogeneity. Here, the dependence can be viewed as error dependence, and with this assumption we should use the spatial error model (SEM) or spatial Durbin error model (SDEM).

A fourth argument is the externalities-based motivation which can be both positive and negative in the spatial context. These externalities arise from neighboring provinces and can have sensory impacts, for instance in the case of pollution and environmental degradation. The latter might also cause the loss of habitat for humans and animals, possibly due to lack of water and food availability, and this might affect migration to neighboring provinces. In contrast, a beautiful landscape and availability of jobs might also make neighboring provinces more attractive. Here, we can use the SLX and SDM models because these can model the spatial average of neighboring province characteristics that might affect our dependent variable. Finally, LeSage and Pace (2009) also highlight the model-uncertainty motivation, meaning uncertainty regarding the type of model to employ as well as the conventional parameter uncertainty and uncertainty regarding specification of the appropriate explanatory variables.

The authors compare the SAR and SEM models and argue in favor of the SDM model, which includes spatial lags of dependent and explanatory variables, in the case of uncertainty. In this example, we have uncertainty regarding the presence of spatial dependence in the dependent variable versus the disturbances.

While taking into account the discussed arguments, the most adequate model for this study is the spatial Durbin panel model (SDM), because it will capture the spillover effects of natural disasters from neighboring Iranian provinces that are expected to affect the economic performance. In addition to the theoretical discussion, we have also used likelihood ratio (LR) tests to compare different spatial panel models. The results presented in Table A 3 of Appendix A support the selection of SDM, because it shows the better fit compared to other models with fewer explanatory variables. Furthermore, spatial characteristics of the used data series have been tested using Moran's I and Geary's C. According to the results reported in Table A 4 of Appendix A, several of the used variables show spatial autocorrelation, namely the disaster dummy, the natural logarithm of GDP per capita and its first differences, as well as the variables trade and foreign direct investment inflows. These results provide evidence for spatial patterns in the data series and, therefore, support the argument for the usage of spatial models. For the tests of spatial autocorrelation and the spatial models in this study, we have used a row-standardized spatial weights matrix W based on contiguity which reflects neighboring provinces of first order. It was created based on the political borders of Iran that have existed since the Iranian year 1390 (2011). The spatial contiguity matrix W* is a binary 29 × 29 matrix, of which the entries, w_{ij}^*, are 0 or 1. An entry is equal to one if the provinces i and j are neighbors and 0 otherwise. This can be noted in the following way:

$$w_{ij}^* = \begin{cases} 1\; if\;\; i\; and\; j\; are\; neighbors \\ \quad 0\; otherwise \end{cases} \tag{2}$$

We calculate the row-standardized spatial weights matrix W by dividing each matrix entry by the sum of its row:

$$w_{ij} = \frac{w_{ij}^*}{\sum_{j=1}^{n} w_{ij}^*} \tag{3}$$

A row-standardized matrix has several advantages, for example the coefficient for spatial autocorrelation Moran's I will range from −1 to 1. Moreover, we can interpret the spatial lag of a variable in a specific time period as the average of neighboring provinces in this time period (Anselin 1988, 17–29; Elhorst 2014, 12–13).

Based on existing literature of the topic and described assumptions related to spatial autocorrelation, this study formulates three hypotheses with the focus on the case of Iran:

Hypothesis 1: Spatial spillover effects of natural disasters from neighboring provinces are associated with positive economic growth in a province in the short term.

Hypothesis 2: There is a negative statistically significant direct effect of natural disasters on economic growth in the short term.

Hypothesis 3: The direct effects and indirect spillover effects of natural disasters on economic growth depend on the disaster type.

These hypotheses focus on spatial and temporal characteristics of natural disasters and its interaction with economic performance that have been comprehensively or briefly discussed in previous studies. First, spatial spillover effects of natural disasters are mainly associated with negative impacts on neighboring regions, such as significant job and income losses (Lenzen et al. 2019) and negative effects on GDP growth (Barbosa and Lima 2019). However, there is also empirical evidence for heterogeneous effects on economic activities measured by nighttime light (Felbermayr et al. 2018; 2022). The authors found an increase in economic activities due to spatial spillover effects of natural disasters for precipitation and cold related disasters, and negative spillover effects for droughts, using the global sample. This also applies in the case of low-income group countries as well as the subgroup Central Asia and MENA. Therefore, we expect a positive association between spillover effects from natural disasters and economic performance in Iranian provinces.

Second, the case studies from Iran that are related to natural disasters and economic growth are limited to a number of studies which only use time series data on the country level with very few observations and control variables (Sadeghi, Emamgholi Sefiddasht, and Zarra Nezhad 2009; Sadeghi and Emamgholipour 2008; Yavari and Emamgholipour 2010). They provide evidence for negative direct effects of natural disasters on GDP per capita in the short and long runs. Other cross-country studies have shown that the effects are heterogeneous and depend on different country characteristics, such as institutional development, level of economic development and geographical location (Noy 2009; Loayza et al. 2012; Barone and Mocetti

2014; Felbermayr and Gröschl 2014; Felbermayr et al. 2018; 2022). After the initial shock of the disaster, there is evidence for many cases that there will be a negative effect on the economy, but this effect disappears after only a few years. However, results are different depending on the type and strength of the disaster. Overall, we can summarize that there will be different reconstruction and development paths after the disaster, as seen in Klomp (2016) and Chhibber and Laajaj (2008), and thus the expected effect is not clear.

Third, previous studies have shown that the disaster type matters (Loayza et al. 2012; Felbermayr and Gröschl 2014; Klomp 2016; Felbermayr et al. 2018; 2022), therefore we are interested to study its impact for the case of Iran. As we are dealing only with earthquakes and floods in this study, we can have a look at the possible effects in previous studies. Loayza et al. (2012) found a positive and statistically significant effect of floods on GDP growth, while earthquakes show a negative effect, but in most specifications it is not statistically significant. Moreover, Klomp (2016) shows that there is a statistically significant direct negative effect of geophysical disasters as well as meteorological and hydrological disasters on economic growth in the short term. However, this effect disappears after two years for all types, except for geophysical disasters, even in the case of large-scale disasters. According to Felbermayr and Gröschl (2014) the effects of earthquakes and precipitation are statistically significant and negative. This is also supported by Felbermayr et al. (2018; 2022) who study weather-related disasters and found in their full sample and low-income countries sample that precipitation has a statistically significant negative effect on GDP growth, although the effect becomes positive one year later. When focusing on different regions, this result could be confirmed in the case of Latin America, while the effect one year later becomes insignificant for Southeast Asia. In the case of Central Asia and MENA, the effect will be statistically significant and negative in the same year and the year after. Overall, the expected effect is not clear.

The empirical specification for this study is based on Loayza et al. (2012), Felbermayr and Gröschl (2014), Klomp (2016), and Felbermayr et al. (2018; 2022), who use worldwide samples to study similar relationships. With the following spatial Durbin panel model, we want to test our hypotheses, using maximum likelihood estimation (MLE) and panel data from 1389 to 1395 (2010–2016) for 29 Iranian provinces:

$$\Delta Ln(GDPpc)_{it} = \alpha + \delta W \cdot \Delta Ln(GDPpc)_{jit} + \beta_1 \cdot Disaster_{it} + \theta_1 W \cdot Disaster_{jit} + \beta_2 \cdot Controls_{it} + \theta_2 W \cdot Controls_{jit} + \pi_i + \omega_t + \varepsilon_{it} \quad (4)$$

Here, the dependent variable is the first difference of the natural logarithm of the gross domestic product (GDP) per capita. Its spatial lag of first order with the coefficient is also included in the model, which is calculated with the help of the spatial weights matrix W. It captures the spillover effects from economic growth coming from neighboring provinces. The subscript i represents the Iranian provinces, the subscript t represents the Iranian years, and the subscript j refers to the neighboring Iranian provinces of first order. In addition, the model includes a constant α and an error term ε, and the term *Disaster* represents the dummy which takes the value 1, if a natural disaster took place six months ago, and 0, if not. This dummy is replaced with dummies for earthquake and flood events in some of the estimations.

Since we are using a spatial Durbin panel model, we will include both the spatial lags of the dependent variable (with coefficient δ) and the explanatory variables (with coefficients θ) in the model. The latter includes not just the disaster dummy and its spatial lag, but also a set of control variables, labelled *Controls*, and its spatial lags. These variables are the natural logarithm of population size, the consumer price index (CPI) with base year 1395 (2016), the expenditures of provincial governmental organizations and the province's acquisition of capital assets as a percent of GDP, the foreign direct investment (FDI) inflows as a percent of GDP, the trade volume as a percent of GDP, and one-year lagged natural logarithm of GDP per capita. These established predictors of economic growth are also used in the aforementioned benchmark models. In addition, some of the specifications will include time lags of the dummies for natural disasters, earthquakes, and floods, as well as its spatial lags. For a first glimpse at relationships between used variables, Appendix A includes Table A 5 with a correlation matrix.

Furthermore, the model uses province fixed-effects π and controls for time-specific effects ω using dummy variables for each year. After applying the Hausman test, the fixed-effects model was chosen. Province fixed effects are used to control for individual factors that affect each province over the whole time period, for example culture or religion. In the case of Iran, the predominant religion is Islam although despite this homogeneity, it is a multi-ethnic country. Beyond the ethnic majority group of Persians, there are several ethnic minorities, including Azeris, Kurds, Lurs, Bakhtiaris, and Beluchis, each with their different local languages and cultural traditions. These ethnic groups are concentrated in different provinces, which are sometimes even named after these groups. In addition, the time-fixed effects control for shocks to the outcome variable that affected all provinces in the same year, such as sanctions or an economic crisis.

2.4 Results and Discussion

Post-disaster spillover effects from neighboring provinces show a statistically significant positive association on conventional levels with the first difference of the natural logarithm of GDP per capita in all nine specifications of Table 2. More precisely, the coefficient of *W*Disaster* ranges from 0.069 to 0.095, thus suggesting an average increase of GDP per capita between 6.9% to 9.5% due to the appearance of natural disasters in neighboring provinces in the year of the disaster events. Adding temporal lags of one and two years show that the effect disappears after one year, and therefore we can interpret it as short-term positive externalities from neighboring provinces. These results are also supported by other types of spatial panel models that are reported in Table A 6 and Table A 7 of Appendix A. These positive spillover effects support several findings of Felbermayr et al. (2018; 2022) who use a worldwide sample of grid-based nighttime light emission data as well as meteorological and geological data. They found similar positive spillovers on growth for precipitation in the global sample, low-income countries, and MENA countries, using different specifications. For wind, their results are mixed. This also applies for spatial spillover effects that are lagged by one year. Earthquake disasters are not included in their study.

The increase in economic growth can be explained by a sudden increase in demand in the construction sector and a boost in employment. In addition, businesses and laborers might leave the disaster-affected provinces temporarily or completely and move to neighboring provinces, which would increase economic activity as a result. Furthermore, the natural disaster events might destroy or interrupt businesses and production sites, which are the competition of neighboring provinces, causing a higher demand for products and services from the neighboring provinces, which might also create new jobs. To support these arguments, we can find evidence in previous studies. First, Hosseini et al. (2013) show that during the reconstruction processes of large earthquakes in Iran, the emphasis was put on reconstruction of residential buildings and not on commercial buildings. Therefore, some non-essential sectors will temporarily be unavailable in the disaster-affected parts of the province.

Second, Shiva and Molana (2018) study climate change induced inter-province migration in Iran from 1996–2011 and found that a rise in temperature and a drop in precipitation act as significant push factors for migration. In a similar study, Farzanegan et al. (2022) show that higher levels of air pollution have a positive and significant impact on net outmigration in Iranian provinces between 2011 and 2016. However, these authors focus on climate change-related disasters and air pollution, but not the disasters discussed in this study, thus giving only little evidence and support for our arguments. Third, Pavel et al. (2022) study internal migration in Bangladesh resulting from floods, cyclones, and riverbank erosion, thus providing more evidence for people's behavior after natural hazards and related migration dynamics. Their findings suggest that transient shocks (floods and cyclones) induce households to move to nearby cities, sometimes temporarily, while permanent shocks (coastal erosion) push people to big cities with more opportunities. In general, this supports our previous arguments. Overall, the findings of positive spillover effects from natural disasters on economic growth support our *Hypothesis 1*.

Contrary to existing literature on the case of Iran (Sadeghi, Emamgholi Sefiddasht, and Zarra Nezhad 2009; Sadeghi and Emamgholipour 2008; Yavari and Emamgholipour 2010), we cannot find evidence for a statistically significant direct negative effect of natural disasters on the economic performance in the year of the disaster event. However, the two-year lagged disaster dummy shows a positive relationship that is statistically significant on the 5% level. The coefficient suggests that GDP per capita increases on average by 4% two years after the disaster event. These results are also supported by other types of spatial panel models that are reported in Table A 6 and Table A 7 of Appendix A, which not only include the commonly used spatial models as presented in Elhorst (2014), but also report the results of different estimation techniques such as maximum likelihood estimation (MLE) and ordinary least squares (OLS). A statistically significant positive or non-significant direct effect of natural disasters on economic growth is not a surprising result, as it has been found in previous studies such as Albala-Bertrand (1993) for 28 developing countries, Cavallo et al. (2013) for 196 countries, Loayza et al. (2012) for 68 developing and 26 Organization for Economic Cooperation and Development (OECD) countries, Felbermayr and Gröschl (2014) for 108 countries, and Felbermayr et al. (2018; 2022) for 24,000 grid cells.

Table 2: Results of spatial Durbin panel model (SDM) using maximum likelihood estimations (MLEs, with natural disaster dummy variable)

Dependent variable: ΔLn(GDP per capita)	**(2.1)**	**(2.2)**	**(2.3)**	**(2.4)**	**(2.5)**	**(2.6)**	**(2.7)**	**(2.8)**	**(2.9)**
Disaster	0.008	0.013	0.007	0.002	−0.002	0.004	−0.011	−0.007	−0.003
	(0.021)	(0.021)	(0.02)	(0.018)	(0.018)	(0.018)	(0.015)	(0.015)	(0.014)
Ln(Population)		−0.977*	−0.971*	−0.573	−0.405	−0.385	−0.135	−0.211	−0.18
		(0.525)	(0.5)	(0.503)	(0.398)	(0.336)	(0.325)	(0.322)	(0.323)
CPI			0.014	0.012	0.01	0.01	−0.002	−0.001	−0.001
			(0.01)	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)	(0.006)
Expenditures				−0.054***	−0.049***	−0.049***	−0.048***	−0.044***	−0.042***
				(0.02)	(0.019)	(0.017)	(0.014)	(0.014)	(0.014)
FDI inflows					0.002	0.004	−0.027***	−0.027***	−0.026***
					(0.009)	(0.007)	(0.008)	(0.009)	(0.008)
Trade						−0.002**	−0.001	−0.001*	−0.001
						(0.001)	(0.001)	(0.001)	(0.001)
Ln(GDP p.c.)$_{t-1}$							−0.694***	−0.7***	−0.725***
							(0.086)	(0.096)	(0.082)
Disaster$_{t-1}$								0.023	0.027
								(0.021)	(0.022)
Disaster$_{t-2}$									0.039**
									(0.017)
W*Disaster	0.078*	0.091**	0.095**	0.094**	0.084**	0.069*	0.089**	0.093***	0.09***
	(0.042)	(0.043)	(0.044)	(0.041)	(0.039)	(0.04)	(0.036)	(0.033)	(0.035)
W*Ln(Population)		−0.444	−0.433	−10.095	−0.35	−0.255	−0.856	−10.037	−10.165
		(0.754)	(0.841)	(0.727)	(0.652)	(0.676)	(0.73)	(0.734)	(0.821)
W*CPI			−0.024	−0.025	−0.031*	−0.032*	−0.037*	−0.034*	−0.038*
			(0.019)	(0.018)	(0.018)	(0.017)	(0.02)	(0.02)	(0.021)

W*Expenditures				0.023	0.023	0.025	0.025	0.032	0.031
				(0.028)	(0.025)	(0.021)	(0.019)	(0.022)	(0.025)
W*FDI inflows					0.048***	0.049***	0.042***	0.037***	0.036***
					(0.019)	(0.017)	(0.012)	(0.012)	(0.012)
W*Trade						0.002	−0.002	−0.002	−0.002
						(0.002)	(0.002)	(0.001)	(0.001)
W*Ln(GDP p.c.)$_{t-1}$							0.261**	0.226**	0.264***
							(0.104)	(0.108)	(0.101)
W*Disaster$_{t-1}$								0.026	0.022
								(0.037)	(0.038)
W*Disaster$_{t-2}$									−0.027
									(0.036)
W*ΔLn(GDP p.c.)	0.517***	0.488***	0.498***	0.5***	0.488***	0.511***	0.48***	0.464***	0.484***
	(0.092)	(0.092)	(0.094)	(0.084)	(0.09)	(0.092)	(0.092)	(0.093)	(0.096)
σ^2_e	0.009***	0.009***	0.008***	0.008***	0.008***	0.007***	0.004***	0.004***	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	203	203	203	203	203	203	203	203	203
R^2	0.033	0.001	0.065	0.101	0.134	0.137	0.123	0.119	0.119
Hausman test	FE	FE	FE	FE	FE	FE	FE	FE	FE
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are reported in parentheses. A constant was included in estimations but not reported. Coefficient estimates are obtained using the 'xsmle' Stata syntax outlined in Belotti et al. (2017). *Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Moreover, Felbermayr and Gröschl (2014) found a positive significant effect of their Disaster Index on GDP per capita four years after the disaster event. Klomp (2016) found a significant positive effect of geophysical disasters on economic development two and 10 years after the event. According to Klomp (2016) as well as Chhibber and Laajaj (2008), there are four scenarios of economic recovery after the disaster shock. Two of these scenarios assume an increase of GDP per capita in the intermediate and long run. Scenario B predicts a drop of economic growth directly after the disaster event, followed by a temporary increase, and a return to the pre-disaster development path. The mechanism in the intermediate run is an increase in the return of capital that stimulates overinvestments, and a temporary aid inflow. However, in the long run, the replacement investments cannot keep up with the speed of capital depreciation. Therefore, the initial capital-labor ratio is restored and GDP per capita is returning to its original growth path. This mechanism was also discussed by Sadeghi et al. (2009) in the case of Iran.

Scenario D predicts a drop of economic growth directly after the disaster event, followed by a temporary increase, and then a drop to a lower development path that is still higher than the pre-disaster development path. The mechanism in the intermediate run is that the return on capital stimulates investments and increases the production capacities. Moreover, foreign disaster aid inflow supplies additional capital, and the destroyed capital is replaced by new and more productive capital. That means that in the long run there is a higher balanced growth path, as the technology level has increased. For the case of Iran, the results of Table 2 suggest scenario B, because there is a statistically significant positive effect of the disaster dummy variable after two years, but this effect disappears in later years.

Overall, our empirical results are supported by theory and other empirical studies, such as Albala-Bertrand (1993) and Skidmore and Toya (2002). One explanation is that resources will be allocated to provinces of the disaster occurrence and the disaster relief and reconstruction efforts stimulate economic growth, including financial aid from the central government and international donors. This argument is also connected to Schumpeter's theory of creative destruction, which says that the destruction of an old economic structure will provide the opportunity to replace it with a newer and more modern one, which in the end can also be beneficial for economic growth. Another factor is the huge experience with natural disasters that helps the population and government to go back to normal quickly after the disaster event, at least after small and medium-sized disasters. In addition, Yuan et al. (2018) show that the efforts of disaster relief, such as inflow of resources from government and international donors or the help from civil society, will fade over time. Therefore, we can argue that in the year of the disaster event, the disaster relief efforts will offset the negative effects of natural disasters on economic growth. Overall, we have to reject *Hypothesis 2*, because we do not find a statistically significant negative direct effect of natural disasters on economic growth. The results even suggest a positive effect after two years.

To study the effect of the disaster type, the specifications in Table 3 include dummy variables for earthquakes and floods, instead of all natural disasters. According to the results, the appearance of a flood disaster event is associated with an average increase of GDP per capita by 4.3% to 4.9%. Earthquake disaster events do not show this effect. The time-lagged flood and earthquake dummy variables also do not show statistically significant effects. The positive direct effect follows the mechanism that has been explained related to *Hypothesis 2*. Here, one of the aforementioned studies shows a positive effect of moderate floods (Loayza et al. 2012). This is also plausible for this study, as the time period of the used data does not include the major earthquakes or floods experienced by Iran in the past decades.

When separating the spatial spillover effects of floods and earthquakes, we can only find statistically significant effects on conventional levels in model 3.7 to 3.9 of Table 3, namely on the 5%, 1%, and 10% significance levels, respectively. According to these results, there is an average increase of GDP per capita between 9.7% to 11.7% due to the appearance of earthquakes in neighboring provinces in the year of the disaster events. In the case of floods, we only find weak evidence of a statistically significant positive association between the spatially lagged dummy for floods and the first difference of the natural logarithm of GDP per capita on the 10% significance level in models 3.8 and 3.9 of Table 3. The results suggest an average increase of GDP per capita by approximately 5% due to the appearance of floods in neighboring provinces in the year of the disaster events. However, there is a problem here in separating the effect of earthquakes and floods, because in some years there was an earthquake disaster and a flood disaster in the same province. Additionally, the temporal lags of one and two years are statistically insignificant for both disaster types. Overall, this supports *Hypothesis 3*, because there are differences related to direct and indirect spillover effects depending on the type of natural disaster.

Table 3: Results of SDM using ML estimations (with earthquake and flood dummy variables)

Dependent variable: ΔLn(GDP per capita)	**(3.1)**	**(3.2)**	**(3.3)**	**(3.4)**	**(3.5)**	**(3.6)**	**(3.7)**	**(3.8)**	**(3.9)**
Earthquake	−0.021	−0.024	−0.03	−0.038	−0.041	−0.029	−0.023	−0.011	−0.01
	(0.032)	(0.034)	(0.031)	(0.031)	(0.029)	(0.028)	(0.026)	(0.025)	(0.022)
Flood	0.046*	0.049**	0.043*	0.044**	0.046**	0.043**	0.005	0.006	0.014
	(0.025)	(0.022)	(0.022)	(0.022)	(0.022)	(0.021)	(0.015)	(0.015)	(0.014)
Ln(Population)		−10.015**	−0.996**	−0.569	−0.39	−0.381	−0.085	−0.142	−0.092
		(0.515)	(0.488)	(0.49)	(0.383)	(0.339)	(0.324)	(0.289)	(0.289)
CPI			0.014	0.013	0.011	0.011	−0.002	−0.001	0.000
			(0.01)	(0.009)	(0.01)	(0.009)	(0.007)	(0.007)	(0.006)
Expenditures				−0.055***	−0.05***	−0.05***	−0.049***	−0.044***	−0.043***
				(0.02)	(0.018)	(0.017)	(0.014)	(0.014)	(0.014)
FDI inflows					0.000	0.002	−0.027***	−0.026***	−0.024**
					(0.008)	(0.007)	(0.008)	(0.01)	(0.009)
Trade						−0.001*	−0.001	−0.001*	−0.001*
						(0.001)	(0.001)	(0.001)	(0.001)
Ln(GDP p.c.)$_{t-1}$							−0.686***	−0.695***	−0.716***
							(0.089)	(0.102)	(0.083)
Earthquake$_{t-1}$								0.034	0.038
								(0.031)	(0.031)
Flood$_{t-1}$								0.004	−0.009
								(0.021)	(0.024)
Earthquake$_{t-2}$									0.029
									(0.022)
Flood$_{t-2}$									0.028
									(0.029)
W*Earthquake	0.041	0.026	0.037	0.048	0.06	0.045	0.097**	0.117***	0.101*
	(0.058)	(0.053)	(0.054)	(0.053)	(0.05)	(0.049)	(0.041)	(0.038)	(0.057)
W*Flood	0.037	0.069	0.069	0.058	0.035	0.032	0.042	0.051*	0.052*
	(0.051)	(0.05)	(0.051)	(0.047)	(0.045)	(0.047)	(0.028)	(0.03)	(0.028)
W*Ln(Population)		−0.835	−0.775	−10.412*	−0.611	−0.486	−0.686	−0.728	−0.836
		(0.784)	(0.865)	(0.768)	(0.709)	(0.722)	(0.759)	(0.73)	(0.756)
W*CPI			−0.02	−0.022	−0.029	−0.03*	−0.041**	−0.04**	−0.046**
			(0.019)	(0.018)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)

W*Expenditures				0.029	0.028	0.028	0.025	0.033	0.031
				(0.027)	(0.024)	(0.02)	(0.018)	(0.022)	(0.024)
W*FDI inflows					0.05***	0.049***	0.045***	0.043***	0.038***
					(0.019)	(0.018)	(0.013)	(0.011)	(0.012)
W*Trade						0.002	−0.002	−0.003*	−0.002*
						(0.002)	(0.002)	(0.002)	(0.001)
W*Ln(GDP p.c.)$_{t-1}$							0.25**	0.204*	0.243**
							(0.108)	(0.111)	(0.112)
W*Earthquake$_{t-1}$								0.045	0.016
								(0.054)	(0.066)
W*Flood$_{t-1}$								0.041	0.036
								(0.032)	(0.028)
W*Earthquake$_{t-2}$									−0.08
									(0.066)
W*Flood$_{t-2}$									0.024
									(0.045)
W*ΔLn(GDP p.c.)	0.526***	0.487***	0.497***	0.505***	0.495***	0.517***	0.498***	0.481***	0.492***
	(0.088)	(0.087)	(0.09)	(0.08)	(0.086)	(0.087)	(0.09)	(0.093)	(0.098)
σ^2_e	0.009***	0.008***	0.008***	0.008***	0.007***	0.007***	0.004***	0.004***	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	203	203	203	203	203	203	203	203	203
R^2	0.061	0.000	0.034	0.072	0.13	0.134	0.126	0.124	0.124
Hausman test	FE	FE	FE	FE	FE	FE	FE	FE	FE
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are reported in parentheses. A constant was included in estimations but not reported. Coefficient estimates are obtained using the 'xsmle' Stata syntax outlined in Belotti et al. (2017). *Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

Last but not least, the empirical models include several control variables and their spatial lags as well as the spatial lag of the dependent variable. The latter is statistically significant and positive on the 1% significance level in all estimation results of Table 2 and Table 3, suggesting a positive relationship between economic growth in a province and the economic growth of neighboring provinces. These results are as expected, because economically active units that are closer to each other behave in a more similar manner. This stylized fact is also supported by theory (Easterly and Levine 2001) and empirical results for the case of Iran (Akbari and Movayyedfar 2004) as well as the MENA region (A. M. Seif, Panahi, and Hamidi Razi 2017). A similar control variable is the natural logarithm of GDP per capita from the previous year (t−1), which is highly significant and negative in all models it was included, as seen in several studies before (Felbermayr and Gröschl 2014; Klomp 2016; Felbermayr et al. 2018; 2022). However, the spatially lagged form of this variable is positive and highly significant in all models in which it was included, suggesting positive spillover effects of GDP per capita from neighboring provinces from the year before. This supports the argument from the inclusion of the spatial lag the dependent variable which contains similar information, and LeSage and Pace (2009) time-dependence motivation.

Other control variables show either a direct relationship or indirect spillover effects, or both. First, the natural logarithm of population shows a statistically significant negative relationship with the dependent variable in 4 out of 14 models it was included and supports the findings of Felbermayr and Gröschl (2014), but the results are not very robust. We do not find evidence for spatial spillover effects of population on economic growth in our estimations. Second, the coefficient of the expenditures of provincial governmental organizations and province's acquisition of capital assets as percent of GDP is highly statistically significant and negative in all models in which it was included, supporting the findings of Loayza et al. (2012). We do not find evidence for spatial spillover effects of expenditures on economic growth in our estimations. Third, the consumer price index (CPI) does not show a statistically significant direct relationship with the dependent variable in our models, but it is still included due to possible omitted variable bias and the experience of other authors (Loayza et al. 2012; Felbermayr and Gröschl 2014; Klomp 2016). The expected negative statistically significant effect can be seen in the spatially lagged CPI which shows significance on conventional levels in 9 out of 14 models. This is possibly due to the very high correlation of CPI and its spatial lag (see Table A 5 in Appendix A), but we will keep it in the model, because of the structure of the spatial Durbin model.

Moreover, the trade volume (as percent of GDP) is statistically significant and negative mostly on the 10% significance level in 5 out 8 models in which it was included. This is contrary to the results of previous studies (Loayza et al. 2012; Felbermayr and Gröschl 2014; Klomp 2016) who found positive statistically significant effects. The spatially lagged trade volume is also statistically significant and negative on the 10% significance level in 2 out of 8 models in which it was included, thus providing weak evidence for this relationship. There are also two possible explanations, because on the one hand, there might be an endogeneity problem, meaning that the relationship does not go from trade to growth, but vice versa. This would suggest that an increase in economic growth decreases the trade volume which would be the case in an isolated or inward-oriented economy. Due to extended sanctions by the USA and EU against Iran, the country was basically forced into such a situation. On the other hand, the overall situation of economic sanctions distorted the whole macroeconomy in the time period of this study and affected the trade flows in Iran which both might dampen the expected positive effect of trade on economic growth.

Finally, the foreign direct investment (FDI) inflows (as percent of GDP) show a statistically significant negative relationship with economic growth on conventional significance levels in 6 out of 10 models it was included. This seems to be counter intuitive, but other studies have found similar results, for example Borensztein et al. (1998) who show for 69 developing countries that a positive effect depends on the stock of knowledge and efficiency and not the mere presence of new capital, and the effect might even become negative. Other factors such as the level of economic development, the development of the financial system (Sghaier and Abida 2013), and the level of corruption (Freckleton, Wright, and Craigwell 2012) might also play a role in this context. Another possible explanation is related to the double causality situation of the variables 'economic growth' and 'FDI inflows' that has been shown by Choe (2003) using the Granger causality test with his sample of 80 countries over the period 1971 to 1995. The effect going from GDP growth to FDI is also plausible in our case given the overall macroeconomic situation in Iran due to sanctions and the direct effect of sanctions on FDI.

In contrast to the direct relationship, the spatially lagged FDI inflows, representing the average spillover effects of FDI inflows coming from neighboring provinces, show a positive and highly significant relationship in all models in which it was included. There is a large body of literature discussing technology spillovers due to foreign direct investment inflows which usually refers to a different mechanism, but here we can also see that a province might benefit from investments in neighboring provinces. This follows the same line of argumentation as in the case of positive spillover effects of natural disasters.

2.5 Conclusion

Overall, this study provides new empirical evidence for the relationship between natural disasters and economic growth using the case of Iranian provinces. Therefore, we find results for a lower middle-income country from the Middle East and North Africa (MENA) region that is also considered a disaster-prone country and additionally under different economic sanctions. Despite these characteristics and the specific case, the empirical findings based on cross-province results support the findings of previous cross-country studies, such as Cavallo et al. (2013), Loayza et al. (2012), Felbermayr and Gröschl (2014), Klomp (2016) and Felbermayr et al. (2018; 2022).

First, post-disaster spillover effects from neighboring provinces show a statistically significant positive association on conventional levels with the first difference of the natural logarithm of GDP per capita, but this effect disappears after one year. This increase in economic growth can be explained by a sudden increase in demand in the construction sector and a boost in employment, due to the destruction in neighboring provinces' infrastructure and businesses. In addition, businesses and laborers might leave the disaster-affected provinces temporarily or completely and move to neighboring provinces and therefore, also increase economic activity. Furthermore, the natural disaster events might destroy or interrupt businesses and production sites, which are the competition of neighboring provinces, causing a higher demand for products and services from the neighboring provinces, which might also create new jobs. The results also find weak evidence that post-disaster spillover effects are, rather, driven by earthquakes.

Second, we cannot find evidence for a statistically significant direct negative effect of natural disasters on the economic performance in the year of the disaster event, but the two-year lagged disaster dummy shows a positive relationship. Additionally, the appearance of a flood disaster event is associated with an increase of GDP per capita, while earthquake disaster events do not show this effect. The time-lagged flood and earthquake dummy variables also do not show statistically significant effects. Therefore, we find evidence for a development path that has been presented in literature before (Chhibber and Laajaj 2008; Sadeghi, Emamgholi Sefiddasht, and Zarra Nezhad 2009; Klomp 2016), namely a drop of economic growth directly after the disaster event, followed by a temporary increase, and a return to the pre-disaster development path. One explanation is that resources will be allocated to provinces of the disaster occurrence, and thus the disaster relief and reconstruction efforts stimulate economic growth, including financial aid from the central government and international donors. Another factor is the huge experience with natural disasters that helps the population and government to go back to normal quickly after the disaster event, at least after small and medium-sized disasters.

From the results, we obtain new insights on the impact of natural disasters on neighboring regions that are not directly affected by the disaster events. We have learned that in the case of Iran both the affected provinces as well as the neighboring provinces experience an increase in economic performance in the short or intermediate term, as expected from the theory and previous empirical studies. However, this effect will not last very long, even for the case of neighboring provinces, which have better preconditions to benefit from the situation, as they did not experience direct disaster damage or rent-seeking related to the sudden money inflow. It is more difficult for neighboring provinces to benefit from the situation in the long run, because we argue that the boost in economic activity is related to the reconstruction and replacement of needed services and industries of the directly affected provinces. Once the reconstruction is done, neighboring provinces will very likely return to their pre-disaster development path, if these provinces cannot keep the new human capital or market shares. These finding provide evidence for policy makers of both the affected and neighboring provinces that there is a window of opportunities directly after the disaster event.

Despite the tragedies connected to the impact of natural disasters, the reconstruction period offers the opportunity for the directly affected province to update existing capital and infrastructure, and thus replace old technologies with new ones. From the empirical results of this study, we cannot find more than an increase of GDP per capita in the short term after a disaster event, therefore it seems that Iranian provinces cannot use the disaster situations for improvements of their economies in the long term. Not only under the current situation of economic sanctions, there are several challenges for policy makers in Iran to use the opportunity after the natural disasters, for example institutional development, efficiency of reconstruction, corruption and rent-seeking, as well as access to investments, construction materials, and technology. According to Seddighi and Seddighi (2020), the Iranian government has mainly focused on response and recovery in the past 100 years, and not on mitigation and preparedness. Enhancing disaster preparedness for effective response, and to 'Build Back Better' (in recovery, rehabilitation, and reconstruction), is one of the pillars of the Sendai framework for disaster risk reduction, but the Iranian policies have not taken this into account yet. Overall, it needs long-term policies and strategies for all aspects of disaster prevention and relief.

This study also has some limitations due to the short time period of the sample used. On the one hand, we cannot make statements about the long-term direct and indirect spillover effects of natural disasters on economic growth, and on the other hand the time period 2010–2016 does not include the very large natural disasters such as the 1990 Manjil-Rudbar earthquake, 2003 Bam earthquake, or 2019 flood. The empirical results help to understand the effects of natural disasters on economic growth in the country of Iran in the short term for small and medium-sized natural hazards. Additionally, there are also other disaster types that have not been included in this study, because it did not occur in the time period according to data from EM-DAT. Last but not least, the findings suggest direct and indirect positive effects of natural disaster on economic growth, but this should not lead to the conclusion that natural disasters are something positive for the development of society. Natural hazards are associated with losses of life, psychological damage (K. A. Hosseini, Hosseinioon, and Pooyan 2013), drug addiction, displacement, poverty, inequality, and many other long-term negative consequences.

3. Nighttime Light Development after the 2003 Bam Earthquake in Iran: A Synthetic Control Analysis

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Abstract

This study provides new empirical evidence for the consequences of a large-scale natural disaster on economic activity in the disaster-prone country of Iran. We are using 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, Kerman Province, Bam County, and the neighboring counties experienced a boost in economic activity in the years following the earthquake. When using statistical inference tests for the SCM, we show that the impact of the earthquake is only statistically significant on the county level, and not on the province level. In addition, economic activity of Bam County and its neighboring counties return to their pre-disaster development path after seven and nine years, respectively.

JEL Codes:

E01, H84, O11, O44, O53, Q51, Q54, R11, R12

Keywords:

Natural disaster, natural hazard, synthetic control, earthquake, economic development, economic growth, nighttime light

3.1 Introduction

Over the past about 30 years (1992-2020), the country of Iran experienced 143 natural disasters, from which 16 can be labeled as large-scale disasters. This includes floods, earthquakes, droughts, storms, and others, which affected accumulated more than 51 million Iranians, while killing more than 33,000 people, and causing an estimated damage of more than US$25 billion, adjusted for inflation using consumer price index (EM-DAT 2021). Due to the combination of geography and institutional development, the country is extremely vulnerable to natural hazards, which makes it the Middle Eastern country that has experienced the largest number of natural disasters in the past decades. Therefore, it is an interesting case study for investigating the impact of large-scale natural disasters on economic development. We have chosen the case study of the 2003 Bam earthquake because it is the largest natural disaster in the period of available data, and Bam and its cultural landscape is an important UNESCO World Heritage Site[2]. It is considered one of the deadliest earthquakes in Iranian history that killed almost 30,000 people, affected more than 250,000 people, caused a damage of more than US$700 million, adjusted for inflation, and destroyed about 80% of the city of Bam (Fallahi 2007; EM-DAT 2021).

One of the main contributions of this study is that we are creating a counterfactual case of Kerman Province and Bam County to investigate the impact of the earthquake. Previous studies on the case of 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; K. A. Hosseini, Hosseinioon, and Pooyan 2013; Yuan et al. 2018; Fischer 2021), but we are interested in the long-term effects of large-scale natural disasters. 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, and then estimate the economic development of the counterfactual province and county, which reflect the development path, if the impact of the disaster event did not happen. The difference between the development paths of the treated province and county in comparison to its synthetic versions will provide us estimations of the impact of the 2003 Bam earthquake.

We are measuring economic activity in the 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 does not only reflect the development of the formal economy, but also the development of the informal economy which was on average 17.1% of GDP in Iran in the period 1991-2017

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

(Medina and Schneider 2019). Therefore, it will give us a more precise measure about the true impact of the earthquake on economic development. Second, NTL provide us a longer time period than available official gross domestic product (GDP) data on the provincial and county levels and it has consistent borders over the whole time period. We are using province and county level data for mainly two reasons which have an advantage over cross-country studies. First, the impact of a natural disasters does not necessarily affect the national GDP of a country, except for geographically very small countries. Second, other economic shocks such as international sanctions (in post-2011) that affected the whole country of Iran will be reflected in the donor provinces of the SCM approach and thus not affecting the measurement of the natural disaster impact, assuming that all provinces or counties are affected by these shocks.

This is the first study on the case of Iran which measures the costs of natural disasters by creating counterfactual cases of the affected province and counties. It has also an advantage over previously used approaches because the estimated synthetic control will reflect the development of the province and counties in absence of the disaster. This is also the first study that uses the SCM to investigate spatial spillovers to neighboring geographical units. The main findings of this study are that Kerman Province and Bam County, and its neighboring counties experienced a boost in economic activity in the years following the disaster, and then returning to their pre-disaster development paths after less than ten years. This is in line with previous theoretical models and empirical findings (Albala-Bertrand 1993; Skidmore and Toya 2002; Chhibber and Laajaj 2008; Klomp 2016; Yuan et al. 2018; Fischer 2021; Onuma, Shin, and Managi 2021). The chapter is structured as follows. Section 3.2 presents an overview of the relevant literature related to the topic, and Section 3.3 explains the data and methodology. In Section 3.4, the results including statistical inference are presented, and Section 3.5 discusses the findings. Section 3.6 concludes the chapter.

3.2 Literature Review

There is a large body of literature that studies and discusses theoretically and empirically the relationship between economic performance and natural disasters, however, with inconclusive results, that means heterogeneous results depending on the characteristics of the countries and disaster events (Noy 2009; Loayza et al. 2012; Cavallo et al. 2013; Felbermayr and Gröschl 2014; Klomp 2016; Noy and duPont IV 2018; Fabian, Lessmann, and Sofke 2019; Onuma, Shin, and Managi 2021; Felbermayr et al. 2022).

3.2.1 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 in the short or intermediate term. 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 to human capital relative to investment capital and increase total factor productivity through the adoption of newer and more productive technologies. Positive shocks on the economic performance by natural disasters are also discussed by Klomp (2016) who argues with Schumpeters' creative destruction theory which means that the disaster shocks can work as an accelerator for upgrading the destroyed capital stock. In his empirical results, the author shows a significant positive effect of geophysical disasters on economic development two and ten years after the disaster event.

Chhibber and Laajaj (2008) developed four possible scenarios of economic recovery after the disaster shock (see also Figure 1 in Chapter 2 of this thesis). Two of these scenarios assume an increase of GDP per capita in the intermediate and long run (scenarios B and D), and the two other scenarios assume a decrease of GDP per capita in the same time period (scenarios A and C). Scenario A predicts a drop of economic growth directly after the disaster event, followed by a retrace to the pre-disaster development path, and scenario B describes a drop of economic growth directly after the disaster event, followed by a temporary increase, and a return to the pre-disaster development path. In the first two scenarios, the economic performance returns to its pre-disaster levels. In scenario C, the authors see a drop of economic growth directly after the disaster event and then a slight increase to a new long-term growth path that is hypothetically lower than without the disaster event happening, and scenario D shows a drop of economic growth directly after the disaster event, followed by a temporary increase, and then a drop to a lower development path that is still higher than the pre-disaster development path.

3.2.2 Previous Global Studies

Empirical evidence for these scenarios is provided in several studies that show how the type and size of a disaster and the country characteristics, such as the level of economic development, the level of institutional development, and geographical aspects, among others, are responsible for the different development paths. A study by Noy (2009) focuses on the short-term effects of natural hazards on the macroeconomy. He shows that countries with a higher literacy rate, better institutions, higher per capita income, higher degree of openness to trade, and higher levels of government spending are better able to withstand the initial disaster shock and prevent further spillovers into the macroeconomy. Other studies have also shown that the impact of natural disasters on economic development can be negative or positive, depending on different characteristics (Loayza et al. 2012; Klomp 2016; Felbermayr and Gröschl 2014; Felbermayr et al. 2022)

Related to the long-term consequences of natural disasters on economic growth, there are studies from Lynham et al. (2017), Noy and duPont IV (2018), and Onuma et al. (2021) who discuss this aspect in more detail. Lynham et al. (2017) use the case study of Hawaii and found that that fifteen years after the event, unemployment was still 32% higher and population was still 9% lower than it would have been had the tsunami not occurred. In addition, Noy and duPont IV (2018) argue that several factors should be taken into consideration when assessing the long-term outcomes of natural disasters, for example the type and severity of the event, the underlying composition of the economy, and the total area impacted. Onuma et al. (2021) take into account many of the previously discussed issues and study the effect of natural disaster on economic growth in the short (0-5 years), middle (6-10 years), and long term (11-30 years), while taking into account the severity of the disaster, and the income level of the affected countries, as well as the disaster types. The sample with 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. In the case of income levels, we can see that geophysical disasters show a positive effect in the long run in upper middle-income countries, and a negative effect in high income countries.

Some studies have also used nighttime light data to evaluate the impact of natural disasters (Bertinelli and Strobl 2013; Elliott, Strobl, and Sun 2015; Klomp 2016; Fabian, Lessmann, and Sofke 2019; Felbermayr et al. 2022). Bertinelli and Strobl (2013) and Elliott et al. (2015) focus on the impact of hurricanes and typhoons to evaluate the damage at spatially disaggregated levels. Fabian et al. (2019) also focus on the local level and investigate the impact of earthquakes on economic development on different sub-national levels using worldwide NTL. They find that earthquakes reduce economic activity in the short term (approximately five years), and the effects are stronger the smaller the area of a unit of observation. Klomp (2016) examined the impact of large-scale natural disasters on economic development, measured by NTL, on the country level. According to his results, natural disasters reduce the number of lights visible from outer space significantly in the short run as well.

The topic of post-disaster spillovers has gained more attention in recent years with a handful of published studies (Lenzen et al. 2019; Barbosa and Lima 2019; Fischer 2021; Felbermayr et al. 2022). According to these studies, the indirect spillover effects of natural disasters much like direct effects are heterogeneous and depend on the characteristics of the countries and disasters.

Felbermayr et al. (2022) use spatial econometric panel methods and nighttime light data to study the spillover effects after natural disasters that are affecting economic activities. They find especially evidence for weather shocks, and substantial heterogeneity across income groups and regions. Two other case studies on Australia and Brazil show the negative effects of natural disasters on the economy. Lenzen et al. (2019) analyze the economic damage and spillovers from a tropical cyclone using the case study of Australia. Their results show how industries and regions that were not directly affected by storm and flood damage suffered significant job and income losses throughout upstream supply chains. Barbosa and Lima (2019) study the case of flash floods in Brazil using a difference-in-differences model and show that municipalities directly affected by the flood suffered a decrease in GDP per capita in the year of the disaster, and that there are significant spillovers to neighboring regions.

The synthetic control method (SCM) was already used in a few studies in the context of natural disasters (Cavallo et al. 2013; Barone and Mocetti 2014; duPont IV and Noy 2015; Cerqua and Di Pietro 2017; Lynham, Noy, and Page 2017). Cavallo et al. (2013) show, as other cross-country studies before, that natural disasters, even when focusing on only the effects of the largest natural disasters, do not have any significant effect on subsequent economic growth. They identified two cases in which disasters affected GDP growth in subsequent years. However, these happened in the same years as major political revolutions, thus the negative effects after these years are very likely related to the revolutions and not necessarily related to the earthquakes. One of these examples is the Iranian Islamic Revolution which occurred right after the 1978 Tabas earthquake. Moreover, Barone and Mocetti (2014) investigate the effect of two large-scale earthquakes on economic growth in two different Italian regions, and they find different effects depending on the related financial aid and corruption levels of the regions. Cerqua and Di Pietro (2017) examine how the 2009 L'Aquila earthquake in Italy affected subsequent enrolment at the local university, and according to their results, the earthquake had no statistically significant effect on first-year enrolment in the three academic years after the disaster, but it caused a compositional change in the first-year student population.

3.2.3 Previous Studies on Iran

While the majority of studies on natural hazards for the case of Iran are related to health aspects, geography, engineering, and natural disaster management, there are also a couple of empirical studies on natural disasters and its effects on GDP per capita, savings, and investments in Iran (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), which is presented in Chapter 2 of this thesis, 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 which includes only one large-scale natural disasters (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 founds positive spatial spillover to 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 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 event, but after several months most of the helpers disappeared. The study also discusses the reactions of the governments and challenges in coordination between involved agents. Next 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, 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 is a recipe for increasing the chances of floods. 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 show 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 that addresses the problem of natural disasters in Iran. However, these studies have mainly discussed the immediate impact of natural disasters on a variety of indicators, which addresses the consequences in the short term, or the studies have developed scenarios and discussed possible long-term developments. None of these studies has estimated a counterfactual Iran or the affected region which could help to identify the causal impact of the disaster. One of the main challenges of causality analysis, as mentioned by Holland (1986), is that the unit under some 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 which re-produces the development picture of the affected region before the experience of the disaster perfectly. We will fill this gap by using the SCM and provide empirical evidence for the impact of a large-scale natural disaster in the intermediate and long-term.

3.3 Methodology and Data

This study combines several branches of natural hazard research, because we will use nighttime light data as a measurement for economic activity that has been widely used already in the context of natural disasters and beyond (Ghosh et al. 2009; 2013; X. 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; Farzanegan and Fischer 2021; Felbermayr et al. 2022), and we will use the synthetic control method which was used before 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)[3].

3.3.1 Methodological Approach

We use the synthetic control method (SCM) with data on 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 low densely populated province will hardly be measurable in the national GDP of Iran. This gives us also the possibility to keep factors constant that affected all Iranian provinces and counties at the same time and affected the national GDP, for example the introduced extended sanctions against the Iranian oil trade and financial sector in 2011/2012, which affected the Iranian economy heavily in the following years. 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.

[3] 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 2021; 2022).

The SCM was developed by Abadie et al. (2003; 2010; 2015) and is used to study shocks on an outcome variable which is in our case the natural logarithm of the sum of NTL. The shock is the 2003 Bam earthquake which suggests that the treatment year is 2003 and the treated 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 treated unit. The advantage of the SCM is that we are using the combination of several untreated units to approximate the pre-treatment characteristics of the treated unit, which is much more accurate than using any single untreated unit. We also need a sample that is a balanced panel dataset, where all units are observed at the same time periods $t=1,\ldots,T$. In addition, it should include a positive number of pre-treatment periods, T_0, and a positive number of post-treatment periods, T_1, where $T=T_0+T_1$. Unit 1 ($j=1$) is exposed to the treatment during the period $T_0+1,\ldots,T$, and the treatment 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-treatment 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[4], so that the characteristics of the treated unit are best reflected by the characteristics of the synthetic control. The values of the pre-treatment characteristics, X_1, of the treated 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 in included in a $k\times J$ matrix. This pre-treatment characteristics in X_1 and X_0 may also include pre-treatment values of the outcome variable. The vector X_1-X_0W describes the difference between the pre-treatment characteristics of the treated unit and the synthetic control. A synthetic control, W^*, will be selected that minimizes the size of this difference.

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 treated 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:

$$\sum_{m=1}^{k} v_m (X_{1m} - X_{0m}W)^2 \tag{5}$$

[4] 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 all 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).

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. It is the aim that the synthetic controls reproduce the values that variables with a large predictive power on the outcome variable take for the treated 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-treatment values of the outcome for the treated 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-treatment values of the outcome for unit $j+1$. With the comparison of the post-treatment outcomes between the treated unit and the synthetic control, Y_1-Y_0W^*, we receive the synthetic control estimator of the effect of the treatment. For the post-treatment period t (with $t \geq T_0$), the estimator is given by:

$$Y_{1\,t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{6}$$

Additionally, the corresponding variables X_0 and X_1 are the predictors of the post-treatment outcomes which are not affected by the treatment. 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. Abadie et al. (2010) show with a linear factor model that matching on pre-treatment 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-treatment 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 treatment can be interpreted as produced by the treatment itself, if the unit representing the case of interest (which is in our case the province or county affected by the natural disaster event) and the synthetic control unit have a similar behavior over extended periods of time before the treatment.

When selecting the 2003 Bam earthquake as a case study, we also considered several requirements that are needed to apply the SCM. We needed a sizable number of pre-treatment periods to determine the synthetic control, and we also needed a number of years after the disaster event, so that we can evaluate the impact. In addition, we needed to find a natural disaster event that affected only one province, or very few provinces, at the same time, so that we have enough donor provinces that did not get affected by the shock. In the province-level analysis, we have Kerman Province with the treatment year 2003. For the analysis, we need to restrict the donor pool, so that it only included provinces that were not directly or indirectly affected by the treatment or by other major shocks in the time period of this study. We will exclude provinces from the donor pool that have experienced one of the other 16 large-scale natural disaster events in the same year or are Kerman's neighboring provinces. In the county-level analysis, we will investigate the impact on Bam County and its neighbors. As there are 429 counties and thus more donor pool counties available, we will restrict the donor pool more conservatively and remove all counties and neighboring counties that have experienced one of the large-scale disasters over the whole period of available data.

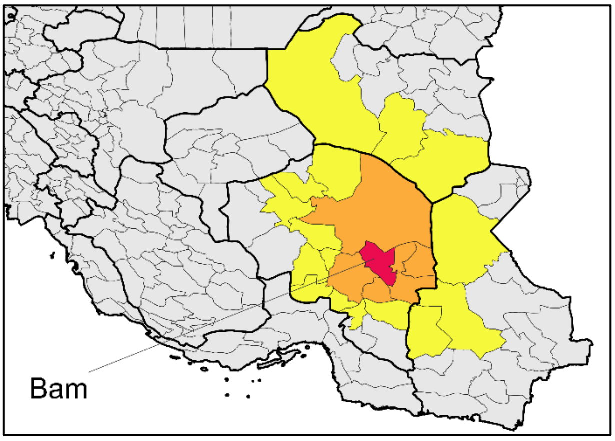
3.3.2 Data: Outcome Variable and Predictors

According to the International Disaster Database (EM-DAT 2021), Iran has experienced 143 natural disasters in the period of 1992 to 2020. To select the case study, we first have 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) number of killed is no less than a thousand; (ii) the number of total affected (injured, affected, and homeless) is no less than a hundred thousand; or (iii) the amount of damages is no less than US$1 billion, adjusted for inflation. This leaves us with 16 large-scale natural disasters, as presented in Table B 1 in Appendix B. The information from the table will also be used to exclude provinces and counties from the donor pool. We choose the case study of Bam, because it is not just the deadliest earthquake in the sample, but it also provides us enough years before and after the treatment to apply the SCM.

In December 2003, the historical city of Bam was shaken by an earthquake that was measured with a magnitude of 6.6 on Richter scale. The city of Bam is located in Bam County of Kerman Province, which is located in south-eastern Iran, as presented in Figure 3. It was one of the deadliest earthquakes in Iranian history that killed 26,796 people, injured more than 20,000 people, left more than 60,000 people homeless, and destroyed about 80% of Bam and 100% of the buildings in the town Baravat (Fallahi 2007; K. A. Hosseini, Hosseinioon, and Pooyan 2013; EM-DAT 2021). In addition, the earthquake also damaged important infrastructure such as the water supply network, sewage, power lines, telecommunication systems, health care centers, educational buildings, irrigation and agricultural systems, gardens, streets, and roads, as well as cultural centers and other cultural heritage sites, for example Bam's historical citadel. It is estimated that 267,628 people were affected by this disaster and the total costs are estimated to be US$703 million, adjusted for inflation (Ghafory-Ashtiany and Hosseini 2008; EM-DAT 2021). In contrast to the residential structures, the industrial structures suffered lower amounts of damage, including cracks in walls and oil spills (Eshghi and Razzaghi 2005).

Figure 3: 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)

<u>*Outcome variable:*</u>

The outcome variable in all our estimations is the natural logarithm of the sum of nighttime light 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 a low quality of national accounts (Elvidge, Baugh, Kihn, Kroehl, Davis, et al. 1997; X. Chen and Nordhaus 2011; Henderson, Storeygard, and Weil 2012; Felbermayr et al. 2022). Second, the 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 the situation that the true effect of natural disasters on the economy will be underestimated which has been 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, and are therefore comparable across units. This is connected to the fourth advantage, because in the time period of this study, namely 1992 to 2020, there were several reforms in Iran related to provincial and county borders, for example the province Alborz that was created in 2010 and was previously part of the province of Tehran. Another example is the former province of Khorasan which was split into the three provinces North Khorasan, Razavi Khorasan, and South Khorasan in 2004.

Moreover, several provinces were created in the 1990s such as Ardabil (1993), Qom (1995), Qazvin (1996), and Golestan (1997). This will make it difficult to compare GDP statistics for all current Iranian provinces over longer time periods, as seen in Chapter 2 of this thesis. Using NTL will solve this problem and will also give us more observations. The same applies to the borders of the Iranian counties which have also changed over time.

This study uses 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, ranging 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), ranging from 2012 to 2020 (Elvidge, Baugh, Kihn, Kroehl, and Davis 1997; Baugh et al. 2010; Elvidge et al. 2017; Li et al. 2020)[5]. The harmonization procedure contains three major steps. First, they aggregated the global average radiance composite images of the VIIRS/DNB dataset from monthly to yearly observations. In addition, noises from aurora, fires, boats, and other temporal lights were excluded during this step. Second, they quantified the relationship between processed VIIRS data and DMSP NTL data in 2013 using a sigmoid function so that the processed VIIRS data have the same spatial resolution and similar radiometric characteristics as the DMSP data. Third, they applied the derived relationship at the global scale to obtain the DMSP-like data from VIIRS and finally generated the consistent NTL data by integrating the temporally calibrated DMSP NTL data (1992–2013) and DMSP-like NTL data from VIIRS (2014–2020).

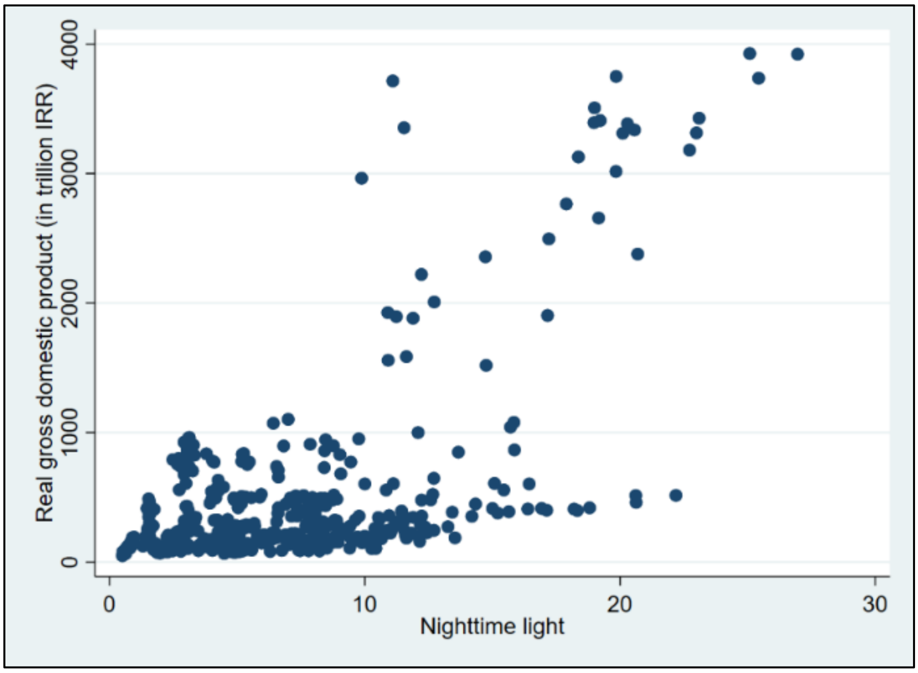
We extract the NTL data with shapefiles from the United Nations Office for the Coordination of Humanitarian Affairs (OCHA), Regional Office for the Middle East and North Africa (OCHA 2019). It uses the latest provincial borders, the first-level administrative divisions, after the reform of Tehran province in the year 2010. The county borders, which refer to the second-level administrative division, are from 2017 and include 429 counties, but there have been reforms after that. With the help of Quantum Geographic Information System's (QGIS) Zonal Statistics tool and the shapefiles, we calculate the sum of light intensity for each of the 31 provinces and 429 counties over the time period 1992–2020. This 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

[5] Version 5 of the harmonized global NTL dataset is available at https://figshare.com/articles/dataset/Harmonization_of_DMSP_and_VIIRS_nighttime_light_data_from_1992-2018_at_the_global_scale/9828827/5. The DMSP/OLS dataset is available at https://eogdata.mines.edu/products/dmsp/, and the VIIRS/DNB dataset is available at https://eogdata.mines.edu/products/vnl/ (websites accessed on 18 November 2021).

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). If we calculate the mean of each province and county, we will receive ranges between 0.14 and 26.95, as well as 0 and 62.88, respectively, which tells us that we can use the datasets for our approach. If a province has a value of 63, we would not be able to determine an increase in economic activity because this is the maximum possible value.

Based on 489 observations of the province-level data, we calculated Pearson's correlation coefficient of 0.63 for the relationship between the real gross domestic product (GDP) of Iranian provinces in trillion Iranian Rial (IRR) and its average NTL using the harmonized global nighttime light dataset (Li et al. 2020). Provincial GDP data used in the correlations and figure are from the Iranian Ministry of Economic and Financial Affairs (MEFA) and are available from 2004 to 2019 (MEFA 2021). The following Figure 4 shows the scatter plot of the relationship, which supports the argument to use NTL as a measure of economic activity, as previous studies have shown (Elvidge, Baugh, Kihn, Kroehl, Davis, et al. 1997; X. Chen and Nordhaus 2011; Henderson, Storeygard, and Weil 2012; Klomp 2016). County-level data on GDP are not publicly available, so we will not present the relationship here.

Figure 4: Relationship between real GDP and nighttime light in Iranian provinces



Predictor variables:

In the estimations with the province-level data, we are using several predictor variables based on previous studies. We will use every second year of NTL of the pre-intervention period which will help to receive a good pre-intervention fit of the treated 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 will not use all years of the outcome variable as predictors, because it might bias the post-treatment values. They show both theoretically and empirically that using all outcome lags as separate predictors renders all other covariates irrelevant. In addition, we will use several other predictor variables that are relevant in the case of natural disasters, namely the pre-intervention average of the outcome variable, the pre-intervention average of the first difference of the outcome variable, the pre-intervention average of the population growth rate, the natural logarithm of the population density, and the 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 2019; 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 demographic aspects. The natural disaster risk will cover geographic and institutional aspects because disaster risk is usually a consequence of these aspects which include exposure to natural disasters due to geography, and man-made factors such as susceptibility, vulnerability, and coping capacities. As the data availability on 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 will not just use donor pool counties from the same province, but from the whole of Iran, which will provide us a larger donor pool.

3.4 Results and Statistical Inference

First, we applied the SCM with province-level data where Kerman Province is the treated unit and 2003 the treatment year. According to the results, synthetic Kerman is best generated by the weighted average of seven provinces (out of 25 provinces in the donor pool), namely Khuzestan (9.5%), Kohgiluyeh and Boyerahmad (1.9%), Lorestan (6.9%), Markazi (4.6%), North Khorasan (10.3%), Razavi Khorasan (58.6%), and Semnan (8.1%). In the following, we will refer to the factual Kerman as treated Kerman, which has experienced the disaster event, and we will refer to the counterfactual Kerman as synthetic Kerman. Table 4 shows the average values of the covariates of treated Kerman and synthetic Kerman before the treatment year 2003. According to the values, synthetic Kerman closely reflects the pre-treatment performance of the NTL covariates of treated Kerman, and synthetic Kerman is similar in terms of the other predictor variables, namely the average of NTL, the growth of NTL, the population growth rate, the population density, and the natural disaster risk. In addition to the values of treated Kerman and synthetic Kerman, we also present in Table 4 an unweighted average of the variables for the seven provinces with weights bigger than zero. The predicted outcome in the pre-treatment period is similar between treated and synthetic Kerman with the selected weights. In comparison to the unweighted average of the same seven provinces, the gaps between treated 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 4: Means of predictors during the pre-treatment period (1992-2002) of Kerman Province

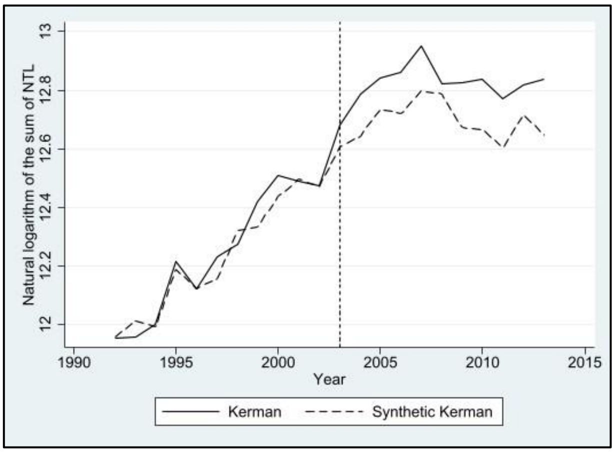
	(1) Treated Kerman	**(2) Synthetic Kerman**	**(3) Unweighted average of variables for provinces with weight > 0**	**(4) Difference (1-2)**	**(5) Difference (1-3)**
NTL (1992)	11.953	11.956	11.572	-0.002	0.382
NTL (1994)	12.000	11.993	11.601	0.007	0.399
NTL (1996)	12.120	12.122	11.742	-0.003	0.378
NTL (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: NTL refers in this table to the natural logarithm of the sum of nighttime light. Population density and natural disaster risk are also used as natural logarithm.

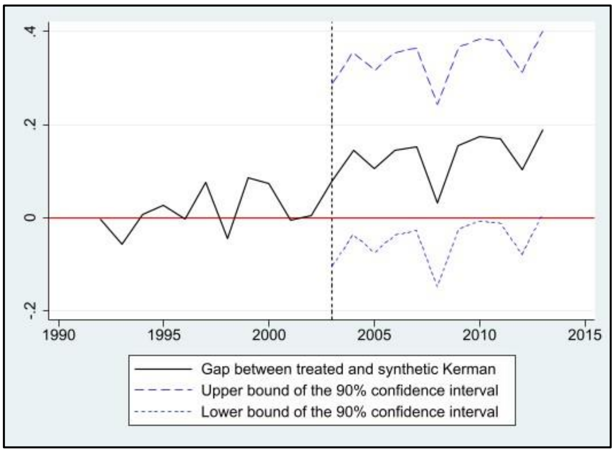
Figure 5a shows the trajectory of the natural logarithm of the sum of NTL of treated Kerman and its synthetic counterpart in the period 1992 to 2013. We can see that synthetic Kerman reproduces the development of NTL of treated Kerman in the period before the 2003 earthquake. The estimate of the effect of the earthquake disaster is shown by the difference between treated and synthetic Kerman. If we compare the trajectories of both cases, we can see that both continue to grow until the year 2007 and reach a peak, and then go down again. However, the development of nighttime lights in synthetic Kerman is lower than the development of treated Kerman which suggests that the earthquake disaster had a positive impact on the NTL development in Kerman. In addition, we can see that Kerman does not return to its pre-disaster development path in the following ten years after the disaster 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 treated and synthetic values. 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 5b presents the estimated gap between Kerman and synthetic Kerman with uniform confidence sets at the 90% 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 treatment of the 2003 earthquake is not significant in the ten years following the disaster.

Figure 5: Synthetic control analysis of Kerman Province



(a) Treated and synthetic Kerman.



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

The other established placebo tests are presented in Figure B 1 in Appendix B. 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, the leave-one-out test, and we have calculated a pseudo p-value based on the ratio of the post-treatment RMSPE to the pre-treatment RMSPE. The ratio is 2.98 for the case of Kerman with a pseudo p-value of 0.23 and it ranks on sixth place of all provinces from the donor pool. The root mean square prediction error (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 treated and synthetic Kerman (see Table 4), 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 B 2 in Appendix B, and show that the bias-corrected gap of NTL between treated 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 can be observed in other studies (Albala-Bertrand 1993; Cavallo et al. 2013; Fabian, Lessmann, and Sofke 2019; Fischer 2021), thus it is not unexpected. A usual 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 will investigate the impact of the Bam earthquake on the county level. An earthquake with a clear epicenter gives us also the possibility to study spatial spillovers to neighboring counties, and we assume that the impact of the disaster event becomes weaker in more distanced counties. We have removed all counties from the donor pool that have been affected by large-scale natural disasters or are the neighboring counties of first order of affected counties which might suffer from spillover effects. This leaves us with 63 counties in the donor pool which are presented in Table B 2 in Appendix B. We follow the same procedure as in the case of Kerman Province, but now we are focusing on Bam County and its neighboring counties of first and second order which are shown in Figure 3b. 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 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 order, 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 16 counties. We will also use a modified version of neighboring counties of first order, because according to our results two of these counties, namely Kerman and Jiroft, do not show significant gaps in their treated and synthetic versions. This leads to insignificant results when using the confidence sets, and it is an additional explanation, 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, it was not every county affected in a measurable way. Table 5 shows the weights that are used to create synthetic Bam County as well as its neighboring counties of different order. Synthetic Bam is best generated by the weighted average of six counties, namely Bonab (39.6%), Khalkhal (19.5%), Shemiranat (7.9%), Tabriz (3%), Tarom (10.7%), and Tehran (19.2%).

Table 5: 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

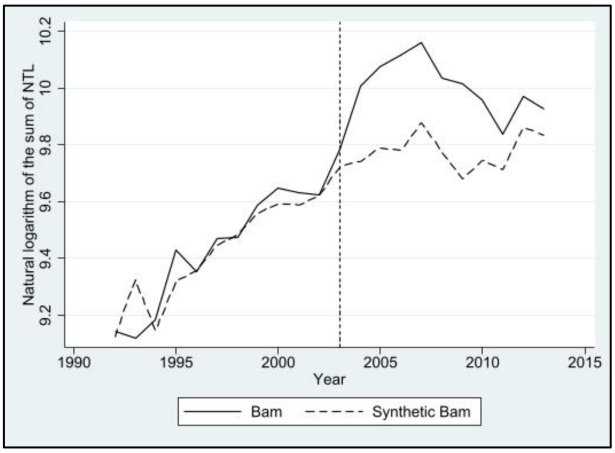
Table 6: Means of predictors during the pre-treatment period (1992-2002) of Bam and its neighbors

	(1) Treated Bam	**(2) Synthetic Bam**	**(3) Treated Bam's n. I**	**(4) Synthetic Bam's n. I**	**(5) Treated Bam's n. I (selected)**	**(6) Synthetic Bam's n. I (selected)**	**(7) Treated 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

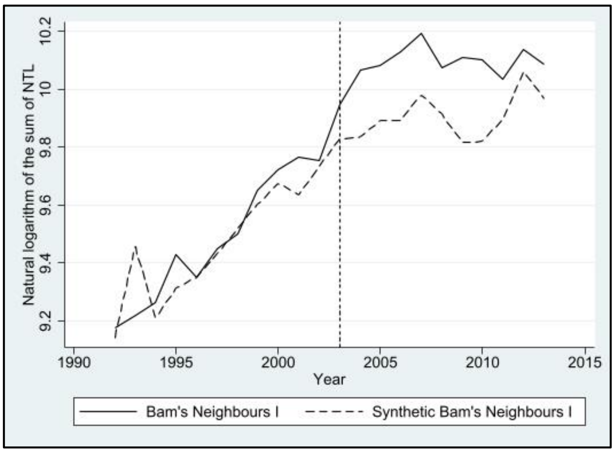
Notes: NTL refers in this table to the natural logarithm of the sum of nighttime light. Population density and natural disaster risk are also used as natural logarithm.

Table 6 shows the average values of the covariates of treated and synthetic Bam before the treatment year 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-treatment performance of the NTL covariates of the treated counties, and we can also see similarities among the other predictor variables, namely the average of NTL, the growth of NTL, the population growth rate, the natural logarithm of the population density, and the natural logarithm of the natural disaster risk indicator. Figure 6 shows the trajectories of the natural logarithm of the sum of NTL of treated 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 NTL of the treated counties in the period before the 2003 earthquake. The difference between the treated and synthetic versions of the counties shows the effect of the earthquake disaster.

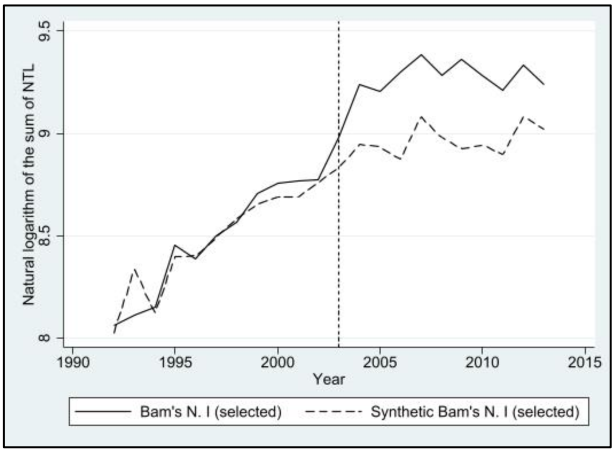
Figure 6: Treated and synthetic trajectories of Bam and its neighbors



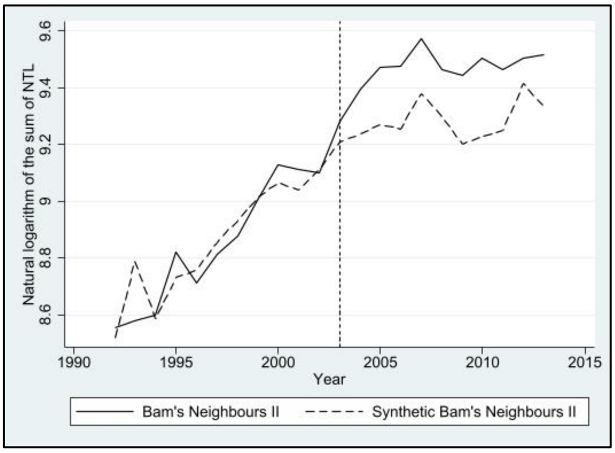
(a) Bam.



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



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

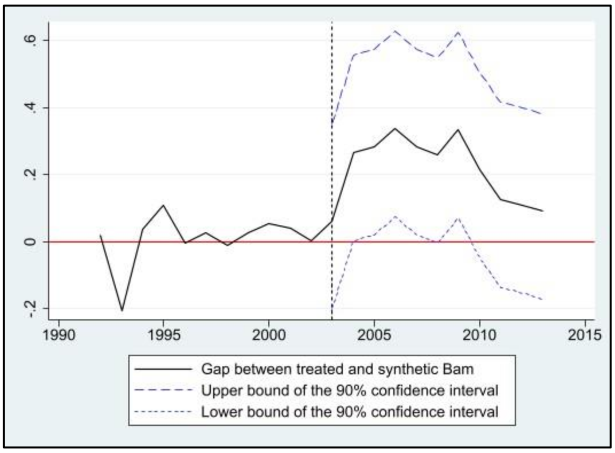


(d) Bam's neighboring counties of second order.

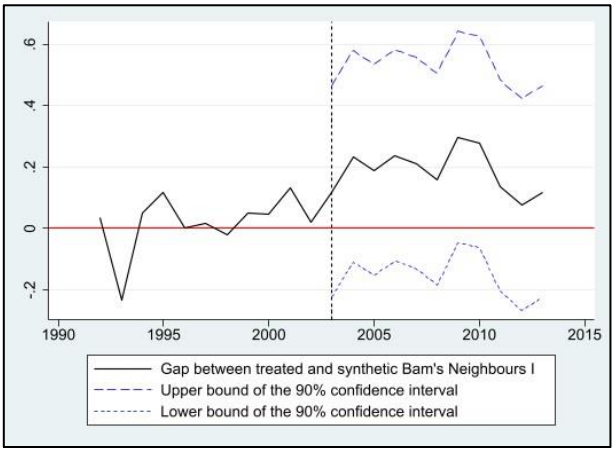
In Figure 6a, which presents the trajectories of treated and synthetic Bam County, we can see the largest gap between the treated and synthetic versions, compared to the other three gaps. The remaining graphs show the trajectories of Bam's neighboring counties of first order, first order (excluding the counties Kerman and Jiroft), and second order. Figure B 3a in Appendix B 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 the further away the county is, the smaller the impact we would expect. 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. In Figure 6b and Figure 6c, we can see the trajectories of Bam's neighboring counties of first order, which is the average of six counties, and the same without the counties Kerman and Jiroft. Both show a gap between its trajectories, but the statistical inference tests in Figure 7 and Figure B 5 in Appendix B 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, which results are presented in Figure 6d. 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 6, we can see an increase in economic activity directly after the disaster 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% level developed by Firpo and Possebom (2018) as well as Ferman et al. (2020) is presented in Figure 7 and reveals that Bam County as well as its neighboring counties of first order (excluding Kerman and Jiroft counties) show significant gaps between the treated and synthetic trajectories. According to the results, the gap between treated and synthetic Bam is significant until about seven years after the earthquake event (see Figure 7a), and the gap for the selected neighboring counties of first order is significant about nine years after the treatment (see Figure 7c). In the other cases, we cannot see a significant gap. Therefore, we can say that the affected counties return to their pre-disaster development paths after 7-9 years.

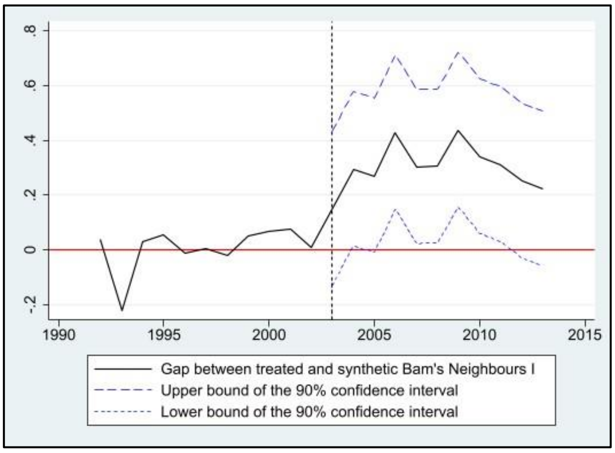
Figure 7: Gap between treated and synthetic counties including confidence sets



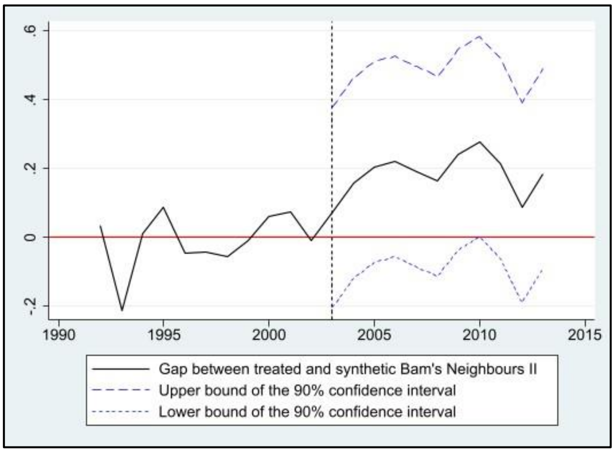
(a) Bam.



(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 the established placebo tests which are presented in Figure B 4 to Figure B 7 in Appendix B. The in-space placebo tests show exceptionally large gap between the treated and synthetic units compared to the gaps of all other counties in the donor pool in the years directly after the treatment in the cases of Bam and its selected neighboring counties of first order. Moreover, the post-treatment RMSPE to the pre-treatment 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 treatment year 2003 produces in all four cases a clear gap directly after the treatment, 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 a similar trajectory when excluding counties from the donor pool with large weights in the original estimations. As an additional sensitivity check of the analysis, we have 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 Figure B 8 to Figure B 11 in Appendix B 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 (see Figure B 8 and Figure B 10). The gaps become smaller than the gaps of the classical synthetic control, but the peaks of the differences between treated and synthetic units stay almost identical. For the other two cases, namely Bam's counties of first and second order, we can see that the gaps between treated and synthetic units almost disappear after bias correction (see Figure B 9 and Figure B 11).

3.5 Discussion

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 presented theory (Albala-Bertrand 1993; Skidmore and Toya 2002; Chhibber and Laajaj 2008; Klomp 2016) and previous empirical studies (Loayza et al. 2012; Felbermayr and Gröschl 2014; Onuma, Shin, and Managi 2021; Felbermayr et al. 2022). One difference to the scenarios of Chhibber and Laajaj (2008) is that we cannot see the initial negative shock of the earthquake disaster in the NTL data, neither on the province-level nor on the county-level. This is because we are using yearly-averaged NTL data which means that the effect is partly removed by the average, which is plausible for the Bam earthquake which happened in December 2003. In addition, a part of the negative impact on NTL is offset by the inflow of relief and reconstruction efforts.

Despite these challenges, an advantage of nighttime light data is that we can evaluate the impact of the disaster event in a small geographical area, and we can also measure the potential spillovers to neighboring areas. These areas might not have been directly affected by the disaster event, in terms of life losses or physical damage, but it might still affect the light intensity. Therefore, the change of the sum of NTL does not only reflect the damage, but it also reflects the overall change in economic activity in the directly or indirectly affected regions. The results suggest that it is not just the direct damage that becomes lesser when moving away from the epicenter, but it is also the economic activity in the neighboring areas that will be lesser affected the further away the disaster happened. We showed that the average effect becomes smaller, the further we go away from Bam County. This also serves as an additional identification strategy of the impact of the earthquake event.

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 to the South-West 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 could start immediately after the main earthquake event, and due to the geographical concentration of the damage, the area was more accessible for helpers, as for example compared to a flood that can last for many days and makes a region not accessible (see Chapter 4 of this thesis).

Another factor is the level of economic development and industrialization of the impacted areas. If we compare population size, economic activity, and human development of Kerman Province with the average Iranian province of the year 2002 (before the earthquake disaster), we can 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 to the county level, where Bam County had a higher population than the average Iranian county with 283,311 people compared to 209,809 people. The economic activity had a value of 15,115 compared to 13,310. In addition, Kerman had with 0.672 a higher Human Development Index, which was calculated by Global Data Lab (GDL 2022), than the average province with 0.667. The index ranges from 0 to 1 and higher values suggest higher human development, considering health, education, and income.

Related to the 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 on industrial facilities including cracks in walls and oil spills which was significantly lower than the damage in residential areas, and those industrial facilities who stopped production were not destroyed, but were cut-off from 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 provinces and counties before the impact of the disasters, which provided the former with better coping capacities and better conditions for turning disaster relief inflows into economic development.

This leads to another important aspects, namely the size of disaster relief inflows, the reconstruction efforts, and the media attention, which are all interlinked. After the impact of the 2003 Bam earthquake, there was a total funding of US$130.2 million from more than 20 international donors (OCHA 2004a). There was an immediate response by the Iranian Red Crescent Society (IRCS), government agencies, military forces, and other volunteers. In addition to the national disaster response, there was international assistance by 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 and taken to hospitals in other provinces. In addition, many volunteers from various sectors of Iranian society poured into the region to help those affected, and other people 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; K. A. Hosseini, Hosseinioon, and Pooyan 2013; Yuan et al. 2018).

Several camps and temporary shelters for the homeless were constructed, and until 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 of charge and long-term bank loans to families who lost their homes. The main reconstruction efforts finished in 2007, and the IFRC ended its mission in February 2007 (OCHA 2007; Ghafory-Ashtiany and Hosseini 2008). Overall, we can see an enormous inflow of people and resources into the region which can explain an increase of nighttime light 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 6a).

Compared to other large-scale natural disasters in Iran, the Bam earthquake has received an enormous amount of national and international attention. An explanation is the extremely high death count and the destruction of major parts of a famous city with a UNESCO World Heritage Site, which both can cause empathy and emotions in people that helped to mobilize national and international support. Due to the mentioned reasons, the Bam earthquake also gained more media attention than previous disasters, which increased the post-disaster aid flows. This phenomenon has already been studied by several authors (Strömberg 2007; Becerra, Cavallo, and Noy 2014). After discussing the disaster response and reconstruction process, we can understand better what the change in nighttime light really measures. The reason for this boost in economic activity was an inflow of financial and human capital which lasted for about seven years, and these resources are missing somewhere else in the country, thus we can also interpret it as economic costs for the country of Iran. This means that we are interpreting a deviation from the pre-disaster development path as a loss, as long as the long-term post-disaster development path is not higher, as we have seen it in scenario D of Chhibber and Laajaj (2008).

3.6 Conclusion

With our empirical investigation, we have looked more closely at one major large-scale natural disaster event in the country of Iran, namely the 2003 Bam earthquake. We used the synthetic control method (SCM) to estimate the development of nighttime light (NTL) in the Iranian Kerman Province and Bam County as well as its neighboring counties which provided us an estimate of the development of economic activity in the hypothetical absence of the disaster event. The first finding is that the estimated synthetic controls on the province level are not robust to the established placebo tests and the confidence sets developed by Firpo and Possebom (2018) as well as Ferman et al. (2020). This is supported by previous studies who have shown that even large-scale natural disasters do not show statistically significant impacts on the country level, and it is suggested to study the impact of natural disaster on lower administrative levels (Albala-Bertrand 1993; Cavallo et al. 2013; Fabian, Lessmann, and Sofke 2019; Fischer 2021).

The second result is that Kerman Province and Bam County experienced a boost in economic activity following the earthquake disaster, which is the difference between the treated and synthetic province/county. We argue that this development took place due to the type and severity of the event (comparably minor damage to economic structures), the underlying composition of the economy (above average economic activity and human capital), and the total area impacted (concentrated in one county). In addition, the high death count and the cultural importance of the UNESCO World Heritage Site helped to gain media attention and to mobilize national and international support. This boost in economic activity can also be interpreted as a loss by other provinces and counties, except for neighboring counties, because of the intensive flow of financial and human capital to Bam County.

As a third finding, we showed how to estimate spatial spillover effects of natural disasters to neighboring geographical units using the SCM and the example of Bam County and its neighbors. We estimated synthetic controls for the average neighboring counties of first, second, and third order, and found that the average impact of the earthquake on NTL was smaller the further away the counties are located. When using the established placebo tests and the 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 values of the synthetic controls were smaller than the values of the treated neighbors which suggests a boost in economic activity due to the earthquake. Thus, we can see positive spillover effects from the reconstruction activities in Bam to neighboring counties, supporting the findings of Chapter 2 of this thesis.

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, after less than ten years. Therefore, we found an effect in the short term (0-5 years) or intermediate term (6-10 years) that was also found by Onuma et al. (2021) for their category of all natural disasters. Other studies also found weak evidence for the long-term impact of natural disasters or none at all (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 disaster events using a counterfactual which can be easily replicated for other countries. By using NTL, we overcome 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. Therefore, this study has a value for researchers from different disciplines who are interested in spatial spillover effects, remote sensing data, natural disasters, economic shocks, and the application of the synthetic control method. Moreover, the results can help policy makers to learn more about the dynamics of natural disasters and the reconstruction process and its impact on economic development in the intermediate or long term. The knowledge about the high economic costs can be an additional argument to shift policies from the focus on response and recovery to a focus on mitigation and preparedness.

4. Nighttime Light Development after the 2001 Flood in Iran: A Synthetic Control Analysis

Abstract

This study provides new empirical evidence for the consequences of a large-scale flood in the country of Iran. We are using the synthetic control method (SCM) and nighttime light (NTL) data to study the impact of the 2001 flood in Iran which affected several of the country's Northeastern provinces. According to the results, the counties Azadshahr, Galikash, and Minudasht, which are located in Golestan Province and were mainly affected, experienced a drop of economic activity in the years following the flood disaster. We estimated the costs to be US$558.5 million which is higher than previous estimations.

JEL Codes:

E01, H84, O11, O44, O53, Q51, Q54, R11, R12

Keywords:

Natural disaster, natural hazard, synthetic control, earthquake, flood, economic development, economic growth, nighttime light

4.1 Introduction

Flood disasters are one of the main challenges in Iran's natural disaster management efforts, because they occur on a regular basis and have costs the Iranian economy about US$16 billion, adjusted for inflation, in the period 1992-2020. In addition, the country experienced on average 2.2 flood disasters per year, affecting on average 443,227 people per year (EM-DAT 2021). For this reason, Iran is an interesting case study for investigating the impact of large-scale floods on economic development. We have chosen the case study of the 2001 flood because it is the largest flood disaster in the period of available data that has enough post-disaster periods available to determine the impact in the intermediate or long term, and it was described by several authors as a once in 200-year-flood (Sharifi, Saghafian, and Telvari 2002; Vaghefi et al. 2019).

To evaluate the true economic costs of the flood disaster, we are comparing the factual development of nighttime light (NTL) with the counterfactual development in the hypothetic absence of the flood. This will provide us an estimation of the costs in terms of economic development that are usually not considered when estimating the direct damage of a disaster event. We will use the synthetic control method (SCM) to construct synthetic versions of Golestan Province and the counties Azadshahr, Galikash, and Minudasht, and then estimate the economic development of the counterfactual province and counties, which reflect the development path, if the impacts of the disaster event did not happen. The difference between the development paths of the treated units in comparison to its synthetic versions will provide us estimations of the true impact of the 2001 flood.

We are measuring economic activity in the Iranian provinces and counties using NTL data from 1992 to 2020 (Li et al. 2020) which has several advantages for our study, for example it reflects the formal and informal economy, it has longer time periods available than official data, and it has consistent borders over the whole time period. In addition, we are using province and county level data, because it helps us to control for shocks that affected the whole Iranian economy in the period of study, and it makes sure that we can measure the impact of the disaster event which might not be possible with higher aggregated data. Overall, we follow the approach of Chapter 3 of this thesis, with the main difference being the disaster type of the studied disaster event. The contribution of this study is that we provide evidence for the impact of a large-scale flood disaster on NTL, and we present an approach to convert NTL to US dollar.

The findings of this study are that Golestan Province and the three counties Azadshahr, Galikash, and Minudasht experienced a decrease of economic activity in the years following the disaster. This supports several previous theoretical models and empirical findings (Chhibber and Laajaj 2008; Felbermayr and Gröschl 2014; Klomp 2016; Onuma, Shin, and Managi 2021), but it is in contrast to the findings of Chapter 3 of this thesis. The remaining chapter is structured in the following way: Section 4.2 gives an overview of the relevant literature related to the topic and Section 4.3 presents the data and methodology. In Section 4.4, the results are presented, followed by the discussion in Section 4.5, and Section 4.6 concludes the chapter.

4.2 Literature Review

As already discussed in the previous chapters of this thesis, there is a huge body of literature on the impact of natural disasters on economic growth and the level of economic development. Several authors discuss theoretical approaches to understand the relationship between natural disasters and economic performance and show that the development after the initial shock depends on many factors and is not necessarily negative (Albala-Bertrand 1993; Skidmore and Toya 2002; Chhibber and Laajaj 2008; Klomp 2016). A large number of empirical findings also confirms this complex relationship, and shows that the impact might depend on the country's characteristics and the characteristics of the disaster event (Noy 2009; Loayza et al. 2012; Cavallo et al. 2013; Felbermayr and Gröschl 2014; Klomp 2016; Noy and duPont IV 2018; Fabian, Lessmann, and Sofke 2019; Onuma, Shin, and Managi 2021; Felbermayr et al. 2022). Among the relevant country characteristics are economic development (e.g., GDP per capita, trade openness), social development (e.g., literacy rate), institutional development (e.g., natural disaster management, level of corruption), and the geographical location of the country. Among the relevant characteristics of the natural disasters are the type of disaster and the severity of the disaster event.

Remote sensing data are commonly used to evaluate the direct damage of natural disasters, and some authors have also used nighttime light (NTL) data to measure the direct and indirect impact of natural disasters on economic activity (Bertinelli and Strobl 2013; Elliott, Strobl, and Sun 2015; Klomp 2016; Fabian, Lessmann, and Sofke 2019; Felbermayr et al. 2022). Most of these studies provide evidence for a drop of NTL as a consequence of the disaster shock. The majority of studies use regression analysis to study the relationship between natural disasters and economic development or growth, but some authors have also used the synthetic control method (SCM) which creates a counterfactual case of the geographical unit that has not experienced the natural disaster (Cavallo et al. 2013; Barone and Mocetti 2014; duPont IV and Noy 2015; Cerqua and Di Pietro 2017; Lynham, Noy, and Page 2017).

Different aspects of natural disasters in Iran have also been discussed in the literature, for example the impact on the economy in the short run. Empirical results, using time-series analysis, suggest that there is a negative impacts of natural disasters on Iran's non-oil GDP, per capita investments, and per capita GDP (Sadeghi and Emamgholipour 2008; Sadeghi, Emamgholi Sefiddasht, and Zarra Nezhad 2009; Yavari and Emamgholipour 2010). In recent years, there is also a discussion about the impact of climate change and related weather events. It is expected that Iran will in the future experience longer periods of extreme maximum temperatures in the south of the country as well as more extreme weather events, including both dry and wet conditions (Vaghefi et al. 2019). This also includes heavy rainfall and related flood disasters, as well as periods of droughts due to the lack of rainfall. There is already empirical evidence on the consequences of such disasters, which can lead to inter-province migration or an increase in housing and residential land prices (Farzanegan, Feizi, and Gholipour 2021; Farzanegan, Gholipour, and Javadian 2022).

Despite the large number of published studies on natural disasters, none of these have used a counterfactual to study the impact of a large-scale flood in Iran. Previous research using remote sensing data have only focused on the evaluation of the direct damage directly after the disaster events, for example Adams et al. (2004) and Chini et al. (2009) for the damage of the 2003 Bam earthquake in Iran, but not on the indirect damage several years after the initial shock that can be measured by the losses in economic development using NTL. This study follows the approach of Chapter 3 of this thesis, but the difference is the type of disaster as well as the disaster relief efforts after the disaster event, which will be further discussed in this chapter. With our study, we provide new empirical evidence for the negative impact of the 2001 flood over a longer time period, which is an addition to the existing literature on this flood event.

4.3 Methodology and Data

In this study, we evaluate the impact of the 2001 flood in Iran's Golestan Province using nighttime light data as a measurement for economic activity that has already been used in the context of natural disasters (Bertinelli and Strobl 2013; Elliott, Strobl, and Sun 2015; Klomp 2016; Fabian, Lessmann, and Sofke 2019; Felbermayr et al. 2022), and we will use the synthetic control method which was used before in the context of sudden shocks to an economy on lower administrative units (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).

4.3.1 Methodological Approach

Following the approach of Chapter 3 of this thesis, we use the synthetic control method (SCM) with data on the provincial and county levels. As previous literature has shown that the impact of a natural disaster event might not be measurable on higher administrative units, such as country level or even province level, we will use both provincial and county level data (Albala-Bertrand 1993; Bertinelli and Strobl 2013; Klomp 2016; Fabian, Lessmann, and Sofke 2019; Noy and duPont IV 2018). The SCM is used to investigate a shock on an outcome variable which is in this case the natural logarithm of the sum of NTL. The treatment year is 2001, which is the year of the flood disaster, and the treated unit in the province-level analysis is Golestan Province. The remaining provinces will be used as the donor pool. In the county-level analysis, the treated units are the counties Azadshahr, Galikash, and Minudasht.

When selecting the 2001 flood as a case study, we considered several requirements that are needed to apply the SCM. As data requirement, we need a balanced panel dataset, with an exception for the predictor variables which can be included as an average for several years. We need a sizable number of pre-treatment periods to capture the behavior of the treated unit and determine the synthetic control. To determine the impact of the treatment, we also need a number of years after the flood disaster. Furthermore, we needed to find a natural disaster event that only affected one or very few geographical units at the same time, so that there are enough units left for the donor pool that have not experienced the treatment. In the province-level analysis, we have Golestan Province with the treatment year 2001. For the analysis, we need to restrict the donor pool, so that it only included provinces that were not directly or indirectly affected by the treatment or by other major shocks in the time period of this study.

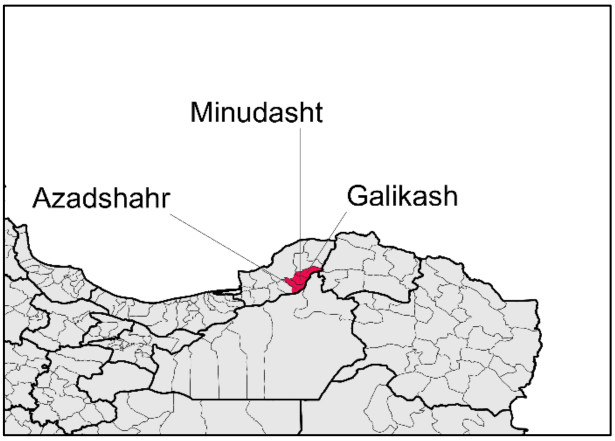
We will exclude provinces from the donor pool that have experienced one of the 16 large-scale natural disaster events, as defined in Chapter 3 of this thesis, in the same year or are Golestan's neighboring provinces (see also Table B 1 of Appendix B). In the county-level analysis, we will investigate the impact on the counties Azadshahr, Galikash, and Minudasht. As there are 429 counties and thus more donor pool counties available, we will restrict the donor pool more conservatively and remove all counties and neighboring counties that have experienced one of the large-scale disasters in the whole period of available data.

4.3.2 Data: Outcome Variable and Predictors

In August 2001, heavy rainfall in the Northeast of Iran turned into a flood disaster that was described as a once in 200-year-flood (Sharifi, Saghafian, and Telvari 2002; Vaghefi et al. 2019), and was only topped by the 2019 flood in recent years. It mainly affected Golestan Province, but also the provinces Semnan and Khorasan (today's North Khorasan, Razavi Khorasan, and South Khorasan), as presented in Figure 8a.

Figure 8: Provinces and counties affected by the 2001 flood

(a) Provinces affected by the flood.



(b) Counties in Golestan province that were mainly affected by the flood.

(Source: Author's illustration)

Alone in Golestan Province more than 300 persons were reported dead or missing and about 217,000 people were affected by this flood event. In addition, it heavily damaged infrastructure such as roads (almost 200 km), several important bridges, water supply, and gas pipelines. Moreover, 10,000 ha of forests and pastureland as well as 15,000 ha of farmland were affected, and 6,000 livestock was killed. The estimated damage ranges between US$75- 400 million (Sharifi, Saghafian, and Telvari 2002; Tourani et al. 2021). Due to several reasons Golestan can be considered a high-risk area for flooding, namely topography, climatic conditions, and economic development. First, the flood-prone catchment areas consist of mountains with high altitude terrains and plain areas within the valleys, as well as several rivers in the plain areas, especially in central and northern parts of the province. Second, the occurrence of iterative droughts and heavy rainfall events. Third, human behavior, such as the development of settlement areas in natural flood beds and deforestation due to the development of the agricultural and industrial sectors, also increases the flood risk.

In addition to these conditions, many Iranian provinces, including those affected by the 2001 flood, have suffered from a severe three-year drought which degraded the natural vegetation, leaving the soil unprotected, and dried the soil surface, preventing water from infiltrating. Thus, the heavy rainfall in August 2001 could not be absorbed by the soil, and the water turned into a destructive flood and debris flow. Another flash flood happened only one year later, in August 2002, again in the Minudasht area of Golestan Province, causing 42 deaths and 30 people missing (Sharifi, Samadi, and Wilson 2012). Therefore, the impact measured in nighttime light activity in the years after 2000 will reflect the impact of both flood events.

Outcome variable:

The outcome variable in all our estimations is the natural logarithm of the sum of nighttime light using the data provided by Li et al. (2020). Using NTL data as a proxy for economic activity has several advantages for this study, for example is has lower measurement error than the official gross domestic product (GDP) data, it includes the informal economy, it can be aggregated to lower administrative units, and it can be aggregated with consistent political boundaries over time, and thus taking into account border reforms (Felbermayr et al. 2022; Farzanegan and Fischer 2021). This study uses version 5 of the harmonized global NTL dataset by Li et al. (2020), ranging from 2012 to 2020, which was extracted for 31 provinces and 429 counties. 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).

Predictor variables:

In the estimations with the province-level data, we are using several predictor variables based on previous studies, including every second year of NTL of the pre-intervention period which will help to receive a good pre-intervention fit of the treated and synthetic units. The other predictor variables are the pre-intervention average of the outcome variable, the pre-intervention average of the first difference of the outcome variable, the pre-intervention average of the population growth rate, the natural logarithm of the population density, and the natural logarithm of the natural disaster risk indicator. The population growth rate is 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 2019; EM-DAT 2021). With the NTL predictors, we cover several aspects that are relevant to determine the synthetic control, including economic, demographic, and geographical aspects. In the county-level analysis, the NTL data are extracted and calculated in the same way as the province-level variables, but the remaining data are from the province level. This will additionally help to control for the characteristics of the province of the selected donor pool counties.

4.4 Results and Statistical Inference

We first applied the SCM with province-level data where Golestan Province is the treatment unit and 2001 the treatment year with the results that synthetic Golestan is best generated by the weighted average of four provinces (out of 26 provinces in the donor pool), namely Alborz (35.6%), Ilam (31.9%), Qom (9.7%), and Sistan and Baluchestan (22.8%).We removed from the donor pool the other four provinces affected by the same flood event, namely Semnan, North Khorasan, Razavi Khorasan, and South Khorasan. Table 7 shows the average values of the covariates of treated and synthetic Golestan before the treatment year 2001. According to the values, synthetic Golestan closely reflects the pre-treatment performance of the NTL covariates of treated Golestan, and synthetic Golestan is similar in terms of the other predictor variables, namely the average of NTL, the growth of NTL, the population growth rate, the natural logarithm of the population density, and the natural logarithm of the natural disaster risk indicator. In addition to the values of treated and synthetic Golestan, we also present in Table 7 an unweighted average of the variables for the four provinces with weights bigger than zero. The predicted outcome in the pre-treatment period is similar between treated and synthetic Golestan with the selected weights. In comparison to the unweighted average of the same four provinces, the gaps between synthetic Golestan and treated Golestan are smaller for most of the predictors. This shows the advantage of the SCM compared to using an unweighted average.

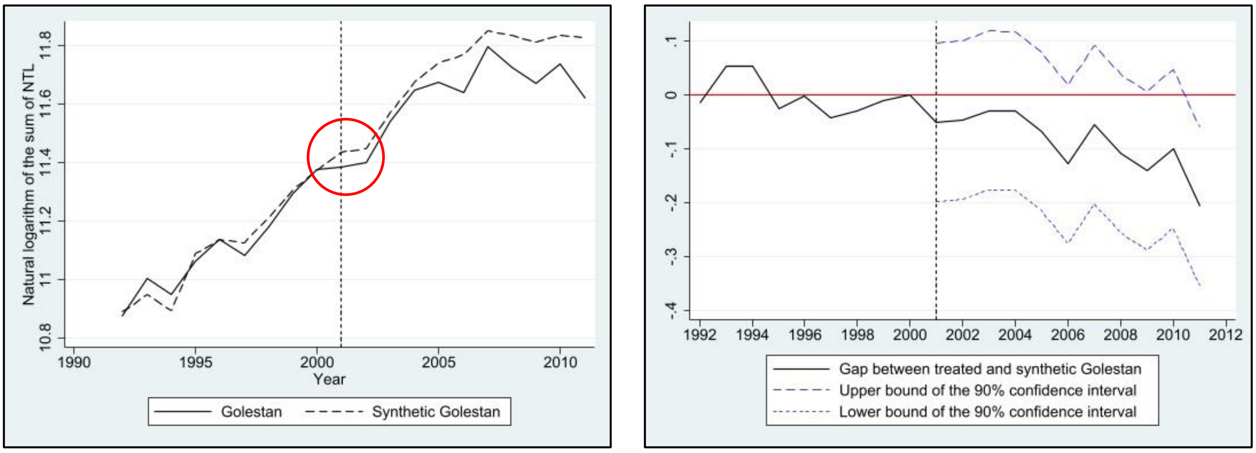
Table 7: Means of predictors during the pre-treatment period (1992-2000) of Golestan Province

	(1) Treated Golestan	**(2) Synthetic Golestan**	**(3) Unweighted average of variables for provinces with weight > 0**	**(4) Difference (1-2)**	**(5) Difference (1-3)**
NTL (1992)	10.874	10.888	10.795	-0.014	0.078
NTL (1994)	10.947	10.891	10.802	0.056	0.146
NTL (1996)	11.135	11.143	11.063	-0.007	0.072
NTL (1998)	11.182	11.219	11.145	-0.037	0.037
NTL (2000)	11.375	11.371	11.289	0.004	0.086
NTL(mean 1992-2000)	11.106	11.108	11.027	-0.002	0.079
ΔNTL(mean 1993-2000)	0.063	0.060	0.062	0.002	0.001
Population growth (mean 1992-2000)	1.444	1.445	1.444	-0.001	0.000
Population density (mean 1992-2000)	4.383	4.560	4.339	-0.177	0.044
Natural disaster risk	3.447	2.359	2.124	1.088	1.323

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

Figure 9a shows the trajectory of the natural logarithm of the sum of NTL of treated Golestan and its synthetic version in the period 1992 to 2011. We can see that synthetic Golestan reproduces the development of NTL of treated Golestan in the period before the 2001 flood. The estimate of the effect of the flood disaster is shown by the difference between treated and synthetic Golestan. However, we can see only a small difference between the two trajectories directly after the disaster event (as marked with a red circle). The development of NTL in Golestan has a steeper slope between 1997 and 2000 than in the following two years. If we interpret synthetic Golestan as the development path where the disaster did not happen, we can see that Golestan returned to its pre-disaster development path after two years. The trajectories also show that other shocks after 2005 had a larger impact on the NTL development than the 2001 flood.

Figure 9: Synthetic control analysis of Golestan Province



(a) Treated and synthetic Golestan.

(b) Gap between treated and synthetic Golestan including confidence sets.

To consider the uncertainty of the estimation of the synthetic control, we used several established placebo tests and the confidence bounds developed by Firpo and Possebom (2018) as well as Ferman et al. (2020). Figure 9b shows the estimated gap between treated and synthetic Golestan with uniform confidence sets at the 90% level. According to the results, the negative effect of the treatment of the 2001 flood is not significant in the years following the disaster event. This finding is supported by other statistical inference procedures which are presented in Figure C 1 of Appendix C. As discussed in Abadie et al. (2010; 2015), we will apply three different placebo tests, namely an in-space placebo test, an in-time placebo test, the leave-one-out test, and we will calculate a pseudo p-value based on the ratio of the post-treatment root mean square prediction error (RMSPE) to the pre-treatment RMSPE. Figure C 1a shows the in-space placebo test where we treat all other provinces from the donor pool with the shock of the year 2001. We can see the gaps of all 27 provinces in our sample, including Golestan which is bold. As the gap of Golestan does not show a distinctive different behavior than the other gaps, we can conclude that the shock does not have a large enough impact than the average fluctuations of the other provinces in the sample, and thus it is not significantly different. In addition to this visual inspection, we can calculate the ratio of the post-treatment RMSPE to the pre-treatment RMSPE which is 3.12 for the case of Golestan with a pseudo p-value of 0.19 and it ranks on fifth place of all provinces from the donor pool, as presented in Figure C 1b.

Moreover, Figure C 1c shows the in-time placebo test where we use other treatment years and keep Golestan as the treated unit. This shows that the random selection of a year with no major political or economic events does not generate the effect which was observed from the shock of the 2001 flood. We are estimating the synthetic control for each of the three years before and after our original treatment year of 2001. The trajectories of the in-time placebo test do not show a synthetic control which is larger than the treated unit, and the trajectories are closer to the treated unit than the synthetic control of the year 2001. We can see that none of the other hypothetic shocks leads to the same difference between treated and synthetic Golestan. Our original estimations are presented in bold, the synthetic controls with treatment year before are presented in blue, and the synthetic controls with treatment year after are presented in red.

Finally, we are applying the leave-one-out test, where we remove provinces from the donor pool that are used as weights in our original estimation. With this approach, we can evaluate to what extent the main result is sensitive to the inclusion of a specific province in the donor pool. Figure C 1d presents the results of the estimations, where we exclude one of the following provinces from the donor pool: Alborz, Ilam, Qom, and Sistan and Baluchestan. We can see that three of the new synthetic controls have similar trajectories than the original synthetic control. However, when removing the province Sistan and Baluchestan the gap between synthetic and treated Golestan after the year 2001 almost disappears. Therefore, the placebo tests support previous findings of the confidence sets which suggest a non-significant impact of the 2001 flood in Golestan on the province level, supporting the findings of the province-level analysis of Chapter 3 of this thesis.

To mitigate the bias in the classic synthetic control estimates that results from discrepancies in predictor values between a treated unit and its donor pool units (see Table 7), we also applied the penalized synthetic control which uses regression-based adjustments to mitigate the bias in the classic synthetic control estimates (Abadie and L'Hour 2021; Wiltshire 2022). The results are presented in Figure C 2 of Appendix C, and show that the gap between treated and synthetic Golestan disappears when using different bias correction approaches. Overall, this provides us evidence that the impact of the 2001 Golestan flood is not measurable on the province level. Consequently, we have done the same analysis on the county level. From the 429 counties in the dataset, we have removed all counties from the donor pool that have been affected by large-scale natural disasters. In addition, we have removed the neighboring counties of first order of affected counties which might suffer from spillover effects, which leaves us with 63 counties in the donor pool (see Table B 2 of Appendix B).

We follow the same procedure as in the case of Golestan Province, but now we are focusing on the three counties Azadshahr, Galikash, and Minudasht. Table 8 shows the weights that are used to create the synthetic counterparts of the three counties. The first county, synthetic Azadshahr, is best generated by the weighted average of seven counties, namely Bilasavar (6.9%), Estehard (8.5%), Fardis (8.7%), Firuzkuh (2.1%), Nazarabad (19.9%), Sahneh (28.3%), and Taleghan (25.6%). The second county, synthetic Galikash, is best generated by only four counties which are Baharestan (23.6%), Bilasavar (1.2%), Charuymaq (5%), and Paveh (70.2%), and the third county, synthetic Minudasht, is best generated by the weighted average of five counties, namely Estehard (6.8%), Firuzkuh (13.8%), Paveh (75.9%), Sardasht (1.6%), and Taleghan (1.9%).

The weights of the synthetic versions of both Galikash and Minudasht consist of a large share of Paveh County, because both counties of interest are very similar in terms of NTL development and Paveh County apparently is the best comparison unit. However, the leave-one-out placebo tests show that we can generate similar versions of the counties without including Paveh County (see Figure C 4d and Figure C 5d in Appendix C).

Table 8: County weights of synthetic Azadshahr, Galikash, and Minudasht

	Weights of synthetic Azadshahr	**Weights of synthetic Galikash**	**Weights of synthetic Minudasht**
Baharestan	0	0.236	0
Bilasavar	0.069	0.012	0
Charuymaq	0	0.05	0
Estehard	0.085	0	0.068
Fardis	0.087	0	0
Firuzkuh	0.021	0	0.138
Nazarabad	0.199	0	0
Paveh	0	0.702	0.759
Sahneh	0.283	0	0
Sardasht	0	0	0.016
Taleghan	0.256	0	0.019
Remaining 52 counties	0	0	0

Table 9 shows the average values of the covariates of the three counties and the synthetic counterparts before the treatment year 2001. According to the values, the synthetic versions closely reflect the pre-treatment performance of the NTL covariates of the treated counties, and we can also see similarities among the other predictor variables, namely the average of NTL, the growth of NTL, the population growth rate, the natural logarithm of the population density, and the natural logarithm of the natural disaster risk indicator.

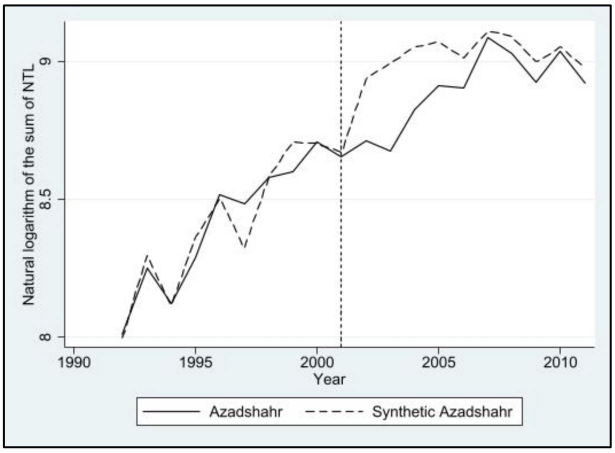
Table 9: Means of predictors during the pre-treatment period (1992-2000) of the counties Azadshahr, Galikash, and Minudasht

	(1) **Treated Azadshahr**	**(2)** **Synthetic Azadshahr**	**(3)** **Treated Galikash**	**(4)** **Synthetic Galikash**	**(5)** **Treated Minudasht**	**(6)** **Synthetic Minudasht**
NTL (1992)	8.010	7.997	7.465	7.444	7.370	7.323
NTL (1994)	8.122	8.115	7.742	7.624	7.543	7.524
NTL (1996)	8.518	8.504	7.901	7.917	7.897	7.857
NTL (1998)	8.578	8.578	7.990	8.063	8.045	8.051
NTL (2000)	8.707	8.702	8.146	8.144	8.232	8.212
NTL(mean 1992-2000)	8.396	8.399	7.841	7.847	7.780	7.788
ΔNTL(mean 1993-2000)	0.087	0.088	0.085	0.088	0.108	0.111
Population growth (mean 1992-2000)	1.382	1.386	1.382	1.386	1.382	1.386
Population density (mean 1992-2000)	7.542	8.336	7.534	8.560	7.799	7.796
Natural disaster risk	3.447	2.981	3.447	2.465	3.447	2.548

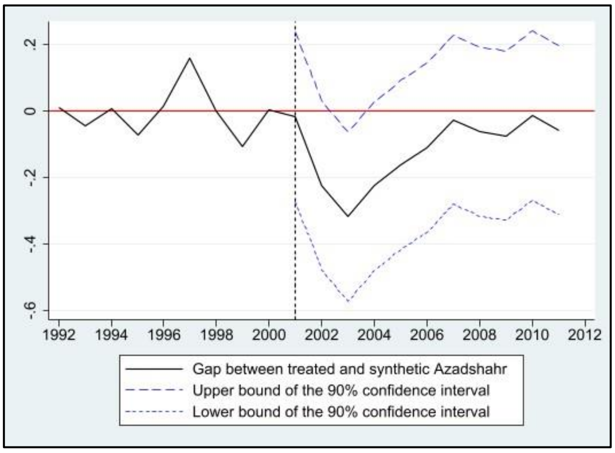
Notes: NTL refers in this table to the natural logarithm of the sum of nighttime light. Population density and natural disaster risk are also used as natural logarithm.

Figure 10 shows the trajectories of the natural logarithm of the sum of NTL of Azadshahr, Galikash, and Minudasht, and its synthetic counterparts in the period 1992 to 2011. We can see that the synthetic versions reproduce the development of NTL of the treated counties in the period before the 2001 flood. The estimate of the effect of the flood disaster is shown by the difference between the treated and synthetic versions of the counties.

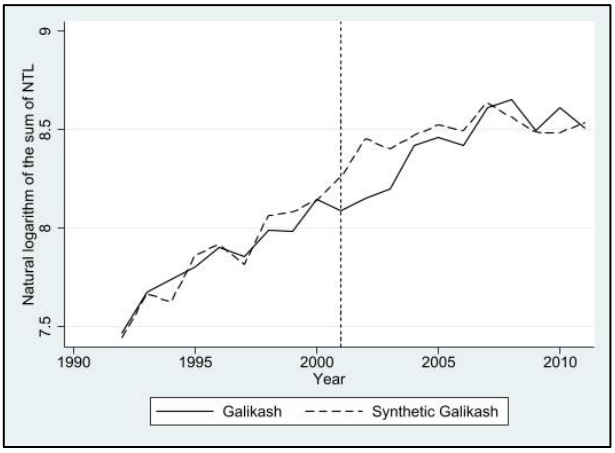
Figure 10: Treated and synthetic trajectories of Azadshahr, Galikash, and Minudasht



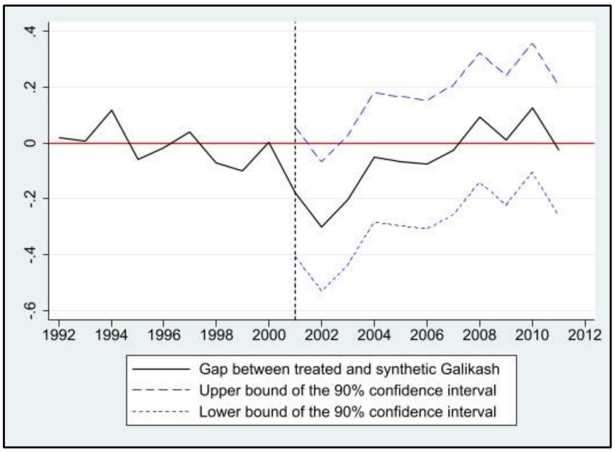
(a) Azadshahr.



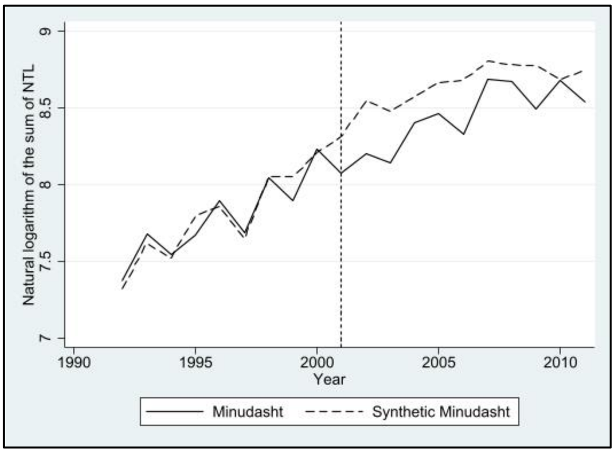
(b) Gap between treated and synthetic Azadshahr including confidence sets.



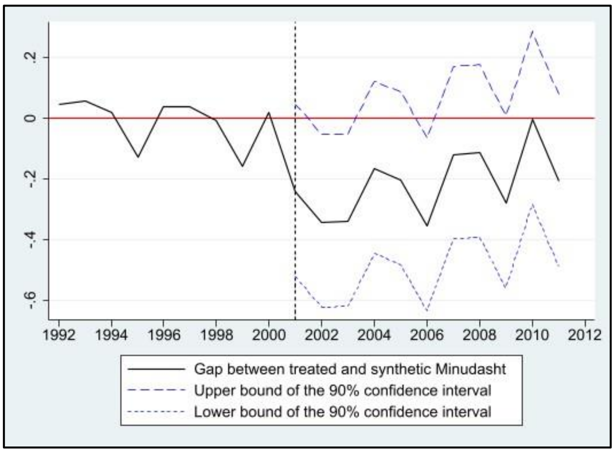
(c) Galikash.



(d) Gap between treated and synthetic Galikash including confidence sets.



(e) Minudasht.



(f) Gap between treated and synthetic Minudasht including confidence sets.

In Figure 10a, we can see that treated Azadshahr shows a drop of NTL from the year 2000 to the year 2001, and then it stays quite flat for some years. If we interpret the trajectory of synthetic Azadshahr as the NTL development without the flood disaster, we can see that the county will return to its pre-disaster development path in the year 2007, that means after about six years after the disaster event. The estimation for Galikash County is presented in Figure 10c and shows a similar development. There is a drop of NTL after the year 2000, and after about four years, the county returns to it pre-disaster development path. Figure 10e presents the results for Minudasht County which is the county that was mentioned in several sources as the most affected by flood events in the studied time period (Sharifi, Samadi, and Wilson 2012).

Next to the flood events in 2001 and 2002, Minudasht County was also affected by two other floods in 2005, as we can see in the graph. Therefore, we can only interpret the difference between synthetic and treated Minudasht as the combined effect of all these flood disasters. According to our results, Minudasht also returns to its pre-disaster development path after about six years. As presented in Figure 10, we have also calculated the uniform confidence bounds (Firpo and Possebom 2018; Ferman, Pinto, and Possebom 2020) at the 90% level. We can see in all three cases that there is a period after the treatment year 2001, where the confidence sets do not include the zero line which suggests that we can be 90% certain about the true effect of the flood disasters on the economic activity measured with nighttime light in the counties Azadshahr, Galikash, and Minudasht. According to the results, the effect is statistically significant three, two, and five years after the treatment, respectively.

In addition to the confidence intervals, we have also applied several placebo tests which are presented in Figure C 3 to Figure C 5 of the Appendix C. The in-space placebo tests show that our counties of interest have an exceptionally large gap between the treated and synthetic units compared to the gaps of all other counties in the donor pool in the years directly after the treatment. In addition, we calculated the ratio of the post-treatment RMSPE to the pre-treatment RMSPE for Azadshahr (2.14), Galikash (2.15), and Minudasht (3.2). The corresponding pseudo p-values are 0.39 and 0.38 and 0.17 respectively. The ratios seem to be quite low and the p-values too high, but this is because we are looking at the 10-year period after the flood events and it is related to the procedure how the values are calculated. If we reduce the time period after the treatment, we will have higher ratios and lower pseudo p-values.

This problem will also become visible, if we look at the graphs of the in-space placebo tests, where we have large gaps of the other donor pool counties especially after the year 2006. Moreover, this is also supported by the confidence sets in Figure 10 where we can see that there is only a significant effect about 2-5 years after the flood event. This highlights the advantage of the confidence sets in contrast to conventional placebo tests for the SCM. The in-time placebo tests show that the treatment year 2001 produces in all three cases a clear gap directly after the treatment, in comparison to other years. Finally, the leave-one-out tests show that we can create a synthetic version of the treated county with a similar trajectory, even if we exclude counties that have a large weight in the final synthetic control versions. When estimating the penalized synthetic controls (Abadie and L'Hour 2021; Wiltshire 2022), we can see that the gap between the treated and synthetic units becomes wider in all three cases, especially when using OLS-based bias correction. The results are presented in Figure C 6 to Figure C 8 of Appendix C. This shows that the impact of the flood disaster is even larger than previously estimated with the classic synthetic control.

In the final step of the analysis, we will calculate the costs of the flood disaster in US dollar with the help of the estimated gaps and a simple regression of the sum of NTL and the real GDP of Iranian provinces. We will use both the gaps of the classic synthetic control and the penalized synthetic control with OLS-based bias correction. With the following specification, we can determine the association between a one-unit increase of NTL and the real GDP.

$$GDP_t = \alpha + \beta_1 * NTL_t + \varepsilon_t \tag{7}$$

We will use the sum of NTL data of Golestan Province from Li et al. (2020) and the real GDP in billion Iranian Rial (IRR) 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 observation and available data from 2004 to 2019, we estimate the slope coefficient β1 which is 0.195 with an R-squared of 0.71. This means that an increase of the sum of NTL by one unit is associated with an increase of GDP by 0.195 billion IRR. To receive the value in US dollar, we will use the official exchange rate from Central Bank of Iran (CBI 2020) for the respective years. Due to regional heterogeneity and to receive a better fit, we only use data from Golestan Province.

According to our empirical results of the SCM and the statistical inference tests, the impact of the flood event was only statistically significant on the county level which gaps will be used for the calculation of the economic costs. In addition, the length of the impact was different which will also be considered, more precisely Azadshahr and Minudasht showed a gap for 6 years after the event, and Galikash for 4 years after the event. The calculated values quantify the opportunity costs of the flood event, which reflects the hypothetical economic wealth that was lost due to this disaster event. Minudasht has lost about US$247.6 million in six years, Azadshahr around US$186.5 million in six years, and Galikash approximately US$124.4 million in four years (more details in Table C 1 in Appendix C), which makes in total US$558.5 million. When considering the gap of the penalized synthetic control with OLS-based error correction, the estimated loss is significantly higher with US$944 million, as presented in Table C 2 in Appendix C. This calculated loss is an addition of the estimated direct damage of US$400 million for the total flood event in Golestan Province (Sharifi, Saghafian, and Telvari 2002).

4.5 Discussion and Comparison

According to the results of the empirical estimation, there is a reduction of economic activity in Golestan Province and the three counties Azadshahr, Galikash, and Minudasht after the 2001 flood. This is supported by the presented theory (Chhibber and Laajaj 2008; Klomp 2016) and previous empirical studies (Felbermayr and Gröschl 2014; Fabian, Lessmann, and Sofke 2019; Onuma, Shin, and Managi 2021; Felbermayr et al. 2022). However, there is a difference to Chapter 3 of this thesis which showed an increase of economic activity after the 2003 Bam earthquake. If we compare the two case studies, we can find some similarities and some differences. First, we can see that there is only weak evidence of the impact of even the large-scale natural disaster events on the province level in both cases. Previous studies have discussed this problem mainly in the context of the country level (Albala-Bertrand 1993; Cavallo et al. 2013; Fabian, Lessmann, and Sofke 2019), but we show that the impact on a lower administrative level such as the province level might not be strong enough to show a statistically significant effect of a disaster event. This was shown for the case of a large-scale flood and a large-scale earthquake, which have different characteristics. An earthquake has usually an epicenter, and we might expect the impact more concentrated in a certain area, and a flood usually affects larger areas.

Second, we cannot find evidence for a long-term effect of large-scale natural disasters on economic activity in both cases. The three counties mainly affected by the 2001 flood in Golestan returned to their pre-disaster development path after 4-6 years, and Bam County with the epicenter of the 2003 earthquake in Kerman returned to the pre-disaster development path after about 7 years. Fabian et al. (2019) found similar results and showed that the negative effect of earthquakes on NTL development and growth persisted for approximately five years, thus finding no evidence of long-run effects. All the counties in our study and Chapter 3 of this thesis returned to their pre-disaster development path, estimated by the synthetic control, within less than ten years after the event.

Third, there are two main differences in the case studies, namely the type of natural disaster and the impact of the disaster events on the provinces and counties. There has been mixed evidence on the impact of floods and earthquakes on the economy (Loayza et al. 2012; Felbermayr and Gröschl 2014; Klomp 2016; Onuma, Shin, and Managi 2021; Fischer 2021; Felbermayr et al. 2022). According to our results of the two case studies, the flood disaster is associated with a direct negative impact on economic activity in the affected areas, but the earthquake disaster shows a positive impact on economic activity in Bam County and its neighboring counties. If we compare the development of both disaster events, we can recognize several differences that affected the NTL development after the initial impact, of which some have already been discussed by Noy and duPont IV (2018), namely the type and severity of the event, the underlying composition of the economy, and the total area impacted.

The flood in 2001 lasted for about three days and was followed by another large-scale flood in 2002 that lasted for about five days. This postponed and interrupted the reconstruction process, and it blocked the access to the area for helpers. Both flood events affected the North-Eastern Iranian provinces and damaged infrastructure such as streets and bridges which made it more difficult to reach the affected areas (Sharifi, Saghafian, and Telvari 2002; Tourani et al. 2021). Due to the large area affected, it was also more challenging to evaluate the immediate impact and allocate the needed resources for relief. In contrast to the flood events, the Bam earthquake was geographically concentrated with the epicenter approximately 10 km to the South-West of Bam City and the direct damage was concentrated in a radius of about 16 km around the city (Fallahi 2007). After the main earthquake in December 2003, no significant surface ruptures or damage was reported in the area, despite the fact that several aftershocks with lower magnitudes were recorded in the time shortly after the event (Tatar et al. 2005). Therefore, disaster response efforts could start immediately after the main earthquake event, and due to the geographical concentration of the damage, the area was more accessible for helpers.

While the disaster type is a contributing factor to the difference of the two disaster events, because it affected the time span of the impact and the type of damage, we argue that there are additional factors which are responsible for such a huge difference, especially the level of economic development before the disaster events as well as the size of the disaster response and relief efforts. Table 10 compares several economic indicators which are available for the time period before the disaster events. If we compare the provinces Golestan and Kerman, we can see that Golestan does not just have a smaller population size, but also a smaller GDP and GDP per capita than Kerman as well as the average province in the time period 2000-2002. This is also supported by the nighttime light data which show that there was three times as much light emission in Kerman than in Golestan, and the difference of the sum of NTL per capita is very similar to the difference of GDP per capita. In addition, Kerman has a higher Human

Development Index which was calculated by Global Data Lab (GDL 2022). It ranges from 0 to 1 and higher values suggest higher human development, considering health, education, and income.

Table 10: Comparison of selected economic indicators

	Province			County				
	Golestan (2000)	Kerman (2002)	Mean (2000-2002)	Azadshahr (2000)	Galikash (2000)	Minudasht (2000)	Bam (2002)	Mean (2000-2002)
GDP (tn. IRR)	9.06	25.28	26.6					
GDP per capita (mm. IRR)	5.32	8.92	11.41					
Population (thous.)	1,702	2,834	2,332	89.5		128.7	282.3	209.8
Population density	84.4	15.8	104.1	104.5		84.5	48.6	55.7
Sum of NTL	87,088	261,638	179,403	6,047	3,451	3,760	15,115	12,964
Sum of NTL per capita	0.05	0.09	0.08					
HDI	0.65	0.67	0.66					

Notes: GDP data are from MEFA (2021). HDI and population data for provinces are from GDL (2022) and for counties from Census 2006 (SCI 2022)*. NTL data are from Li et al. (2020).*

The population density (people per km²) was higher in Golestan than in Kerman which makes the former more susceptible to natural disasters for two reasons. On the one hand, more people living in a smaller area increase the potential damage of the disaster event, and on the other hand, more people in a smaller area are a larger burden on the environment, for example due to deforestation or other forms of environmental degradation that makes an area more prone to natural disasters. Sharifi et al. (2002) argue that deforestation and the wrong settling strategy belong to the factors that turned heavy rainfall into a flood disaster in Golestan Province.

While focusing on the county-level NTL data, we can find similar differences between Golestan and Kerman, which has less data available. The sum of NTL shows that Bam had more than four times as much light emission than Galikash and Minudasht, and more than two times as much as Azadshahr. In addition, Bam had a larger population than the three studied counties Azadshahr, Galikash, and Minudasht. The values for Galikash are included in Minudasht because it was only separated in 2010. Overall, we can see that Kerman was more economically developed and industrialized than Golestan before the impact of the disasters, which gives the former better coping capacities and better conditions for turning disaster relief inflows into economic development.

This leads to other differences between the two natural disasters, namely the size of disaster relief inflows, the reconstruction efforts, and the media attention, which are all interlinked. In the case of the 2001 Golestan flood, there was immediate help from national organizations and efforts from the United Nations (UN) office in Tehran. One day after the start of the flood event, about 350 volunteers and 50 vehicles were mobilized in Golestan Province, as well as seven Iranian Red Crescent Society (IRCS) and army helicopters evacuated about 15,000 people. The IRCS distributed more than 150 tons of food, tents, blankets, and other necessary goods. Additionally, the UN office in Tehran sent a team to Golestan Province six days after the start of the flood disaster to assess the damage. This mission was initiated by the United Nations Development Programme (UNDP) and the team returned on 25 October 2001 (OCHA 2001a; 2001c; 2001b). Despite the death of more than 300 people and an estimated damage of US$400 million, there was relatively little international help reported, for example medicine, clothing, blankets, and food from Kuwait. The Financial Tracking Service of OCHA did not report any funding in response to the 2001 flood.

In contrast, after the impact of the 2003 Bam earthquake, there was a total funding of US$130.2 million from more than 20 international donors (OCHA 2004a). Similar to the other disaster, there was an immediate response by the IRCS, government agencies, military forces, and other volunteers. In addition to the national disaster response, there was international assistance by more than 100 international organizations and countries. Within one week, the International Federation of Red Cross and Red Crescent Societies (IFRC) established a 150-bed field hospital in Bam and drove 15 trucks of donations into the affected area (OCHA 2004b). The IRCS was able to mobilize about 8,500 relief volunteers, and nearly 12,000 people were airlifted and taken to hospitals in other provinces. In addition, many volunteers from various sectors of Iranian society poured into the region to help those affected, and other people 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; K. A. Hosseini, Hosseinioon, and Pooyan 2013; Yuan et al. 2018).

Several camps and temporary shelters for the homeless were constructed, and until 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 of charge and long-term bank loans to families who lost their homes. The main reconstruction efforts finished in 2007, and the IFRC ended its mission in February 2007 (OCHA 2007; Ghafory-Ashtiany and Hosseini 2008). Overall, we can see that not just the impact of the 2003

Bam earthquake was much larger than the 2001 Golestan flood, but also the relief efforts. With almost 30,000 deaths, the Bam earthquake was about hundred times more deadly than the 2001 flood. The same can be observed with the financial damage which was about US$700 million in the case of the Bam earthquake, and thus almost double the size of the higher estimation of US$400 million of the Golestan flood. In Chapter 3 of this thesis, we argue that the Bam earthquake has received an enormous amount of national and international attention, because of the extremely high death count and the destruction of major parts of a famous city with a UNESCO World Heritage Site. This helped to gain more media attention, and thus more post-disaster aid inflows, which the Golestan flood did not experience.

4.6 Conclusion

Following the approach of Chapter 3 of this thesis, we have looked more closely at the 2001 flood in the Iranian Golestan Province. We used the synthetic control method (SCM) to estimate the development of nighttime light (NTL) in Golestan Province and its three counties Azadshahr, Galikash, and Minudasht. With the gap of NTL between the treated and synthetic versions of the three counties, we calculated the true economic costs of the 2001 flood which has the combined size of US$558.5 million in the three mainly affected provinces. This is not just higher than the previously estimated damage of US$400 million (Sharifi, Saghafian, and Telvari 2002), but it also reflects the additional costs of the disaster event, because it does not reflect the damage on capital but the loss in economic development. Like Chapter 3 of this thesis, we only found significant effects on the county level, and we did not find a long-term impact, defined as at least ten years. According to our results, the three studied counties (Azadshahr, Galikash, and Minudasht) returned to their pre-disaster development paths, measured by the synthetic control, after less than ten years, more precisely six, four, and six years, respectively.

Moreover, we have shown that the development of economic activity after the impact of a natural disaster event can turn both positive or negative in the short and intermediate term, which supports theoretical models (Albala-Bertrand 1993; Skidmore and Toya 2002; Chhibber and Laajaj 2008; Klomp 2016). In this context, we have identified that these differences exist mainly due to following reasons: the disaster type, the geography, the type of damage, the pre-disaster economic development of the county, the media attention, and the size of the disaster aid inflows. With this study, we have provided supporting results and arguments for Chapter 3 of this thesis, and especially the comparison of the two cases has provided new insights into the dynamics of the reconstruction process and its impact on economic development in the short and intermediate term.

An additional contribution of this study is, that we used NTL and GDP data to calculate the costs of the 2001 in US dollar. These costs refer the hypothetic loss of economic activity as a consequence of the disaster event, so it exceeds damage estimations that only focus on the direct economic damage. This also shows that the economic costs of natural disasters are usually underestimated. Even the estimated value based on the classical synthetic control might be underestimated, as the value of the penalized synthetic control shows.

5. Disaster Literacy in Iran: Survey-based Evidence from Tehran

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Abstract

Based on a survey with 502 participants which was conducted in 2020/2021, this study investigates the state of disaster literacy in the Iranian capital, Tehran, which is one of the main metropolitan areas of the country. The results of the empirical investigation using logistic regressions suggest that the household's income level, the trust in Iran's natural disaster management, the fear of natural disasters, the perceived frequency of natural disasters, and internet usage show positive associations with the disaster literacy items. Additionally, we created a disaster literacy index (DLI) for Tehran City, ranging from 0 to 100, using 14 disaster literacy items. With ordinary least squares (OLS) estimations and the final index, we provide additional evidence of the previous findings. When comparing the average DLI scores of Northern and Southern phone districts, we reveal a spatial inequality within Tehran City, where the Northern subsample has significantly higher DLI scores than the Southern subsample.

JEL Codes:

C83, D91, H84, P46, Q54

Keywords:

Natural disaster; natural hazard; disaster literacy; disaster preparedness; Iran; survey, inequality

Funding:

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5.1 Introduction

Iran is a disaster-prone country that has experienced more than 250 natural disasters over the past century, including floods, earthquakes, droughts, storms, and others, which affected accumulated more than 60 million people, while killing at least 158,350 people, and causing an estimated damage of more than US$53 billion (adjusted for inflation). In the same period (1922-2021), Tehran and its neighboring provinces (Alborz, Markazi, Qazvin, and Qom) experienced 28 natural disasters, mainly floods and earthquakes, killing at least 55,769 people, affecting around 11 million people, and causing an economic damage of about US$22 billion (EM-DAT 2021).

Especially urban areas that are highly populated such as the capital Tehran are at risk to suffer devastating consequences from natural hazards. Next to the geographical location of vigorous seismic activity with several active fault lines that extent through the city, which have not been considered while constructing most buildings, it is highly vulnerable to earthquakes. Due to the city's geomorphological characteristics (mountains in the north, piedmont zone in the center, and desert in the south), it is vulnerable to flash floods and the overflow of rivers because the watercourses flow through the city on a north-to-south axis (Moghadas et al. 2019). This makes it crucial to educate citizens in terms of disaster preparedness, and thus strengthen disaster resilience and improving individual disaster literacy, which might prevent the harm of people and the loss of lives.

In this study, we evaluate the state of disaster literacy in Tehran City with a self-developed survey, using computer-assisted telephone interviews (CATI). This provided us a cross-sectional dataset of 502 respondents which were interviewed in December 2020 and January 2021. We are using logistic regression models to determine the association between the experience of natural disaster events, among other characteristics, and several items that measure the respondents' disaster literacy.

The research question is the following: *What are the main determinants of disaster literacy within the population of Tehran City?* After identifying the main determinants of disaster literacy, we create a disaster literacy index (DLI) with four stages, namely basic disaster literacy, functional disaster literacy, interactive disaster literacy, and critical disaster literacy, based on Brown et al. (2014). With the DLI and its four stages as dependent variables, we will additionally investigate the determinants of disaster literacy with the method of ordinary least squares (OLS).

The contribution of this study is that it provides new empirical evidence for the individual characteristics that shape disaster preparedness and disaster literacy in a disaster-prone country.

It will add new insights to the existing studies on disaster literacy that have mainly focused on other regions than the Middle East and North Africa (MENA), especially East Asia and Sub-Saharan Africa (Abdul Rahim and Wu 2015; S.-C. Chung and Yen 2016; Daramola, Odunsi, and Olowoporoku 2018; Zhang et al. 2021), despite the abundance of natural hazards in MENA. Moreover, this is the first time that a disaster literacy index was created for the case of Tehran or Iran, which can also provide some lessons for other urban areas in the country. We build on previous studies on disaster preparedness in the city of Tehran (Najafi et al. 2015; K. A. Hosseini et al. 2014; Taghizadeh et al. 2012) and other parts of Iran (Ardalan et al. 2020; Rostami-Moez et al. 2020; Mahdaviazad and Abdolahifar 2014).

The difference to these studies is that we focus on disaster literacy that captures several dimensions of the people's relationship with natural disasters, ranging from the basic understanding of natural disasters to an active role of being a helper in the case of a disaster event. In addition, we follow up older studies on the residents of Tehran, and thus provide an update to the disaster preparedness of residents in the Iranian capital. The remaining chapter is structured in the following way: Section 5.2 gives an overview of the relevant literature related to the topic and Section 5.3 presents the data and methodology. In Section 5.4, the results are presented and discussed, and Section 5.5 concludes the chapter.

5.2 Literature Review

The concept of disaster literacy that is closely related to other concepts such as disaster experience, risk perception, and disaster preparedness, can be defined as "an individual's capacity to read, understand, and use information to make informed decisions and follow instructions in the context of mitigating, preparing, responding and recovering from a disaster" (Brown, Haun, and Peterson 2014).

5.2.1 Theoretical Background

The discrepancy between the needs and abilities of particularly vulnerable groups and existing disaster information and the preparation of educational material led Brown et al. (2014) to develop a model to address this problem. Their model can be explained as follows. Disaster literacy represents a continuum in which knowledge and skills are positioned in an increasing order. The lowest stage is basic disaster literacy, which represents the basic ability to read and understand. The second stage is functional disaster literacy and reflects the ability to understand disaster preparedness, disaster response, and disaster recovery messages. The third stage, the communicative or interactive disaster literacy, represents advanced skills involved in seeking help and managing disaster-related experiences. It is completed by the fourth stage, critical disaster literacy. This category includes the capacity to analyze disaster-related information, be empowered to address barriers, and take personal control to stay safe, manage and recover from disasters. Paasche-Orlow and Wolf (2007) supplement this continuum by a concept in which they consider literacy in the context of predisposed, patient-related internal factors as well as external factors that influence an individual.

In the model of Brown et al. (2014), patient factors and external factors refer to a disaster situation. In the case of a catastrophe, patient factors include their navigation skills, knowledge, beliefs, motivation, or perceived barriers. External factors include complexity (of a disaster), available resources, assistive technologies, or mass media. These factors consequently influence disaster literacy and corresponding outcomes. By including individual capabilities, they aim to meaningfully expand existing models, such as the CERC (Crisis and Emergency Risk Communication) model discussed by Veil et al. (2008) which was designed as a framework to expand communication responsibilities for public health issues in hazardous situations. It includes various communication concepts, instruments, and methods and places them in a five-step, strategy-led development model.

An important aspect regarding the disaster literacy model is to consider the spheres in which a person's understanding of disaster mitigation, preparation, response, and recovery is located. Brown et al. (2014) mention three spheres: (1) the state and local emergency operations systems responsible for delivering warnings and mobilizing recovery efforts; (2) the varied commercial and nonprofit service providers that people rely on before and after a disaster, such as transportation, emergency shelter, medical and mental health, water and electric utilities; and (3) the resources and factors that influence a person`s inclination and ability to deal with a disaster, such as support services, the media and other sources of information.

However, the concept of disaster literacy is still in its infancy, but it is recently gaining an increasing amount of attention, for example due to its significant benefits to the individual and public health and the sustainability of healthcare systems (Çalışkan and Üner 2021; Liu et al. 2020). A review of the literature on disaster literacy reveals that in the case of the terminology of disaster literacy, distinctions are blurred, and various terms are used synonymously. As examples, the terms ‘disaster prevention literacy’ (Abdul Rahim and Wu 2015; S.-C. Chung and Yen 2016), ‘disaster management literacy’ (Daramola, Odunsi, and Olowoporoku 2018), and ‘disaster awareness’ (Dikmenli, Yakar, and Konca 2018) can be cited.

Caliskan and Üner (2021) conducted the first effort to organize the various concepts systematically with the aim to develop an integrated definition and a conceptual model covering the different disaster literacy dimensions. They analyzed the definitions of disaster literacy presented in several studies and conceptualized their following definition of disaster literacy: “Disaster Literacy is individuals’ capacity to access, understand, appraise, and apply disaster information to make informed decisions and to follow instructions in everyday life concerning mitigating/prevention, preparing, responding, and recovering or rehabilitation from a disaster in order to maintain or improve quality of life during the life course” (Çalışkan and Üner 2021). Additionally, the authors illustrate an existing dichotomy in research on disaster literacy. On the one hand, there is a research line that leads their work on disaster literacy on a theoretical level (Brown, Haun, and Peterson 2014; C.-Y. Chen and Lee 2012; Kanbara et al. 2016; B. Seif, Ghanizadeh, and Seyedin 2018), and on the other hand, there is research on disaster literacy that is driven by an applied methodology in the form of surveys (Abdul Rahim and Wu 2015; Daramola, Odunsi, and Olowoporoku 2018; S.-C. Chung and Yen 2016; Zhang et al. 2021).

5.2.2 Previous Empirical Studies

As we conducted a survey to evaluate the state of disaster literacy in Iran, we will discuss several survey-based related studies from other countries in the following. Abdul Rahim and Wu (2015) used the disaster prevention literacy model of Chen and Lee (2012) to assess the knowledge, skills, and attitude of Taiwanese students related to an earthquake disaster, and they found that citizens with at least elementary school education are in possession of some knowledge about earthquakes. This supports the importance of school curricula that equip students with disaster recognition knowledge. Additional evidence on the case of Taiwan comes from Chung and Yen (2016), who show that elementary school administrators and teachers had a higher disaster prevention literacy, and older participants with a long time of service, working at disaster-stricken schools, and with personal experiences of disasters had a higher disaster prevention literacy.

Daramola et al. (2018) focused on disaster management literacy in Nigeria and developed a Disaster Severity Index, which includes several dimensions, such as (1) the types and frequency of experienced disasters, (2) the sources, types, and manners of the utilization of disaster-related information available to the households, and (3) the effects of available disaster-related information on disasters’ impacts. Their results suggest that the disaster management literacy in the investigated area has potential for improvement, especially among women, and in terms of distribution of information about pre-, during-, and post-disaster management.

Additionally, Zhang et al. (2021) study the state of disaster literacy in China. Using the disaster literacy concept by Brown et al. (2014) and their own model, they conducted a survey in five Chinese provinces. The evaluation of the collected data showed that the average score was 87.85 out of 160 points, indicating that the participants had low disaster literacy. Their empirical investigation revealed that socio-economic characteristics such as age, the field of study, grade, place of residence, educational level of parents, and employment had a positive effect on the disaster literacy score, as did the experience of natural disasters, previous disaster training, and preparation within the family.

While there are a relatively small number of empirical studies on the concept of disaster literacy, there is an overwhelming number of studies that deal with disaster preparedness, risk perception, and risk reduction in the context of natural disasters. These authors mainly focus on certain socio-economic characteristics that are important in the context of the mentioned concepts, for example gender (Cvetkovic et al. 2018; Tyler and Fairbrother 2018; Oral et al. 2015), age (Al-rousan, Rubenstein, and Wallace 2015; Hattori et al. 2021; Kim and Zakour 2017; Rosenkoetter et al. 2007), income (Martins et al. 2018; 2019; De Silva and Kawasaki 2018; Ferdinand et al. 2012), education (Hoffmann and Muttarak 2017; Botzen, Aerts, and van den Bergh 2009), religiosity (Rhys Lim et al. 2019; McGeehan and Baker 2017; Bentzen 2019; Sibley and Bulbulia 2012), homeownership (Thistlethwaite et al. 2018; Josephson, Schrank, and Marshall 2017), marriage (Hung 2017), fear (Aronson 2008; Wirtz, Rohrbeck, and Burns 2019), and trust in government (Choi and Wehde 2020; Gotanda et al. 2021; Q. Han et al. 2021; Z. Han et al. 2017). Previous disaster experience and disaster training as well as threat and risk perception are also important aspects, as numerous studies have shown (Castañeda et al. 2020; Cui and Han 2019; Shapira, Aharonson-Daniel, and Bar-Dayan 2018; Onuma, Shin, and Managi 2017; McLennan, Marques, and Every 2020; Karanci, Aksit, and Dirik 2005; Xu et al. 2018; Basolo, Steinberg, and Gant 2017).

This research is the first of its kind dedicated to the concept of disaster literacy in Iran, but there have been several studies from Iran that focused on various aspects of natural disasters in Iran, including disaster preparedness (Ardalan et al. 2020; Rostami-Moez et al. 2020; Najafi et al. 2015; K. A. Hosseini et al. 2014; Mahdaviazad and Abdolahifar 2014; Izadkhah and Hosseini 2010; K. A. Hosseini et al. 2019; Taghizadeh et al. 2012). Three of these survey-based studies focused on the city of Tehran using different samples and methodologies in the years 2009, 2013, and 2014, but none of these studies was as comprehensive as our survey in terms of the development of the questionnaire and the empirical strategy. Taghizadeh et al. (2012) and Hosseini et al. (2014) only focused on earthquake preparedness. Najafi et al. (2015) studied the socioeconomic determinants of disaster preparedness behaviors, but did not include questions about the fear of natural disasters or the opinion on Iran's disaster management, among others, that we have included in our survey. The other mentioned studies have focused on other administrative units such as the city of Shiraz, Hamadan Province, or the whole of Iran

(Mahdaviazad and Abdolahifar 2014; Ardalan et al. 2020; Rostami-Moez et al. 2020). There are also several case studies that focus on the disaster preparedness related to specific earthquake disasters, for example Izadkhah and Hosseini (2010) and Hosseini et al. (2019) who evaluated disaster preparedness after five major earthquakes in Iran.

5.3 Data, Hypotheses, and Methodology

5.3.1 Data

In this study, we evaluate the state of disaster literacy in Tehran using cross-sectional data of a self-developed survey, collected by computer-assisted telephone interviews (CATI)[6]. The theoretical framework from Brown et al. (2014) and previously discussed empirical studies were used as a basis for the development of the questionnaire. It consists in total of 61 questions, including 32 questions capturing aspects related to the experience with natural disasters and the disaster literacy items, as well as 29 questions related to socioeconomic characteristics and personal attitudes. The questionnaire was tested for reliability using Cronbach's alpha which resulted in a value of 0.89, indicating a good internal consistency (Tavakol and Dennick 2011). The interviews were conducted between 28 December 2020 and 8 January 2021 among a representative sample of 502 Iranian residents of Tehran City. The margin of error of the sample is approximately +/- 4.4%.

To achieve a sample that represents the residents of Tehran, we have used a multi-stage cluster sampling with four stages, as presented in Figure D 1 in Appendix D. This is a consequence of the arrangement of the landline telephone numbers (first stage) which have eight digits, where the first two digits identify one of the seven phone districts, and the second two digits identify the exchange, followed by four digits identifying the household. According to the percentage of the population living in the telephone district, the number of telephone interviews in the corresponding district were conducted. Since the population covered by the exchanges is unknown, the second stage involved distributing the interviews evenly among the respective exchanges. In the third stage, the random digit dialing (RDD) sampling method was used at each telephone area code to reach random households in Tehran, where in the fourth stage a randomly selected household member was chosen. On basis of the standard definitions of the American Association for Public Opinion Research (AAPOR 2016), the contact rate of the survey was 88.9%, the cooperation rate 82%, and the overall response rate 70%. The interviews lasted 17-67 minutes, correlating with age and education, with an average of 33 minutes.

[6] The survey was conducted by IranPoll (www.iranpoll.com), and it was financially supported by German Academic Exchange Service (DAAD Project ID: 57526976) (www.daad.de), Bourse & Bazaar Foundation (www.bourseandbazaar.com), and Institute of International Education (IIE) (www.iie.org).

Due to the random sampling procedure to determine the survey participants, we have a representative distribution of characteristics such as age, gender, marital status, education, and employment status. To further highlight the representativeness of the sample, a comparison with the results of the official Iranian 2016 Census (SCI 2018) shows that shares of the mentioned characteristics come close to the population of Tehran City. The small differences in age, education, and employment, might be explained by the survey design, because phone interviews can only reach certain demographics. Thus, we need to keep this in mind when interpreting the results. A more detailed comparison of characteristics is presented in Table D 1 in Appendix D.

5.3.2 Hypotheses

Based on the theory and previous empirical results, we have developed several hypotheses that will help to answer the following research question: *What are the main determinants of disaster literacy within the population of the Tehran City?* We are interested to learn how disaster literacy is affected by previous experience with natural disasters, emotions towards natural disasters, level of education, household income, and specific natural disaster trainings. This leaves us with the following five hypotheses:

Hypothesis 1: Having experienced natural disasters is associated with a higher probability of being disaster literate.

The hypothesis was formulated under the assumption that experiencing a natural disaster changes an individual's perception of it. Thus, previous experience with natural disasters can be associated with higher disaster literacy, which also has been shown by previous studies (Zhang et al. 2021; Rostami-Moez et al. 2020; S.-C. Chung and Yen 2016; Hoffmann and Muttarak 2017; Najafi et al. 2015; Taghizadeh et al. 2012). However, these studies only show a significant difference when not controlling for other factors, except for Hoffmann and Muttarak (2017), and the two studies on Iran show that there is only a significant effect for the experience of destructive earthquakes, but not for the experience of natural disasters in general (Rostami-Moez et al. 2020; Taghizadeh et al. 2012).

Hypothesis 2: Fearing natural disasters is associated with a higher probability of being disaster literate.

The underlying assumption of this hypothesis is that the fear of disaster events happening will lead to the situation where the individual will educate themselves to be prepared for the occurrence of the events. Psychological studies, however, have shown that this is not always the case. Aronson (2008) illustrates with two examples from the United States how the fear of disasters, on the one hand, can be used to influence people's behavior, and on the other hand does not necessarily lead to people becoming more disaster literate. He argues that people need recommendations for actions that are concrete, effective, and doable, otherwise they will fall into a state of denial. Additionally, Wirtz et al. (2019) found that anxiety may simultaneously both positively and negatively influence the undertaking of precautionary behaviors through three paths, namely a positive path mediated by perceived vulnerability, a negative path mediated by self-efficacy, and a direct negative effect. The role of fear was not yet discussed in previous studies on disaster preparedness in Iran.

Hypothesis 3: A higher level of education is associated with a higher probability of being disaster literate.

As education is associated with gaining more knowledge, we assume that the education system will also transfer knowledge about natural disasters, especially in a disaster-prone country like Iran. An example for the implementation of earthquake response measures in the primary school curriculum can be found in Taiwan (C.-Y. Chen and Lee 2012) and there are school drills related to earthquakes in Iran on a regular basis since 1996 (K. A. Hosseini and Izadkhah 2020). A positive association between higher levels of education and higher levels of disaster preparedness was shown by several studies from Iran (Taghizadeh et al. 2012; Ardalan et al. 2020; Rostami-Moez et al. 2020). In contrast, Najafi et al. (2015) did not find statistically significant associations between education and disaster preparedness for residents in Tehran. Moreover, Botzen et al. (2009) show for the case of the Netherlands that increasing knowledge about causes of flooding will increase the risk awareness, and a higher education level is associated with lower risk awareness. This means that general education will not increase disaster literacy, but only specific disaster training will do. Additionally, Hoffmann and Muttarak (2017) show based on surveys from the Philippines and Thailand that the effect of education depends on the context, for example it only enhances disaster preparedness in households that did not experience disasters. The authors argue that education improves abstract reasoning and anticipation skills which means that better educated people will undertake preventive measures without needing to first experience the disaster and then learn later.

Hypothesis 4: Being from a wealthier household is associated with a higher probability of being disaster literate.

Due to the better access to financial resources and information, we assume that high-income households are more disaster literate. This hypothesis is supported by previous findings of Martins et al. (2018; 2019) in their study of disaster preparedness in New York. According to their results, low-income households are more vulnerable during a disaster event, because they are less able to access communication technologies to search for self-protective disaster information and to communicate their needs during an emergency. Some of the studies on the case of Iran also included measurements of household income and came to similar conclusions (Rostami-Moez et al. 2020; Najafi et al. 2015). In contrast, Ferdinand et al. (2012) show with a case study from the Caribbean that poor communities can have strong mechanism to manage disasters, because of the strong social capital, but this is difficult to harmonize with broader community efforts to address disaster risk reduction. The authors argue that poverty acts as a double bind because it ties poor people together in coping with the disaster event, and the coping mechanism creates a barrier for engagement of other organizations that aim to reduce vulnerability and build resilience.

Hypothesis 5: Trusting Iran's natural disaster management is associated with a higher probability of being disaster literate.

This hypothesis is based on the assumption that the trust in the political and economic institutions of the country, especially those related to natural disaster management, will convince the citizens to educate themselves in disaster preparedness and become more disaster literate. The positive association between trust in government and natural disaster preparedness was already discussed by several authors, for example in a case study from the United States (Choi and Wehde 2020). Their results suggest that trust in the Federal Emergency Management Agency (FEMA) and trust in the local government are both statistically significant and positively associated with emergency preparedness, while trust in the federal government showed the opposite effect. This means, when people believe that FEMA and local governments will provide effective assistance to people and their community in the case of a natural disaster, they tend to prepare for emergency situations more. In contrast, Han et al. (2017) provide evidence for a negative association between trust in government and disaster preparation behavior. The authors focus on earthquake survivors of the 2010 Yushu earthquake that have already experienced government support, and therefore might not see the necessity to prepare themselves for future disaster events. These results follow the Samaritan's dilemma[7] argument in the context of natural disaster prevention and relief (Cohen and Werker 2008; Raschky and Schwindt 2016). The role of trust in Iran's natural disaster management was not yet discussed in previous studies on disaster preparedness in Iran.

5.3.3 Methodology

Our empirical analysis has three steps. First, we select 14 items from the 61 interview questions that reflect the individual disaster literacy. For the empirical investigation of the determinants of disaster literacy, we are using logit regressions. In the second step, we create a disaster literacy index (DLI) for the city of Tehran, which represents the four stages of disaster literacy, namely basic disaster literacy, functional disaster literacy, communicative/interactive disaster literacy, and critical disaster literacy. Finally, in the third step, we use OLS estimations to find the main determinants of disaster literacy among citizens of Tehran. For the first empirical analysis using logit regressions, we have recoded the 14 disaster literacy items from a five-point Likert scale to binary variables. These binary variables are the dependent variables in the following specification:

$$DL_i = \alpha + \beta_1 \cdot Fear_i + \beta_2 \cdot Frequency_i + \beta_3 \cdot Experience_i + \beta_4 \cdot Training_i + \beta_5 \cdot Trust_i + \beta_6 \cdot Controls_i + \varepsilon_i \quad (8)$$

We aim to explain each of the 14 disaster literacy items (*DL*) by the respondents' feelings towards natural disasters (*Fear*), the perception about the frequency of natural disasters (*Frequency*), the experience with natural disasters (*Experience*), previous disaster trainings (*Training*), and the trust in Iran's disaster preparedness (*Trust*). Previous disaster training will not be included in the estimation where it is the dependent variable. Constant (α) and error term (ε) are also included. In addition, we control for several other socio-economic characteristics (*Controls*) that are relevant in the context of natural disaster literacy, such as age, gender, marital status, religiosity, internet usage, household size, house ownership, employment status,

[7] The Samaritan's dilemma describes a moral hazard in the context of natural disasters and refers to the situation that governments will not or very little invest in disaster prevention, if disaster relief is free, for example due to the inflow of international disaster relief. This dilemma can also be applied to the individual or household level, where it might be costly to invest in disaster prevention, both in terms of disaster-proof infrastructure and disaster training. Having effective and free public disaster management institutions might therefore disincentivize citizens to prepare for natural disasters by themselves.

household income, level of education, and phone district. Except for age and household size, all explanatory variables are binary. Moreover, we consider the four-stage survey design, when declaring the primary sampling unit (PSU), the strata, and the weight. These will be used to calculate the Taylor-linearized standard errors (Wolter 2007). Due to missing answers for some of the questions, the sample in the estimations was reduced, but it still has a similar distribution of characteristics compared to the official Iranian 2016 Census (SCI 2018) and the full sample, as Table D 1 in Appendix D shows. The F-statistics are calculated using an adjusted Wald test which considers the survey design (Korn and Graubard 1990).

In the next step, we use the replies of 14 survey questions to construct the disaster literacy index (DLI) for the city of Tehran that ranges from 0 to 100, where 0 means no disaster literacy and 100 the highest possible disaster literacy according to our definition. The aim is to represent the four stages of disaster literacy discussed by Brown et al. (2014), namely basic disaster literacy (3 questions), functional disaster literacy (3 questions), communicative/interactive disaster literacy (4 questions), and critical disaster literacy (4 questions). As the quality of disaster literacy increases over the four stages, we will use different weights in the final index, so that the first stage counts 10 points, the second stage 20 points, the third stage 30 points, and the fourth stage 40 points. This will also counteract the different number of questions in each stage. The final index will be calculated as follows:

$$DLI = \left(\frac{10}{12} \cdot \sum_{i=1}^{3} q_i\right) + \left(\frac{20}{12} \cdot \sum_{i=4}^{6} q_i\right) + \left(\frac{30}{16} \cdot \sum_{i=7}^{10} q_i\right) + \left(\frac{40}{16} \cdot \sum_{i=11}^{14} q_i\right) \tag{9}$$

At the first stage (A: basic disaster literacy), which is reflected in the first parentheses in equation (9), three questions (q) were asked related to basic reading and comprehension of disaster-related information (see Q1-Q3 in Table 11). As we were using a five-point Likert-scale from 0 to 4, the maximum of the sum of points is 12, or after weighting 10 points, which each respondent can achieve in this stage. We divide the sum in this stage by 12, as we have three questions with a maximum score of 4, to control for the different number of questions in each stage, and then multiply it with 10 to give it the weight of 10% in the final score. At the second stage (B: functional disaster literacy), which is reflected in the second parentheses in equation (9), another three questions (q) were asked (see Q4-Q6 in Table 11). After weighting, the maximum score in this category is 20 points.

The third stage (C: communicative/interactive disaster literacy), which is reflected in the third parentheses in equation (9), includes four questions (q) related to advanced skills in seeking help and managing disaster situations (see Q7-Q10 in Table 11). As we were using a five-point Likert-scale from 0 to 4, the maximum of the sum of points is 16, or after weighting 30 points, which each respondent can achieve in this stage. We divide the sum in this stage by 16, as we have four questions with a maximum score of 4, to control for the different number of questions in each stage, and then multiply it with 30 to give it the weight of 30% in the final score. Finally, the fourth stage (D: critical disaster literacy), which is reflected in the fourth parentheses in equation (9), addresses skills concerning analyzing disaster-related information, empowerment to address barriers, and the ability to take personal control to stay safe, cope with, and recover from disasters (see Q11-Q14 in Table 11). It consists of four questions (*q*), and in this last category the maximum score is 40 points after weighting.

Once we have calculated the disaster literacy index (DLI) for each respondent, we continue with the third step of our analysis. In this empirical investigation, we are using an OLS regression to study the relationship between the DLI and several disaster-related questions as well as different socio-economic characteristics. We are using our sample of 418 respondents and equation (8), where the dependent variable is our disaster literacy index (*DLI*) ranging from 0 to 100, and it will be explained by several explanatory variables, of which some refer to our five hypotheses. We will use the same explanatory variables described under equation (8). The variable *Experience* is used to investigate Hypothesis 1, and the variable *Fear* refers to Hypothesis 2. Additionally, we added several control variables (*Controls*), of which four are utilized to study Hypothesis 3 and Hypothesis 4. The variable *Trust* refers to Hypothesis 5. The constant (α) and error term (ε) are also included. Like in previous estimations, we will use the Taylor-linearized standard errors.

5.4 Results and Discussion

The description of responses of the 14 disaster literacy items as well as seven other relevant questions is presented in Table 11. Additional socio-economic characteristics are presented in Table D 1 in Appendix D.

Table 11: Answers to survey questions (shares in percent), Tehran

Number	Label	Question	n	[0]	[1]	[2]	[3]	[4]
Q1 (A)	Reading	During the past year, how much have you read material related to natural disasters?	501	28.3	23.4	38.7	8.2	1.4
Q2 (A)	Understanding	To what degree do you agree or disagree that you need to increase your understanding of natural disasters? (Reversed coding)	496	54.2	33.1	8.7	2.4	1.6
Q3 (A)	Knowledge	In your opinion, how much various aspects of natural disasters are known to scientists?	488	2.9	9	40.8	29.7	17.6
Q4 (B)	Warnings	During the past month, to what degree have you seen or heard messages that encourage people to take steps to become prepared for an emergency?	496	62.7	21.6	11.5	2.6	1.6
Q5 (B)	Information	In case of a natural disaster, to what degree are you aware of where you should receive essential information from?	498	21.3	23.1	42	8.6	5
Q6 (B)	Organizations	To what degree are you aware of organizations in Iran who are responsible for reducing the damage of natural disasters?	500	35.4	22.6	33.8	3.6	4.6
Q7 (C)	Evacuation	In case you needed to evacuate your house during a natural disaster, to what degree are you aware of the routes you should use?	497	3.6	1.8	22.3	35.6	36.6
Q8 (C)	Family	After a natural disaster, how necessary do you think it is to try to establish contact with your parents or relatives to inform them that you are safe?	500	1.8	1.2	1	15.4	80.6
Q9 (C)	Authorities	In case of a natural disaster, to what degree are you aware of which government agency you should contact?	501	26.2	21.6	32.3	7.6	12.4
Q10 (C)	Training	How much have you participated in a practice or drill to prepare for a natural disaster?	500	65.6	16	13.4	3.6	1.4
Q11 (D)	Awareness	To what degree are you aware of which kinds of natural disasters are more likely to occur in the region you live?	499	20	18	41.5	7.4	13
Q12 (D)	Shelter	In case your house become inhabitable because of a natural disaster, to what degree are you aware of where you can stay?	501	45.3	18.4	23.4	6	7
Q13 (D)	First Aid	In case of an emergency, how prepared do you think you are to provide basic first aid?	498	24.3	27.7	37.2	5.8	5
Q14 (D)	Assistance	If the area you live were to be struck by a natural disaster, to what degree do you think you would be able to assist the rescue workers and help those affected by the natural disaster?	495	15	23.8	42	11.7	7.5
Q15	Fear	How afraid are you of natural disasters?	501	12.8	12.4	30.3	19	25.6
Q16	Frequency	How frequently do natural disasters happen in the region where you live?	497	7.7	49.3	29.6	11.1	2.4
Q17	Trust	How prepared do you think Iran is to handle a severe natural disaster? (3 = Very prepared)	493	14.4	11.6	58.8	15.2	
Q18	Religiosity	In general, how religious do you consider yourself to be? (3 = Very religious)	485	6.6	8.9	69.7	14.9	
Q19	Experience	Have you ever personally experienced a natural disaster? (Binary variable: 0 = No, 1 = Yes)	502	80.1	19.9			
Q20	Internet	Do you use the internet? (Binary variable: 0 = No, 1 = Yes)	494	16	84			
Q21	House	What kind of a house do you reside in? (Binary variable: 0 = Other, 1 = Single family house)	492	90.2	9.8			

Notes: The questions were originally asked in Persian language and not in the here presented order. If not otherwise mentioned, answer [0] refers to "Not at all" and answer [4] refers to "Quite a lot".

The disaster literacy items with the strongest positive affirmations are questions Q7 and Q8, which both belong to communicative/interactive disaster literacy (stage C). Accordingly, 80.6% of respondents strongly agree that it is necessary to contact their family after a disaster event, and 36.6% of respondents are aware of the routes to evacuate their houses. In contrast, the strongest negative approval was shown in questions Q2, Q4, Q6, Q10, and Q12. This means that in each stage of disaster literacy there is at least one item which most respondents completely disapproved. Accordingly, 54.2% of respondents have very low understanding of natural disasters, 62.7% of respondents have not seen any messages that encourage preparedness, and 35.4% of respondents are not aware of Iranian organizations that reduce the damage of natural disasters. Moreover, 65.6% of respondents have not participated in any training to prepare for natural disasters, and 45.3% of respondents do not know where to stay if their house becomes inhabitable.

Due to different scaling, the household size, the household income, and the share of respondents in each phone district were not reported in the table. The mean of the household size (n = 499) is 3.2 and the values range from 1 to 6. For the monthly household income, we defined three different categories, namely low-income household (below 30 million Iranian Rial), middle-income household (30-60 million Iranian Rial)[8], and high-income household (above 60 million Iranian Rial). In the interviews, 461 respondents answered the questions about income, and the shares are 35.8%, 44.5%, and 19.8%, respectively. Moreover, the distribution of respondents in the seven phone districts are 13.2% (District 2), 18.9% (District 3), 13% (District 4), 16.1% (District 5), 14.9% (District 6), 14.9% (District 7), and 9% (District 8).

5.4.1 Determinants of Disaster Literacy

The results of the empirical investigation using logit regressions are presented in Table 12, Table 13, and Table 14 where we report the average marginal effects. Each column has a different dependent variable which is one of the 14 questions that refer to the four stages of disaster literacy. According to the results, several variables show positive associations with the disaster literacy indicators, namely *Fear, Frequency, Training, Trust, Internet, Employed*, and *Income*. In contrast, the variables *Married* and *Education* show negative associations with the disaster literacy indicators, and *Age, Female,* and *Religiosity* suggest mixed results. Moreover, the variables *Experience, Household size,* and *House* are statistically insignificant on conventional levels in all 14 specifications.

[8] In the Iranian year 1399 (March 2020 to March 2021), when this survey was conducted, the average annual income of Iranian households was 588,200,000 IRR, which is about 49,000,000 IRR per month (SCI 2021).

Referring to Hypothesis 1, we cannot see that the experience of natural disasters alone has an impact on the individual disaster literacy (Table 12 to Table 14). This supports previous studies on the case of Iran. Taghizadeh et al. (2012) determine disaster preparedness with a random sample from Tehran in 2009 and found that respondents had a higher score, if they have experienced a natural disaster, but this effect became statistically insignificant when controlling for other factors. Najafi et al. (2015) show with their random sample from Tehran in 2014 that respondents have higher scores of disaster preparedness, if they experienced a natural disaster, but the authors do not control for other factors. The same applies to two studies from China and Taiwan (Zhang et al. 2021; S.-C. Chung and Yen 2016). This suggests that other factors are more important for becoming disaster literate. Rostami-Moez et al. (2020) include in their survey of the Iranian Hamadan Province from 2019 not just earthquake experience, but also destructive earthquake experience, and their results suggest that only destructive experience shows a statistically significant positive association with disaster preparedness, when controlling for other factors.

The city of Tehran has not suffered from a large-scale natural disaster in the past century which means that respondents did not experience a large-scale natural disaster in their lifetime, except if they moved to Tehran from an area that has experienced one of the major natural disasters. The unique situation is that Tehran City is located in a high-risk area for earthquakes and floods, but it has not yet experienced large-scale natural disaster events which makes it relevant to investigate the impact of fear of natural disasters on the individual disaster literacy, which refers to our Hypothesis 2. In Table 12 to Table 14, we can see that *Fear* has a positive and statistically significant association with *Knowledge* (Stage A), *Information* (Stage B), *Family* (Stage C), and *Awareness* (Stage D). We recoded the responses of Q15 (*Fear*), so that the two strongest supporting answer possibilities are coded with 1 and the remaining answer possibilities are coded with 0. The recoding of the dependent variables is mentioned in the table under “Recoding” where “1=4,3” means that the response is coded with 1 for the two strongest supporting answer possibilities, and 0 otherwise.

Table 12: Determinants of disaster literacy (stages A-B), marginal effects

	(1) A-Reading	(2) A-Understanding	(3) A-Knowledge	(4) B-Warnings	(5) B-Information
Fear	0.043	-0.013	**0.095****	0.013	**0.064****
	(1.404)	(-0.715)	**(2.525)**	(0.359)	**(1.972)**
Frequency	0.050	0.022	-0.023	**0.094***	0.025
	(1.199)	(0.951)	(-0.445)	**(1.812)**	(0.500)
Experience	0.006	-0.036	-0.075	-0.044	-0.020
	(0.194)	(-1.117)	(-1.449)	(-0.964)	(-0.501)
Training	0.035	0.004	0.009	**0.179*****	**0.154*****
	(1.106)	(0.129)	(0.176)	**(4.557)**	**(4.526)**
Trust	0.054	0.014	0.023	**0.108****	**0.086****
	(1.532)	(0.523)	(0.479)	**(2.078)**	**(2.050)**
Age	-0.000	-0.000	**0.004****	0.001	**-0.003****
	(-0.277)	(-0.199)	**(2.414)**	(0.380)	**(-2.391)**
Female	**-0.060***	0.022	-0.001	0.034	0.035
	(-1.680)	(1.163)	(-0.021)	(0.784)	(0.995)
Married	-0.013	-0.017	-0.045	0.002	-0.036
	(-0.440)	(-0.797)	(-1.077)	(0.045)	(-0.981)
Religiosity	-0.008	**0.040***	**-0.108***	**-0.119****	0.068
	(-0.191)	**(1.736)**	**(-1.944)**	**(-2.081)**	(1.640)
Internet	0.079	**0.080***	0.011	0.078	0.011
	(1.136)	**(1.870)**	(0.218)	(1.396)	(0.209)
Household size	-0.018	-0.006	0.013	-0.020	-0.002
	(-1.176)	(-0.551)	(0.738)	(-1.279)	(-0.153)
House	0.007	0.000	-0.086	0.007	0.013
	(0.134)	(0.007)	(-1.167)	(0.126)	(0.239)
Employed	-0.032	-0.042	0.017	0.004	0.001
	(-0.878)	(-1.331)	(0.374)	(0.098)	(0.028)
Income (middle)	0.058	0.001	-0.010	0.020	**0.085****
	(1.504)	(0.032)	(-0.250)	(0.505)	**(2.197)**
Income (high)	**0.078***	-0.021	-0.040	-0.052	**0.106****
	(1.761)	(-0.705)	(-0.592)	(-0.785)	**(2.315)**
Education (secondary)	0.075	-0.027	**-0.094***	**-0.080***	-0.064
	(1.288)	(-1.128)	**(-1.883)**	**(-1.704)**	(-1.366)
Education (tertiary)	0.091	**-0.060***	**-0.145****	**-0.176*****	0.009
	(1.431)	**(-1.862)**	**(-2.348)**	**(-2.955)**	(0.199)
District dummies	Yes	Yes	No	Yes	Yes
Observations	418	418	418	418	418
F-statistic	1.87***	3***	1.8**	1.95***	2.52***
Recoding	1=4,3	1=4,3	1=4	1=4,3,2	1=4,3
Estimator	Logit	Logit	Logit	Logit	Logit

*Notes: Linearized standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

Table 13: Determinants of disaster literacy (stages B-C), marginal effects

	(6) B-Organizations	(7) C-Evacuation	(8) C-Family	(9) C-Authorities	(10) C-Training
Fear	0.025	-0.020	**0.083****	0.014	-0.009
	(0.939)	(-0.413)	**(2.056)**	(0.346)	(-0.252)
Frequency	-0.086	0.040	0.122	0.030	0.015
	(-1.563)	(0.606)	(1.621)	(0.529)	(0.282)
Experience	-0.013	-0.078	0.009	0.062	0.013
	(-0.417)	(-1.280)	(0.186)	(1.485)	(0.321)
Training	**0.102*****	**0.129****	**-0.108****	**0.119*****	
	(3.571)	**(2.165)**	**(-2.477)**	**(2.714)**	
Trust	0.010	0.028	0.062	**0.097***	**0.170*****
	(0.304)	(0.509)	(1.313)	**(1.905)**	**(3.047)**
Age	-0.000	-0.000	**0.003***	0.000	**-0.004****
	(-0.536)	(-0.265)	**(1.926)**	(0.152)	**(-2.459)**
Female	0.055	**0.103***	-0.065	0.029	0.012
	(1.572)	**(1.909)**	(-1.564)	(0.687)	(0.274)
Married	-0.013	-0.067	0.064	0.008	**-0.084****
	(-0.463)	(-1.237)	(1.520)	(0.184)	**(-2.053)**
Religiosity	0.009	-0.012	0.087	0.077	**0.093****
	(0.265)	(-0.183)	(1.509)	(1.523)	**(2.171)**
Internet	0.025	0.004	0.037	**0.141***	0.065
	(0.403)	(0.050)	(0.553)	**(1.946)**	(0.846)
Household size	0.013	-0.014	0.014	0.018	0.025
	(1.090)	(-0.576)	(0.682)	(0.931)	(1.435)
House	-0.012	-0.078	0.033	-0.066	-0.025
	(-0.290)	(-0.959)	(0.486)	(-0.955)	(-0.408)
Employed	-0.042	**0.110****	0.008	0.043	-0.006
	(-1.294)	**(2.003)**	(0.199)	(0.986)	(-0.120)
Income (middle)	0.034	0.033	0.025	**0.109****	0.021
	(0.874)	(0.598)	(0.592)	**(2.196)**	(0.485)
Income (high)	0.046	-0.045	-0.029	**0.113***	0.030
	(1.003)	(-0.595)	(-0.534)	**(1.896)**	(0.546)
Education (secondary)	-0.061	0.020	0.036	**-0.108***	0.002
	(-1.382)	(0.269)	(0.626)	**(-1.901)**	(0.027)
Education (tertiary)	0.016	0.070	0.061	-0.037	0.031
	(0.366)	(0.859)	(0.976)	(-0.588)	(0.439)
District dummies	Yes	No	Yes	Yes	Yes
Observations	418	418	418	418	418
F-statistic	2.14***	1.62*	1.6**	1.97***	2.11***
Recoding	1=4,3	1=4	1=4	1=4,3	1=4,3,2
Estimator	Logit	Logit	Logit	Logit	Logit

*Notes: Linearized standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

Table 14: Determinants of disaster literacy (stage D), marginal effects

	(11) D-Awareness	(12) D-Shelter	(13) D-First Aid	(14) D-Assistance
Fear	**0.073***	0.038	0.008	0.053
	(1.946)	(0.790)	(0.290)	(1.378)
Frequency	**0.137*****	0.004	0.047	0.065
	(2.818)	(0.054)	(1.238)	(1.294)
Experience	-0.016	0.055	-0.020	0.015
	(-0.340)	(0.952)	(-0.561)	(0.347)
Training	**0.164*****	**0.289*****	**0.128*****	**0.194*****
	(3.868)	**(5.334)**	**(3.859)**	**(4.546)**
Trust	0.066	-0.025	-0.006	0.030
	(1.489)	(-0.458)	(-0.177)	(0.606)
Age	-0.002	**-0.005****	-0.001	-0.001
	(-1.194)	**(-2.472)**	(-1.152)	(-0.450)
Female	**0.158*****	0.073	0.002	0.036
	(3.680)	(1.348)	(0.069)	(0.892)
Married	-0.057	0.027	-0.005	-0.045
	(-1.252)	(0.499)	(-0.159)	(-1.076)
Religiosity	0.046	0.061	0.029	0.029
	(0.965)	(0.950)	(0.786)	(0.574)
Internet	**0.370****	0.094	0.088	-0.040
	(2.560)	(1.149)	(1.367)	(-0.656)
Household size	-0.019	-0.033	0.004	0.002
	(-1.073)	(-1.432)	(0.260)	(0.093)
House	0.030	-0.007	-0.058	-0.003
	(0.445)	(-0.092)	(-1.191)	(-0.056)
Employed	-0.007	-0.060	0.018	**0.118*****
	(-0.156)	(-1.031)	(0.462)	**(2.613)**
Income (middle)	0.009	0.011	-0.015	**0.085***
	(0.197)	(0.194)	(-0.410)	**(1.839)**
Income (high)	0.032	0.039	0.046	**0.155*****
	(0.560)	(0.511)	(0.931)	**(2.780)**
Education (secondary)	-0.070	**-0.153****	-0.075	-0.041
	(-1.053)	**(-2.193)**	(-1.538)	(-0.748)
Education (tertiary)	0.064	**-0.160****	-0.015	-0.043
	(0.948)	**(-2.046)**	(-0.297)	(-0.751)
District dummies	Yes	Yes	Yes	Yes
Observations	418	418	418	418
F-statistic	3.13***	1.85**	2.24***	2.31***
Recoding	1=4,3	1=4,3,2	1=4,3	1=4,3
Estimator	Logit	Logit	Logit	Logit

*Notes: Linearized standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

According to our results, the fear of natural disasters has an impact on all four stages of natural disaster literacy. More precisely, respondents who fear natural disasters have a 9.5 percentage point (pp) higher probability to belief in the knowledge of scientists related to natural disasters, and they have a 6.4 pp higher probability to know where to get essential information from during a natural disaster. Moreover, respondents who fear natural disasters have an 8.3 pp higher probability to contact their families during a natural disaster event, and they have a 7.3 pp higher probability to know which type of natural disasters are common in the region. This shows that the fear of natural disasters can help to motivate residents to be better prepared for the impact of natural disasters. However, the results also show that fear does not have a positive association with all indicators of disaster literacy, which especially applies to practical skills of stages C and D, such as evacuation routes, knowledge about the responsible authorities, disaster training, finding a shelter, first aid, and assistance of others during a natural disaster. This supports the arguments of Aronson (2008) who shows that under certain circumstances the fear of natural disasters can lead to an improvement of disaster literacy.

The perception about the frequency of natural disasters shows also statistically significant positive associations with two disaster literacy indicators, namely *Warnings* (stage B) and *Awareness* (stage D). We recoded the responses of Q16 (*Frequency*), so that the two strongest supporting answer possibilities are coded with 1 and the remaining answer possibilities are coded with 0. According to the results, respondents who perceive a high frequency of natural disasters have a 9.4 pp higher probability to have seen emergency messages in past months, and they have a 13.7 pp higher probability to know which type of natural disasters are common in the region.

In reference to Hypothesis 3, we can see that the respondents' formal secondary and tertiary education is not positively associated with the 14 disaster literacy indicators. As presented in Table 12 to Table 14, we have included binary variables for the respondents' highest level of education, which is measured in four categories, namely illiterate, primary education, secondary education, and tertiary education. The reference category for interpretation is primary education and being illiterate, which are not included in the models. According to the results, secondary education is negatively associated with four of the disaster literacy items, namely *Knowledge*, *Warnings*, *Authorities*, and *Shelter*, which cover all four stages of disaster literacy, and the variables are statistically significant on conventional levels. Thus, respondents with secondary education have a 9.4 pp lower probability to belief in the knowledge of scientists related to natural disasters, and they have 8 pp lower probability to have seen emergency messages in past months. In addition, respondents with secondary education have 10.8 pp lower probability to know which government agency to contact in the case of a natural disaster, and they have a 15.3 pp lower probability to know where to stay after their house becomes inhabitable.

Similar results are reported for respondents with tertiary education. More precisely, they have a 6 pp lower probability to have a high understanding of natural disasters, and they have a 14.5 pp lower probability to belief in the knowledge of scientists related to natural disasters. Moreover, respondents with tertiary education have a 17.6 pp lower probability to have seen emergency messages in past months, and they have a 16 pp lower probability to know where to stay after their house becomes inhabitable. Based on these results, we can see that the respondents with higher than primary education (meaning secondary and tertiary education) are less disaster literate than lower educated respondents. This shows that the formal education system does not teach the necessary skills to be prepared for natural disasters. It also shows that respondents with lower education are paying more attention to emergency messages and know more about responsible authorities and are more aware where to stay after their house becomes inhabitable. As the empirical results of previous studies are mixed, our results partly support previous findings, especially Botzen et al. (2009) and Najafi et al. (2015). First, Botzen et al. (2009) show for the case of the Netherlands that higher levels of education are associated with lower risk awareness. Second, Najafi et al. (2015) who conducted a survey in Tehran in 2014 and did not find statistically significant associations between education and disaster preparedness.

Additionally, we have included more control variables which are also related to the education of citizens, but not through the formal education system, namely natural disaster trainings and usage of the internet. We recoded the responses of Q10 (*Training*), so that the two strongest supporting answer possibilities are coded with 1 and the remaining answer possibilities are coded with 0. As Q10 is one of our disaster literacy items, we include it only in the 13 other models. It shows a statistically significant and positive association with 9 disaster literacy items, covering three stages of disaster literacy (B, C, and D). The disaster trainings have equipped participants with practical skills, but not with basic understanding of natural disasters. In addition, disaster trainings gave respondents the confidence to handle the disaster situation, thus we can see a negative association between training and the necessity to contact their families during a natural disaster event. Using the internet (Q20) is also statistically significant and positively associated with several disaster literacy items, namely *Understanding*, *Authorities*, and *Awareness*, covering three stages of disaster literacy (A, C, and D).

Referring to Hypothesis 4, we can see that the household’s income level is statistically significant and positively associated with several indicators of disaster literacy. As presented in

Table 12 to Table 14, we have included binary variables for the respondents' levels of household income, which is measured in three categories, namely low income, middle income, and high income. The reference category for interpretation is low income, which is not included in the models. According to the results, respondents living in middle-income households have an 8.5 pp higher probability to know where to get essential information from during a natural disaster, and to be able to actively assist others during a disaster event, and they have a 10.9 pp higher probability to know which government agency to contact in the case of a natural disaster. Similar results can be observed for respondents from high-income households. They have a 7.8 pp higher probability to have read material related to natural disasters in the past year, and they have a 10.6 pp higher probability to know where to get essential information from during a natural disaster. Additionally, respondents living in high-income household have a 11.3 pp higher probability to know which government agency to contact in the case of a natural disaster, and they have a 15.5 pp higher probability to be able to actively assist others during a disaster event.

The results suggest that the income level of the household is an important determinant of an individual's disaster literacy. The argument is that wealthier households have better access to financial resources, information, and social networks to cope with the negative impact of natural disasters. Our results show that wealthier household have on average better access to information, better knowledge of administrative processes, and better skills and financial resources to actively help others during and after the impact of a natural disaster event. This supports previous findings of several discussed studies (Najafi et al. 2015; Rostami-Moez et al. 2020; Martins et al. 2018; 2019).

In reference to Hypothesis 5, we can see that the respondents' trust in Iran's natural disaster management is statistically significant and positively associated with several indicators of disaster literacy. We recoded the responses of Q17 (*Trust*), so that the two strongest supporting answer possibilities are coded with 1 and the remaining answer possibilities are coded with 0. It refers to the trust in the Iranian institutions to handle a natural disaster. According to the results, respondents with trust in the Iranian disaster management have a 10.8 pp higher probability to have seen emergency messages in past months, and they have an 8.6 pp higher probability to know where to get essential information from during a natural disaster. In addition, the respondents have a 9.7 pp higher probability to know which government agency to contact in the case of a natural disaster, and they have a 17 pp higher probability to have absolved a disaster training. This supports the findings of several previous studies (Choi and Wehde 2020; Gotanda et al. 2021; Q. Han et al. 2021) which have shown that trust in institutions can lead to an improvement to self-protective behavior before and during emergency situations. According to our results, respondents who trust in natural disaster management institutions pay more attention to emergency messages, know where to get essential information from, know the responsible government agencies, and are more willing to participate in disaster trainings.

In addition to our main variables of interest, we have also included other control variables, of which *Age*, *Female*, and *Religiosity* show statistically significant but mixed results. The respondents' age shows positive and statistically significant associations with the belief in the knowledge of scientists and the need to contact the family in case of an emergency, but it shows negative and statistically significant associations with information gathering, disaster training, and finding a new shelter. Being female is statistically significant and positively associated with the knowledge about evacuation routes and the knowledge about the natural disasters that occur in the region, but it is statistically significant and negatively associated with reading of disaster-related material in the past year. Related to religiosity, we recoded the responses of Q18, so that the strongest supporting answer possibility is coded with 1 and the remaining answer possibilities are coded with 0. According to the results, highly religious respondents have higher odds to have a good understanding of natural disasters and to know evacuation routes, but they have lower odds to belief in the disaster knowledge of scientists and to have seen emergency messages in the past months. The results are statistically significant on conventional levels.

5.4.2 Disaster Literacy Index (DLI) for Tehran

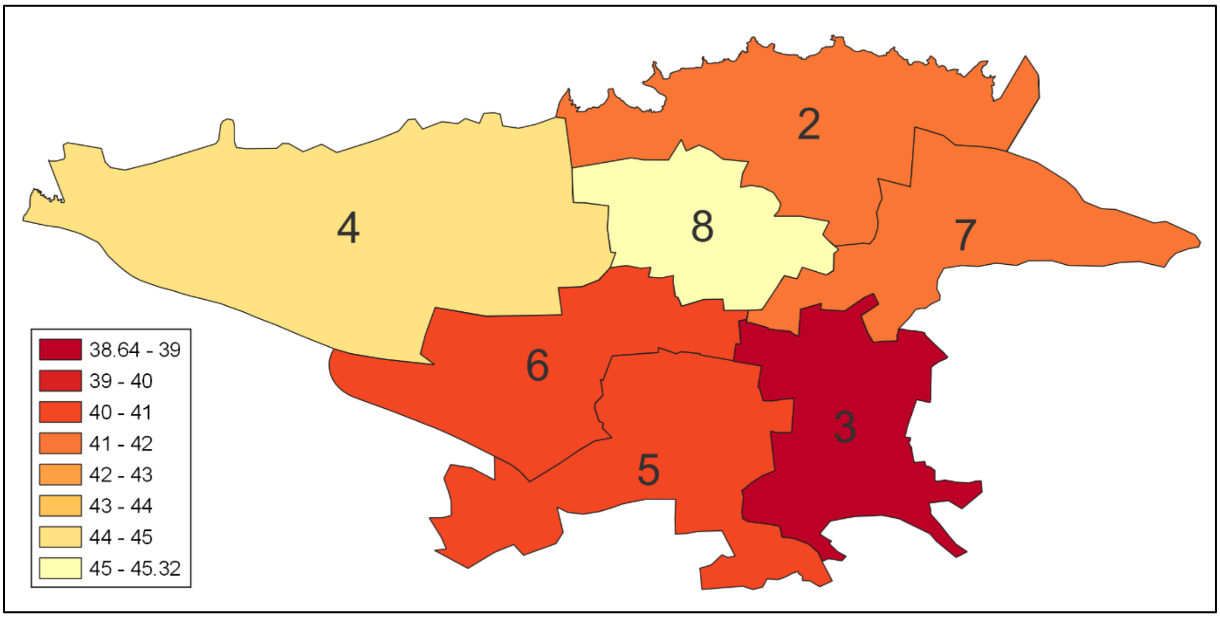
Out of the 502 respondents who participated in the survey, 35 individuals had to be dropped for the calculation of the index due to missing data on disaster literacy items, resulting in a sample of 467 individuals for the creation of the disaster literacy index (DLI). As presented in Table 15, the average DLI for our sample is 41.4 with a standard deviation (SD) of ± 13.6. The lowest value achieved by a respondent was 5.2 points, and the highest value achieved was 88.1 points, while the maximum possible score is 100 points. Thus, a medium disaster literacy of the sample can be identified.

Table 15: The disaster literacy index (DLI) for the population of Tehran

Variable	n	Mean	SD	Min	Max
Stage A – Basic Disaster Literacy	467	3.726	1.253	0	8.333
Stage B – Functional Disaster Literacy	467	5.614	3.62	0	20
Stage C – Interactive Disaster Literacy	467	16.831	4.383	1.875	30
Stage D – Critical Disaster Literacy	467	15.203	7.737	0	40
Disaster Literacy Index (DLI)	467	41.374	13.628	5.208	88.125

As the four stages have different weights, we cannot directly compare the means, so we divide the means by the maximum possible points of the stage, which results in 0.37, 0.28, 0.56, and 0.38, respectively. According to these results, the highest average score was achieved in interactive disaster literacy (stage C), and the lowest score in functional disaster literacy (stage B). For an overview of the spatial distribution of disaster literacy in Tehran, Figure 11 illustrates the average scores of the DLI in each of the seven phone districts in Tehran City. The means are 41.54 (District 2), 38.64 (District 3), 44.22 (District 4), 40.78 (District 5), 40.03 (District 6), 41.82 (District 7), and 45.32 (District 8).

Figure 11: Average DLI in Tehran's phone districts



(Source: Authors' illustration)

We can see a North-South divide within the city of Tehran, where the northern phone districts have higher scores of disaster literacy (with a mean of 43) and the southern districts have lower scores (with a mean of 39.7). With the help of a two-sample t-test and one-way analysis of variance (ANOVA) tests, we have investigated the difference of the means of the subsamples, namely Northern (2, 4, 7, and 8) and Southern (3, 5, and 6) phone districts as well as the seven phone districts. The t-statistic of the t-test with the Northern and Southern sample is 2.63 which is statistically significant on the 1%-level, suggesting a statistically significant difference between the DLI in the two subsamples. This result is supported by the ANOVA test with an F-statistic of 6.93 which is also statistically significant on the 1%-level.

This divide correlates with other spatial inequalities of the city of Tehran which have been discussed in previous literature, for example multi-dimensional urban disaster resilience

(Asadzadeh, Kötter, and Zebardast 2015; Moghadas et al. 2019), earthquake-proof buildings (JICA and CEST 2000), earthquake risk (Kamranzad, Memarian, and Zare 2020), poverty (Movahhed et al. 2016), and human well-being (Kamal, Harouni, and Basakha 2019). The common aspect of the studies is that the Northern districts of Tehran City are more disaster-resilient, more earthquake-proof, and have a lower earthquake risk. In addition, the Southern districts have higher levels of poverty and lower levels of human well-being. Therefore, Southern districts are more vulnerable to natural disasters. Our results show an additional important difference between Northern and Southern districts in terms of disaster resilience and coping capacities, namely disaster literacy.

To determine the individual characteristics that are responsible for the differences of the DLI among participants in our sample, we used a multiple regression approach, and the results are presented in Table 16. The five specifications differ in the used dependent variables which are the DLI and its four stages, as labeled in each column. Except for the dependent variables and the explanatory variables *Age* and *Household size* who are continuous, all explanatory variables are binary.

This second empirical investigation using OLS estimations serves two purposes. First, it can be understood as a robustness check, as we are using a different estimator, and second, it shows that the final index represents the cross-individual differences that we have discovered using the individual disaster literacy items. The results of Table 16 support the previous findings, namely that *Fear* (Hypothesis 2), *Income* (Hypothesis 4), and *Trust* (Hypothesis 5) are positively associated with the DLI scores, while *Experience* (Hypothesis 1) and *Education* (Hypothesis 3) do not show statistically significant results on conventional levels. An exception is secondary education in stage D which is negative and statistically significant on the 10% level. Additionally, we can see that the perceived frequency, disaster training, and being female are positively associated with the DLI scores. The respondents' age and being married show a negative association. The strongest determinants of the final DLI score are trust in Iran's natural disaster management, internet usage, being from a high-income household, perception about high frequency of natural disasters, and being from a medium-income household. This means for example that respondents who trust Iran's disaster management have on average a DLI score 5.5 higher than the average respondent of the sample, and respondents who use the internet have on average a 5.4 higher DLI score.

Table 16: Determinants of the disaster literacy index and its stages

	(1) Stage A	(2) Stage B	(3) Stage C	(4) Stage D	(5) DLI
Fear	**0.334***** **(2.706)**	0.143 (0.422)	0.325 (0.785)	0.663 (1.044)	1.220 (0.981)
Frequency	0.238 (1.415)	0.636 (1.330)	**1.044*** **(1.779)**	**2.471***** **(2.604)**	**4.531***** **(2.690)**
Experience	-0.061 (-0.429)	0.126 (0.323)	0.160 (0.308)	0.247 (0.319)	0.671 (0.445)
Training	**0.304*** **(1.658)**	**3.104***** **(6.129)**		**7.249***** **(7.509)**	
Trust	0.180 (1.216)	**0.829**** **(2.247)**	**1.761***** **(3.922)**	1.171 (1.624)	**5.456***** **(4.169)**
Age	-0.002 (-0.445)	-0.013 (-1.007)	**-0.038**** **(-2.448)**	**-0.077***** **(-2.739)**	**-0.177***** **(-3.696)**
Female	0.127 (0.978)	0.553 (1.373)	0.697 (1.492)	**1.790**** **(2.309)**	**3.567**** **(2.474)**
Married	-0.207 (-1.444)	-0.417 (-1.026)	-0.551 (-1.139)	-0.607 (-0.785)	**-2.909*** **(-1.934)**
Religiosity	-0.097 (-0.516)	0.563 (1.174)	0.961 (1.622)	0.366 (0.387)	2.837 (1.549)
Internet	**0.815***** **(3.889)**	0.669 (1.242)	0.713 (1.058)	**2.673**** **(2.243)**	**5.376**** **(2.375)**
Household size	-0.015 (-0.236)	0.095 (0.571)	0.234 (1.125)	-0.285 (-0.782)	0.292 (0.447)
House	**-0.393*** **(-1.763)**	-0.224 (-0.331)	0.263 (0.368)	0.512 (0.481)	-0.129 (-0.054)
Employed	-0.007 (-0.047)	-0.105 (-0.250)	0.654 (1.303)	0.943 (1.162)	1.131 (0.751)
Income (middle)	0.116 (0.784)	**0.748*** **(1.886)**	**1.153**** **(2.498)**	**1.672**** **(2.189)**	**4.025***** **(2.784)**
Income (high)	0.041 (0.223)	0.566 (1.018)	0.673 (1.104)	**3.230***** **(3.248)**	**5.046***** **(2.757)**
Education (secondary)	-0.134 (-0.704)	-0.393 (-0.776)	0.098 (0.150)	**-2.231*** **(-1.962)**	-2.717 (-1.258)
Education (tertiary)	-0.221 (-0.994)	0.362 (0.596)	0.894 (1.147)	-0.537 (-0.404)	0.664 (0.258)
District dummies	Yes	Yes	Yes	Yes	Yes
Observations	418	418	418	418	418
R-squared	0.09	0.20	0.14	0.31	0.20
Estimator	OLS	OLS	OLS	OLS	OLS

*Notes: Linearized standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

5.5 Conclusion

With our empirical results, we provide evidence for the determinants of natural disaster literacy in Tehran City which is one of the main metropolitan areas in the country of Iran that is highly vulnerable to earthquakes and flash floods. We used logistic regressions and the responses to our survey to find the main determinants of disaster literacy among the citizens of Tehran City. According to the results, the households' income level (middle and high), the trust in Iranian disaster management, the fear of natural disasters, the perceived frequency of natural disasters, the usage of internet, being employed, and the participation at specialized natural disaster trainings are positively associated with several of the 14 disaster literacy items on conventional significance levels. In contrast, the experience of a natural disaster, the level of education (secondary and tertiary), the household size, and owning a house show statistically significant and negative associations with the disaster literacy items or show statistically insignificant results. Age, gender, and religiosity show mixed results. After the first analysis, we used the newly developed disaster literacy index (DLI) and OLS estimations to check the robustness of our findings. The variables religiosity, being employed, and tertiary education lost their statistical significance, but the remaining results were confirmed.

Based on these findings, we have learned that the experience of natural disasters alone does not improve the disaster literacy of citizens, and the formal education system does not educate citizens enough in terms of disaster literacy. However, specialized disaster trainings are proven to be efficient to increase the levels of disaster literacy. This leads us to the first policy recommendation, namely including disaster preparedness training in the school curriculum (in addition to the yearly earthquake drills) or offer specialized courses in areas that are more vulnerable to natural disasters and have lower DLI scores, for example Southern districts in Tehran City. As Iran has a mandatory military service for men, natural disaster trainings could also be included in the basic training. This would increase the disaster literacy of about half the population, and it will educate those people who are usually among the first responders during large-scale natural disasters.

We also found that the households income level plays a role, thus a second recommendation is that policies need to be implemented to reduce income inequality and fight poverty within the city of Tehran. In reference to the previous point, it means also that trainings need to be targeted at especially low-income households. Additionally, our results suggest that the trust in disaster management institutions also helps to motivate citizens to become more disaster literate, for example by joining natural disaster trainings. Therefore, the third recommendation is to improve the relationship between citizens and the responsible organizations for natural disaster management.

Our results also reveal possibilities how to convince citizens to become more disaster literate, namely the fear of natural disaster, the perceived frequency, and the internet. Therefore, educating citizens about the possible risks and frequency of disaster in the region, in addition to suggesting solutions in form of disaster trainings, will help to motivate citizens to become more disaster literate. Related to the internet, it will be necessary to provide a good infrastructure to citizens and educate old people in using the internet. These steps will help to increase the disaster literacy of the citizens of Tehran City and will improve the urban disaster resilience and reduce the vulnerability, especially by helping to cope with the impacts of natural disaster events on the individual level. Finally, increasing disaster literacy will help to save the own life and the life of others during and after a natural disaster event.

6. The Impact of the COVID-19 Pandemic on Marriage and Fertility Behavior: Survey-based Evidence from Iran

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Abstract

With a representative survey of 1214 participants which was conducted in early 2022, this study investigates the impact of the COVID-19 pandemic on the family development in Iran. The results of the empirical investigation using logistic regressions suggest that the concern about the continuation of the pandemic and the respondents' vaccination status show negative associations with childbirth during the pandemic. The experiences of life loss and job loss are positively associated with a decrease of the respondents' child desires. In contrast, spending more time with the family is positively associated with an increase of the respondents' child desires. The experience of unemployment due to the pandemic is positively associated with marriage during the pandemic. Additionally, we found heterogenous effects depending on the respondents' gender, location, and social class. Overall, the results have implication for the development of the fertility rate and population development in Iran, which can also affect economic development in the long term.

JEL Codes:

C83, D91, D1, J12, J13, P46, Q54

Keywords:

COVID-19, pandemic, disaster, Iran, survey, logistic regression, marriage, fertility, family planning, inequality

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6.1 Introduction

After the outbreak of the coronavirus (COVID-19) in the Chinese city of Wuhan in December 2019, it took less than two months until Iran reported its first case of an infection in February 2020 in the Iranian city of Qom (Yavarian et al. 2020). Similar to most parts of the world, Iran suffered from the direct and indirect consequences of this pandemic. It affected the physical and mental health of citizens, as well as the social and economic life. Since the outbreak of the pandemic in Iran, more than 144,000 people have lost their lives and more than 7.5 million Iranians have been infected (WHO 2022). This makes it one of the largest disasters experienced by the country in modern times, which is exceeded in death count only by the Iran-Iraq War. Between February 2020 and November 2022, Iran has experienced seven waves[9] of COVID-19 with several lockdowns. This led to the situation that people had to stay at home with their families more hours per day than before the pandemic, which had an impact on the social and family life.

In this study, we investigate the impact of the COVID-19 pandemic and the related change of social life on the family planning behavior of Iranian citizens. We conducted a representative survey in Iran, using computer-assisted telephone interviews (CATI) which provided us a cross-sectional dataset of 1214 respondents which were interviewed in January and February 2022, during the sixth wave of the pandemic. We are using logistic regression models to determine the association between the experience of the pandemic, measured by eight different questions, covering the direct and indirect effects of the pandemic, and the family development, measured by four different questions, which refer to childbirth desires, actual childbirth, and marriage during the pandemic. Additionally, we investigated heterogeneity of responses across genders, locations, and five social classes, which are used as a proxy for the respondents' income level and social values. Thus, the research question is the following: *Did the COVID-19 pandemic affect family development in Iran?* With the sub question: *Did respondents from various genders, locations, and social classes show a different behavior?*

The contribution of this study is that it provides new empirical evidence on the social impact of the COVID-19 pandemic in Iran. The studied outcome variables also have implications for the fertility rate in Iran, and therefore not just on the social development, but also on the economic development. The highlight of our study is that we are interested in the impact of the COVID-19 pandemic and the related change of social life on marriage and fertility intentions of both women and men in Iran, which has not been studied yet. Many previous surveys only focus on women's intentions (Tan, Ryan, and Lim-Soh 2021; Afshari, Abedi, and Beheshtinasab 2022;

[9] More information on the seven waves of COVID-19 in Iran are presented in Figure E 1 in Appendix E.

Akinyemi et al. 2022; T. Chen et al. 2022; Zimmerman et al. 2022). Moreover, it is the first study that systematically investigates the heterogeneity across genders, locations (rural versus urban), and social classes, while other studies have only briefly touched this topic (Fostik and Galbraith 2021; Manning, Guzzo, and Kamp Dush 2021; Akinyemi et al. 2022; Bailey, Currie, and Schwandt 2022; Zimmerman et al. 2022). Finally, to the best of our knowledge, it is also the first comprehensive study on the case of Iran, and the first study on this scale from a lower-middle income country. The remaining chapter is structured in the following way: Section 6.2 gives an overview of the relevant literature related to the topic and Section 6.3 presents the data and methodology. In Section 6.4, the results are presented and discussed, and Section 6.5 concludes the chapter.

6.2 Literature Review

There is recently growing interest in the consequences of pandemics on the people's marriage and fertility behavior, especially due to the COVID-19 pandemic. In this context, there is already a body of literature on the behavior and decision-making under situations of uncertainty, such as war and conflict, man-made and natural disasters (including pandemics), and economic crises.

6.2.1 Theoretical Considerations

There are different theoretical approaches that discuss the connection between situations of uncertainty and family development decisions. A starting point to understand fertility dynamics is the demographic transition theory which describes the transition from a high fertility and high mortality society to a low fertility and low mortality society. This happens due to several economic and social changes, for example improvements in the provision of education and healthcare services, as well as changes of societal values, and it is usually connected to modernization, industrialization, and urbanization. Abbasi-Shavazi et al. (2009) summarize several relevant theories in this context, such as the child survival theory, the demand theory, the status enhancement theory, the gender equity theory, and an institutional perspective.

The first theoretical approach argues that high infant and child mortality rates promoted high fertility rates because the interests of households were in the number of children who survived and not the number of children who were born. Therefore, improvements in healthcare will reduce fertility desires if it increases the likelihood of child survival. Within the second approach, which can be labeled as demand theory, we are assuming that the fertility desire falls when the costs of an additional child exceed the benefits of having that child. The transition from agrarian family production to a modern industrial economy increases the costs of an additional child because children are no longer an economic asset through their labor, but they become an economic liability through the cost of education. To compete in the new labor market, parents need to invest more in each child. The third theoretical approach argues that in addition to the improvement in economic welfare, individuals also want to improve their social status within the community. Having many children might reduce the available time and capital that is needed to build a successful career. With few children, there will be also more resources available to invest in the child's career and enhance the social status as well.

Another change that is important in the context of fertility decisions is the standing of women within the household, which refers to the gender equity theory. In modern societies with fewer children, women will get in touch with other women outside the household, for example in the child's school, in healthcare facilities, or even at the workplace. This will empower women and can reduce the number of additional children as well. The fifth theoretical approach highlights the role of social, cultural, political, and religious institutions. As social and cultural norms, which can be understood as rules about social interactions within society, only change slowly over time, they are usually seen as stabilizers of the status quo, especially in the context of family and reproduction. Abbasi-Shavazi et al. (2009) argue that the leadership after the Islamic Revolution in Iran, which was not just the political but also the religious authority, was able to create a national family planning program that rewrote the existing social and religious norms about the size of family and number of children.

While previous theories have explained how societal changes affect the fertility decisions, we now want to look at the role of times of uncertainty such as war and conflict, man-made and natural disasters, and economic crises. Rodgers et al. (2005) summarize three theoretical approaches that link political and sociocultural events as well as man-made and natural disasters with an increase of fertility rates, namely the community influence theory, the replacement or insurance theory, and the terror management theory. First, the community influence theory suggests that parents want to raise children in a positive and supportive community. In the case of the COVID-19 pandemic, this would mean that a competent response to the crisis might increase the fertility desires of couples. A related concept is the 'narratives of the future'[10] framework that sees the rise of social and economic uncertainties as an important driver of fertility decisions (Vignoli et al. 2020).

[10] Vignoli et al. (2020) developed the theoretical framework of 'narratives of the future' to understand the role of uncertainty in recent fertility trends, and they argue that uncertainty is rarely considered in traditional explanations of fertility. Within this framework, people use works of imagination to produce their own narratives of the future, which are the basis for their (fertility) decisions. However, these are imagined futures, as the long-term future cannot be predicted with any degree of certainty. Within the process of decision-making, there are several aspects that play a role, such as structural constraints and past experiences, expectations, and imaginaries.

Second, the replacement or insurance theory, which builds on the child survival theory. It suggests that couples observed the loss of life, especially the loss of life of children, and they might perceive that life is more fragile than before. This can motivate couples to have more children, which will replace lost lives or will be an insurance for the potential loss of a child. Aassve et al. (2020) argues against the replacement theory in the context of COVID-19, because the virus is more lethal to older people. Third, the terror management theory suggests that in a situation where mortality becomes more visible, people will turn to traditional values and behaviors, such as having children and raising families. Nitsche and Lee (2022) discuss the terror management theory in the context of the COVID-19 pandemic, and argue that negative emotions, such as anxiety, anger, loneliness, and other worries at the beginning of the pandemic should have a positive effect on the fertility desires.

Rodgers et al. (2005) adds that while the three theories predict an increase of fertility after the impact of the disaster, there are different short- and long-term implications and geographical considerations. Within the community influence theory, we would expect a long-term effect that builds over time, as the trust in the community increases, and the community response to disasters stays positive and supportive. The effect should be the strongest at the location of the disaster, and weaker at geographically distanced locations. Within the replacement theory, we would expect an immediate impact on the fertility behavior which would dampen over time, similar like buying an extra life insurance after the unexpected death of a relative and then later canceling the contract. The effect would be mainly measurable in the geographical area directly affected by the disaster, as well as connected areas. Finally, within the terror management theory, we would expect that those are mainly affected who directly experienced the disaster and got influenced on a psychological level. However, the effect might dampen quickly if life goes back to normal and the immediate threat of life disappears.

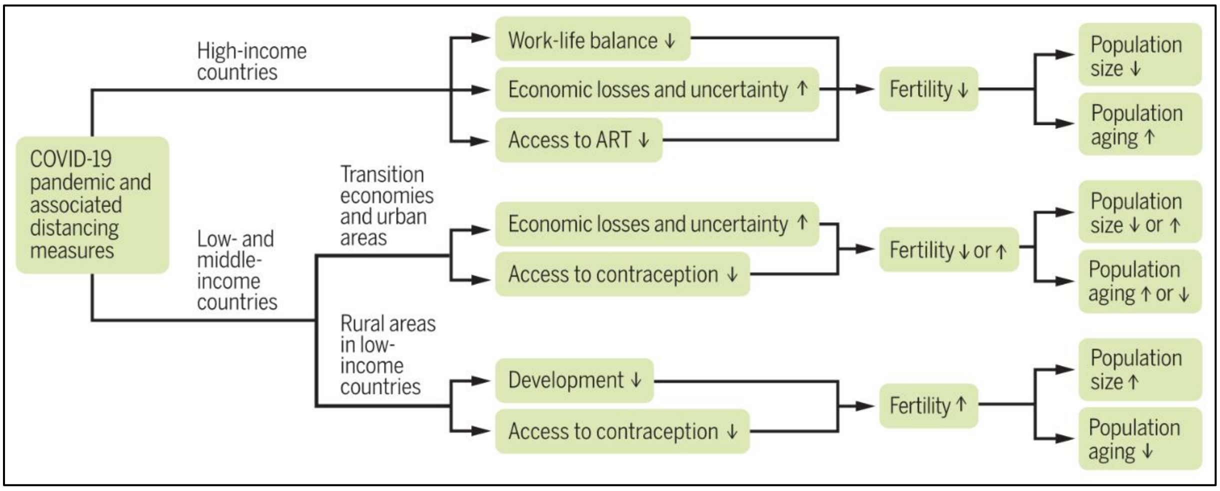
Chin and Wilson (2018) discusses an economic theory of household fertility decision-making, previously labelled as demand theory, in the context of the human immunodeficiency viruses (HIV) and acquired immunodeficiency syndrome (AIDS). The authors argue that the disease risk will affect the demand for children through mainly two channels, namely the adult health risk and the child health risk. First, the health risk for adults reduces the time horizons for decision making, as the life expectancy becomes lower. This will also reduce labor productivity and increase demand for care labor in the home, and thus reduce household income. Depending on the level of industrialization, this can mean an increase of childbearing, so that children can work at home or add to the household income through external work. But it can also mean a decrease of the number of children in the household, because children become an economic burden. Second, the health risk for children increases the shadow price of child quantity and quality. This means that children become an economic liability through the risk of death in combination with the cost of education, which can decrease the fertility desires.

Ahmed and Tan (2022) and Wilkins (2021) summarize several mechanisms through which disasters might affect the fertility rate. First, they argue, backed by empirical evidence, that crisis-induced psychological stress can lead to a decrease in fecundity, and thus a reduction of fertility. This medical argument is opposing the terror management and replacement theory. Second, the contact between partners can be disrupted, for example by geographical separation or death, which will reduce the number of children. This separation can happen because of temporary labor migration due to conflict or an economic crisis. But the type of disaster can also cause more bonding and time spent between couples, for example the lockdowns during the COVID-19 pandemic, which can increase the number of children. But a lockdown also means a reduced work-life balance and an increased burden on the parents, which can reduce the wish for additional children.

Third, the previous experience or perceptions of the probability of a disaster can increase voluntary birth control, as discussed in the community influence theory, or it can increase fertility desires, as discussed in the terror management and replacement theory. Fourth, a disaster can also postpone or prevent marriages, due to separation of couples or financial problems, or it can facilitate marriages which can reduce the financial burden of the parents, usually, of the bride. Fifth, the disaster can also damage or disrupt the health system which means worse reproductive health at conception and a worse access to family planning services, reproduction technology, and contraceptives. This can affect the health of the mother and the baby negatively and can decrease fertility. Overall, we can see that discussed theories and mechanisms address many aspects of marriage and fertility decisions during a disaster. The different explained effects might happen simultaneously, so that we cannot clearly state if a disaster like the COVID-19 pandemic will have a positive or negative impact on the marriage and fertility behavior.

Based on the experience of previous disasters and theoretical considerations, Aassve et al. (2020) developed a model which expects different impacts of the COVID-19 pandemic in high-income countries, in contrast to low- and middle income countries. Within the latter, the authors also expect differences between transition economies and urban areas, compared to rural areas in low-income countries. Following Figure 12 illustrates the expected effects of the pandemic. The abbreviation ART stands for assisted reproductive technology.

Figure 12: Possible post-pandemic fertility trajectories according to regional income level



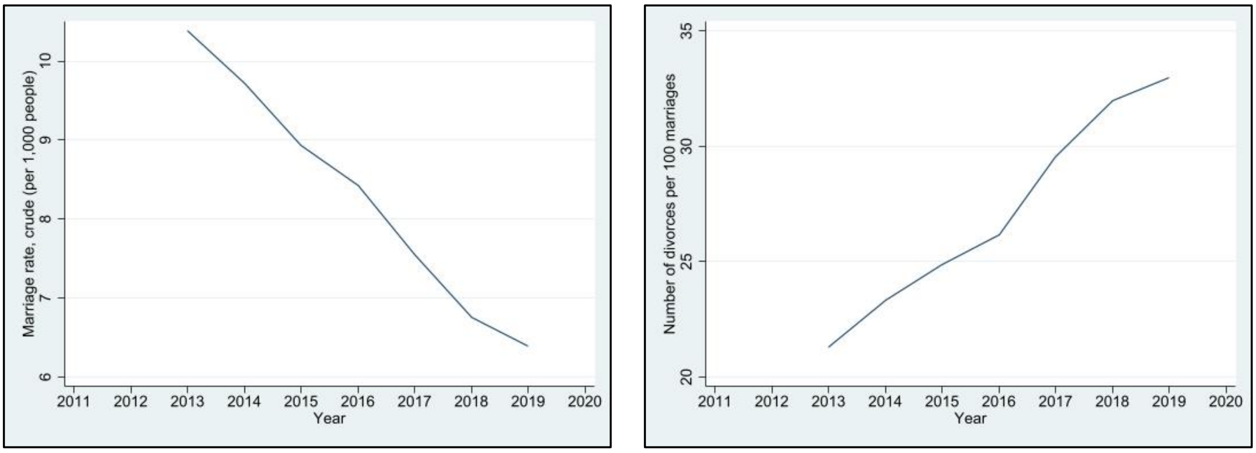
(Source: Aassve et al. (2020))

According to World Bank (2022), Iran is categorized as a lower middle-income country, so we expect a different effect of the COVID-19 pandemic on the fertility decisions in rural and urban areas. This will be considered in the further analysis.

6.2.2 Marriage and Fertility Behavior in Iran

As a context for the marriage and fertility decision of individuals, we also need to consider historical developments and population management policies in Iran. Marriage is the legal precondition for a couple to live together and have a child (Rahbari 2022), so it is an important determinant of the fertility decision. This also means that, for example, an economic crisis does not only directly affect the fertility decision, but it will also indirectly affect this decision by preventing or postponing the marriage to after the crisis. Several empirical studies on the case of Iran have shown that economic conditions are an important determinant of marriage and divorce decisions, for example reflected in the cost of housing or the gold price (Gholipour and Farzanegan 2015; Farzanegan and Gholipour 2016; 2018). In addition, Bagi (2022) shows that Iranians in younger cohorts delay their marriages and marry at older ages mainly due to tertiary education and employment. This can reduce fertility rates, because usually an early marriage and an early first child is associated with a larger family size. Aghajanian et al. (2018) argue that the decrease in traditional marriages gives additional room for temporary marriages, which are not just a form of legalized prostitution, as often claimed, but these marriages are a reflection of changing attitudes such as individualism, autonomy, and secularism. Figure 13 shows the crude marriage rate per 1000 people and the number of divorces per 100 marriages.

Figure 13: The development of marriages and divorces in Iran, 2013-2019



(a) Marriages. (b) Divorces.

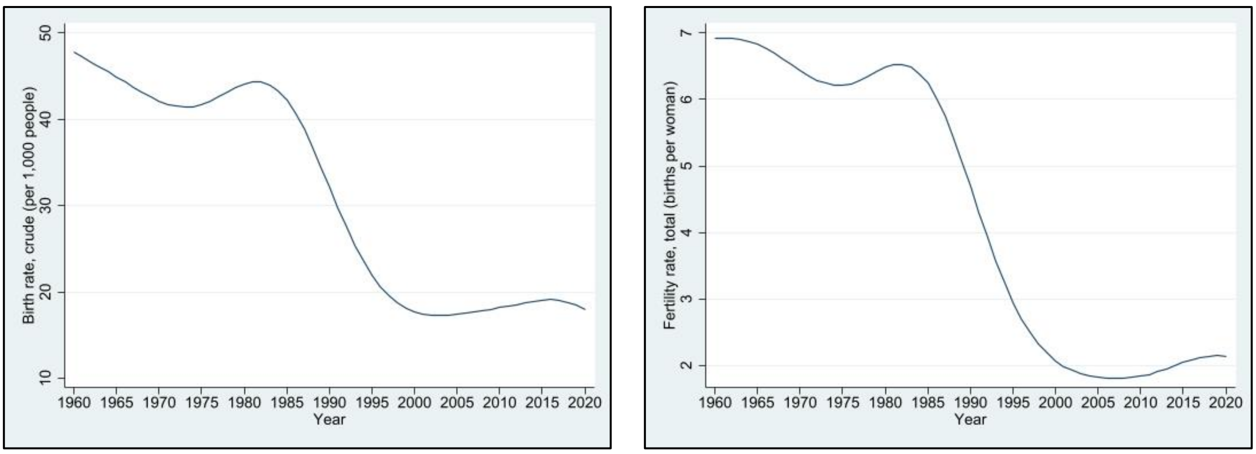
(Source: Authors' illustration using data from National Organisation for Civil Registration (NOCR 2021))

Over the past decade, we can see a decrease in the marriage rate and an increase of the divorce rate which both will negatively impact the fertility rate in a country where marriage is the legal precondition for having children. However, it is not just the change of marriage behavior that is responsible for the change in fertility intentions of Iranians, but it is also the result of family planning policies. With a drop from 7 births per women in 1979 to 1.9 births per women in 2006, Iran experienced the largest and fastest fall in fertility ever recorded (Abbasi-Shavazi, McDonald, and Hosseini-Chavoshi 2009). This highlights the importance of the topic in the context of Iran. The drastic fertility transition is the result of several family planning policies that took place especially after the revolution in 1978/79. During the Pahlavi period (1925-1979), there were huge modernization and industrialization efforts with several reforms that affected family life, for example an increase of marriage age and compulsory education for girls in the 1920s, and changes in divorce right, limitation of polygamy, improvement of health services, and access to contraceptives in the 1960s. However, this did not substantially reduce the fertility rate, because it did not consider the socio-cultural and religious context.

Directly after the revolution, previous policies were rejected by religious leaders, so that the office of population and family planning was abolished, the marriage age was reduced again, and contraceptives became less available. In addition, the Iran-Iraq War (1980-88) motivated couples to produce more children to replace the eventual loss of life during the war, which supports the arguments of the replacement theory. However, with the end of the war, the opinion of the leadership changed, because they feared that the large population increase would have social, psychological, economic, and cultural impacts on peoples' lives, for example in terms of food security, availability of jobs, and provision of public infrastructure. This led to the First

Five Year Development Plan (FFYDP) in 1989, which started the new population control and family planning policy. Over the following years, the government made huge efforts to promote small family size norms and keep family sizes at reasonably low levels of two to three children. Abbasi-Shavazi et al. (2009) argue that the new family planning policy was so successful, because it involved several government organizations and targeted both urban and rural households at different levels. As a part of the policy, all economic incentives for high fertility and large families were removed. It included a comprehensive communication strategy which promoted the new family norms in schools and via mass media, which could even reach rural areas due to improvements in electrification. In addition, the new family planning policy had the support of religious leaders and birth control was advertised as social and religious duty. The spread of public health services could also reduce infant mortality, which reduces, according to the child survival theory, the number of children, and it provides access to contraceptives, which made birth control easier for couples. Figure 14 presents the development of the birth and fertility rates in Iran.

Figure 14: The development of the birth and fertility rates in Iran, 1960-2020



(a) Birth rate. (b) Fertility rate.

(Source: Authors' illustration using data from World Bank (WDI 2022))

After continuously decreasing over a period of 25 years, there was an uptick of the fertility rate between 2008 and 2019 from 1.8 births per woman to 2.1 births per woman, as presented in Figure 14b. During the same time period, the government was designing a new population policy, because the low fertility rate started to cause concern. In 2010, the government announced that the aim is to double the size of Iran's population to about 150 million people (Ladier-Fouladi 2021). This was supported by the Supreme Leader and resulted in a decree in 2014 which started the new population policy. Ladier-Fouladi (2021) argues that this new policy is partly responsible for the uptick of the fertility rate because it lead to several efforts to affect the fertility behavior. It included financial incentives, for example the compensation for each member of the household as a replacement for energy subsidies, and information campaigns in the mass media and during Friday prayers that were used to alter the public opinion on contraceptives. In addition, vasectomy and tubal ligation were criminalized by the parliament, and employment priorities were given to married men with children.

Several empirical studies reveal some of the characteristics for the individual fertility decision in Iran. Kiani (2011), Azmoude et al. (2019), and Hosseini et al. (2021) provide survey-based evidence on the woman's attitude to fertility, which includes factors such as the duration of marriage, the woman's age, the husband's age, the age at marriage, the level of religiosity, as well as employment and education. Moeeni et al. (2014) use household-level data and show that an increase of real per capita educational expenditure and real total expenditure of the household is associated with a lower probability of having more children. In addition, the wife's limited power over household decision-making positively affects the probability of having more children. They also found differences in the probability of having more children in low-, middle-, and high-income households. Sabermahani et al. (2017) use province-level data and show that marriage, paying cash subsidies, and Sunni population have positive effects on the fertility rate, and women's education, unemployment, family planning policies, and total annual household expenses have negative effect on the fertility rate.

6.2.3 Empirical Studies on COVID-19 and Similar Catastrophes

Previous theoretical considerations about the effect of societal change and times of uncertainty on marriage and fertility decisions have also been empirically investigated. One part of the literature focuses on the impact of war and conflict on marriage and fertility rates. Heuveline and Poch (2007) show for the case of Cambodia that the time of violence and political turmoil under the Khmer regime resulted in an increase of marriages and a baby boom after the crisis. Ladier-Fouladi (2021) presents a similar development in Iran during and after the Iran-Iraq War, where marriages were postponed until after the war due to the drafting of soldiers. In contrast, Cetorelli (2014) shows for the case of Iraq that the embargo and the 2003-2011 war in Iraq with its spread of poverty and deterioration of living conditions lead to a shift in the marriage pattern. Because of the uncertain situation, girls married at a younger age and also gave birth to the first child at a younger age.

In addition to the marriage situation, large catastrophes can have direct effects on reproductive organs (Abu-Musa 2008; Bolouki and Zal 2020) and on the life situation which both can have negative effects on the fertility rate and fertility intentions. A situation of war and conflict does not just mean that people die, but it also can cause the separation of couples and families, the displacement and migration of people, and the underregistration of births, which all can reduce the fertility rate in the short term. This was shown for several conflicts in Africa and Asia, where some authors found a drop in birth rates during the crises and a spike of birth rates afterwards (Agadjanian and Prata 2002; Blanc 2004; Heuveline and Poch 2007; Woldemicael 2008; Kraehnert et al. 2019; Thiede et al. 2020; Ahmed and Tan 2022). In contrast, Svallfors (2022) does not find a significant impact of conflict on women's fertility desires for the case of Colombia.

Another part of the literature focuses on the impact of natural disasters on marriage and fertility decisions. Several authors have shown that natural disasters increase the number of marriages, especially child marriages, in South Asia (Dewi and Dartanto 2019; Asadullah, Islam, and Wahhaj 2021; Dietrich et al. 2022). Additionally, Das and Dasgupta (2022) show for the case of a large-scale earthquake in India that it reduced the marriage age and the marriages into wealthier households in the affected areas. They argue that the negative economic shock due to the natural disaster pushed parents to marry off their daughters early to save on dowry expenditures. In addition, many studies from different parts of the world found an increase of birth rates after hurricanes, tsunamis, and earthquakes (Cohan and Cole 2002; Carta et al. 2012; Nobles, Frankenberg, and Thomas 2015; Behrman and Weitzman 2016; Davis 2017; Nandi, Mazumdar, and Behrman 2018).

However, the impact of natural disasters is not always that simple. Other studies show a decrease of birth rates after flood disasters and earthquakes in high income countries (Tong, Zotti, and Hsia 2011; Hamamatsu et al. 2014). Sellers and Gray (2019) show an increase in fertility desires after the delay of monsoon season in Indonesia in wealthier household, while there is a decrease in poorer households. Lin (2010) presents evidence for heterogenous effects depending on the disasters type and country characteristics, such as country-specific factors such as social attitudes, cultural values, network behavior, history, politics, and people's fertility preferences. Norling (2022) supports this argument and shows that the clearest effect comes from droughts, and the impact of other disasters is more complex. Rising temperatures reduce fertility rates and above-average precipitation is associated with higher likelihood of having a child in dry areas (Simon 2017; Barreca, Deschenes, and Guldi 2018; Eissler, Thiede, and Strube 2019; Cho 2020). The increase in temperatures and the lack of water can cause droughts that can impact agricultural production and the access to food which might lead to famine (Lindstrom and Berhanu 1999). High temperatures can also affect the health of mothers

and children, and thus result in poor pregnancy outcomes such as miscarriages, stillbirths, and low birth weights (Davenport, Dorelien, and Grace 2020).
Previous studies on the effect of pandemics, before COVID-19, focus mainly on the impact of influenza and HIV/AIDS on marriage and fertility rates. Boberg-Fazlic et al. (2021) find evidence for a baby boom directly after the 1918-19 influenza pandemic in Sweden, followed by a decline in fertility in the long term. They also show an increase of births by married women, especially in families with higher income. There are mixed results on the impact of the HIV/AIDS pandemic on fertility and marriage decisions in Africa. On the one hand, Chin and Wilson (2018) show for 14 countries from Sub-Saharan Africa a positive association between the HIV/AIDS pandemic and the fertility rates. But on the other hand, there are several studies that provide evidence that an HIV infection and the risk of infection can reduce both child quality, as reflected in children's schooling and health, and child quantity (Hunter et al. 2003; Terceira et al. 2003; Castro et al. 2015).
Another part of literature discusses the impact of economic recession on marriage and fertility decisions. The economic hardship during times of recession will also have an impact on individual relationships, especially marriages, and can cause marital problems and divorces (Aytac and Rankin 2009; Chowdhury 2013). Hill (2015) shows that the Great Depression in the USA delayed marriages in the short term, and he presents evidence that poor labor market condition for men reduced marriages, and poor female labor market conditions increased marriages. Sobotka et al. (2011) argue that the situation of unemployment during an economic recession will lead to a delay in marriages and a decline in first-birth rates. This applies especially to countries where marriage is the traditional and legal precondition for the birth of children.
The role of unemployment was also highlighted by other studies (Schneider 2015; Alderotti et al. 2021; Matysiak, Sobotka, and Vignoli 2021; Gatta et al. 2022). Matysiak et al. (2021) investigated the impact of the Great Recession in Europe between 2002 and 2014. They found that the fertility decline in the 28 member states was strongly related to unemployment, especially during the time of recession. Schneider (2015) found a similar relationship for the case of the USA. Several authors also show that high uncertainty about the future is associated with a decline in fertility (Aassve, Le Moglie, and Mencarini 2021; Comolli and Vignoli 2021), but this effect might depend on other individual characteristics, for example the income level. Davalos and Morales (2017) show for the case of Colombia that periods of recession are associated with fertility decline in poor areas and fertility growth in well-off areas.

Finally, the most recent part of literature focuses on the impact of the COVID-19 pandemic on marriage and fertility rates. The first observation at the beginning of the pandemic was a delay in marriages and divorces due to administrative challenges. The situation of lockdowns, quarantines, limitations of public gatherings, and distancing regulations affected both the supply and demand side of marriage and divorce services. Ghaznavi et al. (2022) and Komura and Ogawa (2022) show a decline of marriages, divorces, and births in the first months after the pandemic in Japan, which is the result of stay-at-home policies such as the nationwide state of emergency declarations. But the practical barriers cannot always explain the decline in marriages, as Hoehn-Velasco et al. (2022) show for the case of Mexico. There was also a drop in marriages and divorces during the first months of the pandemic, but only divorces returned to pre-pandemic baseline levels. Several studies from the USA also argue that the decline in marriages cannot only be explained by the closure of government agencies (Wagner, Choi, and Cohen 2020; Manning and Payne 2021; Westrick-Payne, Manning, and Carlson 2022). These studies also show a decline in marriages and divorces at the beginning of the pandemic, followed by a rebound in some states. Guetto et al (2021) provide survey-based evidence from Italy and show that the prospects of the continuation of the pandemic reduces marriage intentions, and they argue that cohabitation seems to be more compatible with uncertain times than traditional marriages.

Moreover, there is also empirical evidence for the impact of the COVID-19 pandemic on birth rates and fertility behavior from different countries. Aassve et al. (2021), Pomar et al. (2022), and Sobotka et al (2022) study the impact of the pandemic on birth and fertility rates in high-income and upper-middle income countries and show heterogeneity across their samples of mainly European countries, where several countries experienced a significant drop in crude birth rates at the beginning of the pandemic, which stabilized or slightly increased in subsequent months. Bailey et al. (2022) show a similar pattern for the USA, namely that fertility experienced an impact by the pandemic, first by a baby bump, and then followed by an increase of fertility among US-born women. Additionally, Kearney and Levine (2022) support these findings for the USA (and individual states) and provide evidence that a larger increase in the aggregate unemployment rate, a larger reduction in household spending, and higher cumulative COVID-19 caseloads were associated with larger decline in birth rates at the beginning of the pandemic. Lima et al. (2021) show also a temporary baby bust for several cities in Brazil. In contrast, Bujard and Andersson (2022) present results from Germany and Sweden, where the decline in fertility only started with the beginning of mass vaccination campaigns. This suggests that people adjusted their behavior to get vaccinated before becoming pregnant, as societies were opening up with post-pandemic life conditions. Nisen et al. (2022) show an increase of fertility during the pandemic in Finland.

In addition to country-level studies with focus on fertility and birth rates, there are also several studies that use surveys to determine individual characteristics that are responsible for the change of fertility behavior. The majority of studies come from Europe and North America and highlight the role of economic uncertainties, such as the job situation and household finances, or individual characteristics such as age, education, and mental well-being, or regional differences, such as severeness of COVID-19 infections in the region and access to healthcare facilities (Luppi, Arpino, and Rosina 2020; Arpino, Luppi, and Rosina 2021; Tavares, Botelho Azevedo, and Arpino 2022; Kurowska, Matysiak, and Osiewalska 2022; Malicka, Mynarska, and Swiderska 2021; Emery and Koops 2022). Existing studies also reveal that there are differences among subgroups of the population, for example depending on the location (urban versus rural), household income level, or being part of an ethnic or another visible minority (Fostik and Galbraith 2021; Manning, Guzzo, and Kamp Dush 2021; Akinyemi et al. 2022; Bailey, Currie, and Schwandt 2022; Zimmerman et al. 2022).

Luppi et al. (2020) show for five European countries that fertility plans have been revised in all countries with different magnitudes by either postponing or abandoning fertility plans, but there are differences between countries, and within countries, depending on individual characteristics, such as age, education, or severeness of COVID-19 infections in the region. Arpino et al. (2021) and Tavares et al. (2022) additionally show for several European countries that economic uncertainties, such as the worsening of the job situation or household finances, reduced fertility intentions. In contrast, Manning et al. (2021) provide evidence for the fertility intentions in the USA and show that characteristics such as life satisfaction, higher age, Asian and Latino ethnicity, and being married are positively associated with fertility intentions. In addition, respondents reported the importance of the economic and health situations.

A study from China revealed that the COVID-19 pandemic lowers the fertility intentions of women in childbearing age, and the economic pressure such as the decline in income emerged as the biggest factor influencing women’s fertility intentions (T. Chen et al. 2022). Another study from China shows that the access to health facilities is the biggest concern for couple’s childbearing decisions (Chu et al. 2022). Tan et al. (2021) compare the impact of the Zika virus (ZIKV) outbreak 2016-17 and the COVID-19 pandemic on women’s fertility desires in Singapore and found some differences. In both cases, women delayed their pregnancies, but in the case of COVID-19, they also reduced childbearing. The authors argue that this was due to fear of infection, change in subjective wellbeing, and income loss, which was associated with the COVID-19 pandemic.

While the previously discussed studies come from high-income and upper-middle income countries, there are also a few studies that include countries from low-income and lower-middle income countries. Wang et al. (2022) use a global sample and panel data to study the impact of pandemic-related uncertainty on fertility rates. They found that pandemic-related uncertainty decreases fertility rates, especially in non-OECD countries. Ameyaw et al. (2021) argue that the COVID-19 pandemic has put additional strain on the healthcare systems in Africa, and thus also disrupted birth-related services, which creates higher risks for the mothers and newborns. This situation in addition to travel restrictions had an impact on the fertility decisions. Until now, there is very few survey-based evidence from low-income and lower-middle income countries concerning the marriage and fertility decisions. Akinyemi et al. (2022) show for the case of Nigeria that women changed their fertility intentions due to the COVID-19 pandemic, which was mainly driven by economic concerns. Respondents reported the loss of household income, food insecurity, and greater reliance on the partner. The change in fertility desires was associated with age groups, higher wealth quintile, and household food insecurity. In another study from Kenya, Zimmerman et al. (2022) did not find a change in fertility desires due to COVID-19 related factors such as income loss, food insecurity, and social distancing. The only exception was the most vulnerable women who reported chronic food insecurity. They had higher fertility desires.

In addition to the studies from other countries, there are also some studies on the case of Iran in the context of fertility and marriage. Wilkins (2021) discusses a drop in marriages, and thus potential children, in Iran at the beginning of the pandemic. There are several studies that focus on marital problems during the pandemic and quarantine, such as parental-burnout, depression, sexual dissatisfaction, internet addiction, and domestic violence, which can lead to divorces or changes in the wish for the first child or additional children (Mousavi 2020; Aghamohseni et al. 2021; Banaei et al. 2021; Neyestani et al. 2022; Yari et al. 2021). Most studies focus on the topic of mental health which can impact the fertility intentions of couples (Ahmadi and Ramezani 2020; Daneshfar et al. 2021; Mirzaei et al. 2021; Hasannezhad Reskati et al. 2022). The fertility desires of Iranian women was studied by Afshari et al. (2022), who surveyed pregnant and non-pregnant women about their attitudes towards fertility and childbearing. They showed that half of the women postponed their pregnancy to after the pandemic, and those women who were employed, not pregnant, and not hospitalized due to COVID-19 had positive attitudes towards fertility.

This is where our study ties on and provides new empirical evidence to the literature. We are interested in the impact of the COVID-19 pandemic and the related change of social life on the marriage and fertility intentions of both women and men in Iran, which has not been studied yet. Moreover, it is the first study that systematically investigates the heterogeneity across gender, location (rural versus urban), and social class. To the best of our knowledge, it is also the first comprehensive study on Iran, and the first study on this scale from a lower-middle income country.

6.3 Data, Hypotheses, and Methodology

6.3.1 Data

In this study, we evaluate the impact of the COVID-19 pandemic on marriage and fertility behavior in Iran using cross-sectional data of a self-developed survey, collected by computer-assisted telephone interviews (CATI)[11]. We used previous theoretical considerations and empirical studies as a basis for the development of the questionnaire. It consists in total of 58 questions, including 21 questions capturing aspects related to the experience of the COVID-19 pandemic, as well as 37 questions related to socioeconomic characteristics and personal attitudes. The questionnaire was tested for reliability using Cronbach's alpha which resulted in a value of 0.99, indicating an excellent internal consistency (Tavakol and Dennick 2011). The interviews were conducted between 17 January 2022 and 4 February 2022 among a representative sample of 1306 Iranians, with 1214 completed interviews. The margin of error of the sample is approximately +/- 2.7%. To achieve a sample that represents the Iranian population, we have used a multi-stage cluster sampling with six stages, as presented in Figure E 2 in Appendix E.

The sampling procedure includes two strata, namely region and type of locality, which are the first two stages. For this reason, Iran is divided into nine regions, and within these regions, it is divided into rural and urban locations. The next two stages are the primary sampling units (PSU), which are cities, towns, and rural districts, and the secondary sampling units (SSU), which are the selection of municipal districts in tier I and tier II settlements. These types of settlements are cities with at least half a million population. Within each defined sampling unit, the random digit dialing (RRD) method with landline telephone was used to randomly select households, which is the fifth stage. Finally, in the sixth stage, the respondents were selected by the next birthday method, where only persons aged 18 years or above were considered. With

[11] The survey was conducted by R-Research (https://r-research.net/), and it was financially supported by German Academic Exchange Service (DAAD Project ID: 57571405) (www.daad.de).

this approach all Iranian provinces were covered, but not every province was selected in the sample, as the sample was not stratified by province. On basis of the standard definitions of the American Association for Public Opinion Research (AAPOR 2016), the contact rate of the survey was 89%, the cooperation rate 75%, and the overall response rate 67%. The interviews lasted 15-51 minutes, with an average of 24 minutes.

An overview of the sampling distribution of completed interviews in each region compared to the share of population in each region is presented in Table E 1 in Appendix E. The population in each of the nine regions was calculated based on the official Iranian 2016 Census (SCI 2018). We can see that the completed interviews in each region have a similar share than the population living in these regions. The split between urban and rural population of 74% and 26%, respectively, was achieved among the completed interviews, with a split of 75% and 25%. Due to the random sampling procedure to determine the survey participants, we have also a representative distribution of other characteristics such as age, gender, and education, as presented in Table E 2 in Appendix E. The aim of the sampling procedure was to achieve a sample that represents the general population of Iran, and the achieved shares of characteristics are comparable. The small differences in age and education might be explained by the survey design, because phone interviews can only reach certain demographics, which we need to keep in mind when interpreting the results.

6.3.2 Hypotheses

Based on the theory and previous empirical results, we have developed several hypotheses that will help to answer the following research question: *Did the COVID-19 pandemic affect family development in Iran?* With the sub question: *Did respondents from various genders, locations, and social classes show a different behavior?* We are interested to learn if marriage and fertility behavior in Iran was affected by the COVID-19 pandemic, and if there is heterogeneity among subgroups of the population. We measure the impact of the pandemic with several questions, which are used to test following eight hypotheses:

Hypothesis 1: Having the concern that the COVID-19 pandemic will continue is associated with a lower probability of marriage and fertility desires.

The hypothesis was formulated under the assumption that the uncertainty concerning the development of the COVID-19 pandemic and its consequences will motivate respondents to postpone or cancel plans for marriage and childbirth. This argument was used by several authors to explain the drop in marriages (Wagner, Choi, and Cohen 2020; Guetto, Vignoli, and Bazzani

2021; Manning and Payne 2021; Hoehn-Velasco et al. 2022; Westrick-Payne, Manning, and Carlson 2022) and births rates (Luppi, Arpino, and Rosina 2020; Aassve et al. 2021; Lima, Ferreira Soares, and Monteiro da Silva 2021; Afshari, Abedi, and Beheshtinasab 2022; Bailey, Currie, and Schwandt 2022; Pomar et al. 2022; Sobotka et al. 2022; Wang, Gozgor, and Lau 2022) at the beginning of the pandemic. Based on a survey in Italy, Guetto et al (2021) show that the prospects of the continuation of the pandemic reduces marriage intentions, which supports the theoretical framework of 'narratives of the future'. Luppi et al. (2020) surveyed people in five European countries and found that fertility plans have been revised in all countries as a consequence of the pandemic, but there are differences between and within countries. In a descriptive study, Afshari et al. (2022) showed that half of the surveyed Iranian women postponed their pregnancy to the time after the pandemic.

Hypothesis 2: Having experienced a COVID-19 infection is associated with a lower probability of marriage and fertility desires.

The underlying assumption of this hypothesis is that the experience of an infection with COVID-19 changes the respondents' attitudes towards marriage and childbirth. On the one hand, marriages need at least to be postponed due to an infection with the virus, and on the other hand, the life-threatening experience, especially when being hospitalized, can create fear for the health of newborn children. The health risk for the child is also discussed in the community influence theory (Rodgers, St John, and Colemann 2005) and economic theory (Chin and Wilson 2018). This fear or risk can be stronger, if the healthcare system was not able to cope with the burden of the pandemic, as seen in several countries (Ameyaw et al. 2021; Chu et al. 2022). Afshari et al. (2022) show for the case of Iran that those women who were not hospitalized due to COVID-19 had positive attitudes towards fertility. Other studies on the HIV/AIDS pandemic have also shown that fertility is lower among HIV-infected women (Hunter et al. 2003; Terceira et al. 2003). In addition, several cross-regional studies have shown that higher numbers of COVID-19 cases are associated with larger declines in birth rates (Kearney and Levine 2022; Luppi, Arpino, and Rosina 2020). However, this does not mean that there is a direct relationship between an infection with COVID-19 and the decision to have a child.

Hypothesis 3: Being vaccinated against COVID-19 is associated with a higher probability of marriage and fertility desires.

As the vaccination against COVID-19 increases the protection against the virus, we assume that vaccinated respondents will return to a pre-pandemic behavior, and thus have a higher likelihood to marry and bear children than their non-vaccinated counterparts. A marriage will be safer, if the participants are vaccinated, and it might fulfil existing legal requirements for social gatherings during the pandemic. For that reason, we assume that a vaccination will increase the probability of marriage. Women might also feel safer if they are vaccinated before deciding to get pregnant. This was also shown by Bujard and Andersson (2022) for the cases of Germany and Sweden, where women postponed their pregnancies to after the vaccination. However, there is also skepticism about the side effects of the COVID-19 vaccination and misinformation about the danger for the unborn child (Sparks et al. 2022), which can convince women to postpone pregnancy.

Hypothesis 4: Having experienced a life loss due to COVID-19 is associated with a higher probability of marriage and fertility desires.

The hypothesis was formulated under the assumption of the terror management theory and replacement theory (Rodgers, St John, and Colemann 2005; Nitsche and Lee 2022). First, we assume that in a situation where mortality becomes more visible, people will turn to traditional values and behaviors, such as marriage and having children. Second, we assume that the loss of life will motivate people to have more children, which will replace lost lives. This was already discussed by Abbasi-Shavazi et al. (2009) in the context of the Iran-Iraq War. However, there are also theoretical frameworks that argue for the opposite effect, for example the community influence theory and the economic theory discussed under Hypothesis 2. Therefore, the direction of the impact of the life loss on marriage and fertility desires is not clear.

Hypothesis 5: Having experienced a job loss due to the COVID-19 pandemic is associated with a lower probability of marriage and fertility desires.

The underlying assumption of this hypothesis is that the income loss due to the newly gained unemployment will motivate respondents to postpone or cancel plans for marriage and childbirth. This argument was used by several authors to explain the drop in marriages (Sobotka, Skirbekk, and Philipov 2011; Hill 2015) and birth rates (Schneider 2015; Alderotti et al. 2021; Matysiak, Sobotka, and Vignoli 2021; Kearney and Levine 2022) in the context of economic uncertainties and the COVID-19 pandemic. The theoretical background is the demand theory of demographic transition which assumes that the fertility desire falls when the costs of an additional child exceed the benefits of having that child (Abbasi-Shavazi, McDonald, and Hosseini-Chavoshi 2009). In agrarian family production, however, an additional child will be an economic asset, thus we might see a different effect in rural and urban areas. There might also be a different effect in the marriage behavior depending on the gender of the respondent (Hill 2015), because women might marry for economic reasons, on the one hand to reduce the burden of her parents in the time of crisis (Cetorelli 2014; Das and Dasgupta 2022), and on the other hand to have her own financial security in the future.

Hypothesis 6: Spending more time with the family due to the COVID-19 pandemic is associated with a higher probability of marriage and fertility desires.

As spending more time with family brings married couples physically closer together, we assume that it has increased fertility desires. Experiences from other natural disasters have shown an increase of birth rates after hurricanes, tsunamis, and earthquakes (Cohan and Cole 2002; Carta et al. 2012; Nobles, Frankenberg, and Thomas 2015; Behrman and Weitzman 2016; Davis 2017; Nandi, Mazumdar, and Behrman 2018). This is especially the case, if there is an increase of sexual activity and problems with the access to family planning services and contraceptives as a consequence of the disaster event. However, more time spend with the family due to a lockdown also means a reduced work-life balance and an increased burden on the parents (Mousavi 2020), which can reduce the wish for childbirth. The previous explanation applies only to married individuals, but there are also non-married individuals which will spend more time with their parents, because of lockdowns and quarantines. We assume that this will motivate young adults to marry and leave the parental household, so that they can avoid the parent-child conflict which can be a consequence of being stuck together for too long.

Hypothesis 7: Spending more time in home office due to the COVID-19 pandemic is associated with a higher probability of marriage and fertility desires.

The hypothesis was formulated under the assumption that more time spend in home office will allow parents to combine paid work, career opportunities, and childcare, and thus it will increase marriage and fertility intentions. Several authors have discussed that home-based work can make it easier to combine family and work life (Powell and Craig 2015; H. Chung and Van der Horst 2018; H. Chung and Van der Lippe 2020). In addition, more time spend at home will bring married couples physically closer together, as discussed in Hypothesis 6, which can facilitate the fertility desires. However, spending more time in home office can also blur the boundaries between paid work and family life and exacerbate the work-family conflict (Glavin and Schieman 2012; Kurowska 2020; Kurowska, Matysiak, and Osiewalska 2022). There is very little empirical evidence on this topic in the context of the COVID-19 pandemic. Kurowska et al. (2022) found a negative relationship between home-based work and fertility intentions in Poland during the pandemic. Overall, the final effect of home office on marriage and fertility decisions might depend on other factors, such as gender, employment type, or working hours. Therefore, the direction of the effect is not clear.

Hypothesis 8: Having experienced a decline in household income due to the COVID-19 pandemic is associated with a lower probability of marriage and fertility desires.

The underlying assumption of this hypothesis is that the decline of household income will motivate respondents to postpone or cancel plans for marriage and childbirth. It has a similar topic as Hypothesis 5, but it has wider implications. Asking for the decline in household income does not only account for the individual loss of income due to unemployment, but it takes into account the decline of household income by other members of the household, such as parents or marital partners, and it considers a reduction in working hours or disturbances of self-employed business activities due to the pandemic. Previous studies have found evidence for the negative impact of the loss of household income on marriage and fertility decisions (Tan, Ryan, and Lim-Soh 2021; Akinyemi et al. 2022; T. Chen et al. 2022). Overall, we follow the same theoretical considerations as Hypothesis 5, and we expect heterogenous effects of the household income loss on marriage and fertility desires, depending on gender, location, and social class.

6.3.3 Methodology

For the empirical investigation, we are using logit regressions, where the dependent variable is the measurement of family development (*FD*), as presented in the following specification (10). The variable *FD* will be measured with four questions that asked, if the respondents have married during the COVID-19 pandemic or have plans to marry within the next six months (*Marriage*), and if the respondents have born a child during the pandemic or have plans to have a child within the next six months (*Childbirth*). As the actual childbirth does not reflect the change of the willingness to have children, we have also asked questions on how the willingness to have children have changed since the start of the pandemic, either from willingness to have children to unwillingness (*Child desire decrease*), or from unwillingness to have children to willingness (*Child desire increase*).

$$FD_i = \alpha + \beta_1 \cdot Concern_i + \beta_2 \cdot Infection_i + \beta_3 \cdot Vaccination_i + \beta_4 \cdot Loss_i + \beta_5 \cdot Job_i + \beta_6 \cdot Family_i + \beta_7 \cdot Home_i + \beta_8 \cdot Income_i + \beta_9 \cdot Controls_i + \varepsilon_i \tag{10}$$

We aim to explain the respondents' marriage and fertility behavior (*FD*) by the respondents' concern about the continuation of the COVID-19 pandemic (*Concern*), the experience with a COVID-19 infection (*Infection*), the vaccination status (*Vaccination*), the experience with the life loss of a close relative or family member due to COVID-19 (*Loss*), the experience of a job loss due to the pandemic (*Job*), the increase in time spend with the family since the start of the pandemic (*Family*), the increase in time spend in home office since the start of the pandemic (*Home*), and the decrease of household income due to the pandemic (*Income*). Constant (α) and error term (ε) are also included. In addition, we control for several other socio-economic characteristics (*Controls*) that are relevant in the context of marriage and fertility decisions, such as age, gender, education, social class, employment, life satisfaction, security perception, trust, religiosity, and location (urban versus rural). Except for age, all explanatory variables are binary. Moreover, we consider the six-stage survey design, as presented in Figure E 2 in Appendix E, when declaring the primary sampling unit (PSU), the strata, and the weight. These will be used to calculate the Taylor-linearized standard errors (Wolter 2007). The F-statistics are calculated using an adjusted Wald test which also considers the survey design (Korn and Graubard 1990).

6.4 Results and Discussion

The description of used variables is presented in Table 17. The first four questions (Q1 to Q4) are used as the dependent variables in our estimations, and the following eight questions (Q5 to Q12) are used as the explanatory variables to test our hypotheses. The remaining questions (Q13 to Q22) are used as control variables.

Table 17: Answers to survey questions (shares in percent), Iran

No.	Label	Question	n	[0]	[1]	[2]	[3]	[4]
Q1	Marriage	Did you marry during the pandemic in the years 2020 and 2021 (1399 and 1400)? Do you have the plans to get married within the next 6 months?	1214	94.65	5.35			
Q2	Child desire decrease	Did your willingness to have children have changed since the start of the pandemic? ("Yes, I wanted children before, but now I am not planning to have children.")	1194	90.37	9.63			
Q3	Child desire increase	Did your willingness to have children have changed since the start of the pandemic? ("Yes, I did not want children before, but now I am planning to have children.")	1194	96.65	3.35			
Q4	Childbirth	Do you have a child that was born in 2020 or 2021 (1399 or 1400)? Are you expecting that your child will be born in the next 6 months?	1214	95.63	4.37			
Q5	Concern	In general, to what extent are you concerned that the coronavirus will continue to spread and infect many people in your country over the next 6 months? (4-point Likert scale from [0] "Not at all concerned" to [3] "Very concerned".)	1211	13.54	18.74	28.41	39.31	
Q6	Infection	Did you personally experience a COVID-19 infection?	1198	65.28	34.72			
Q7	Vaccination	Are you vaccinated against the COVID-19 virus?	1125	7.33	92.67			
Q8	Loss	Did you experience the loss of a close relative or a family member due to COVID-19?	1214	59.97	40.03			
Q9	Job	How your current job situation compares with what it was before the COVID-19 pandemic started in March 2020? ("I lost my previous job because of the pandemic.")	1205	90.62	9.38			
Q10	Family	How did the time spend with your family has changed since the beginning of the pandemic? ("The time spend with family has increased.")	1214	60.13	39.87			
Q11	Home	On average, how many days per week did you work from home before the pandemic started in March 2020? And how many days per week, on average, did you work from home during the pandemic, especially between March 2020 and September 2021? (Here: [1] if first difference is positive.)	1214	92.17	7.83			
Q12	Income	Have you experienced a fall in household income as a consequence of the COVID-19 pandemic?	1214	82.7	17.3			
Q13	Age	What is your year of birth? (Here: rescaled to share of five age groups [0] 18-24, [1] 25-34, [2] 35-44, [3] 45-54, and [4] 55-65.)	1211	12.8	14.78	25.85	19.98	26.59
Q14	Gender	What is your gender?	1214	50.58	49.42			
Q15	Education	What is your level of education? (Here: rescaled to 4-point Likert scale [0] illiterate, [1] primary, [2] secondary, and [3] tertiary.)	1214	8.4	12.03	43.57	36	
Q16	Social class	People sometimes describe themselves as belonging to the working class, the middle class, or the upper or lower class. Would you describe yourself as belonging one of them? (5-point Likert scale: [0] lower class, [1] working class, [2] lower-middle class, [3] upper-middle class, and [4] upper class.)	1211	10.49	26.26	46.16	16.85	0.25
Q17	Job type	Where are you currently working? If you do not work currently, characterize your major work in the past! Do you or did you work for? (3-point Likert scale: [0] never employed, [1] private sector, and [2] public sector.)	1171	32.37	45.69	21.95		
Q18	Life satisfaction	All things considered, how satisfied are you with your life as a whole these days? (4-point Likert scale from [0] "Completely dissatisfied" to [3] "Completely satisfied".)	1212	15.35	20.79	46.62	17.24	
Q19	Security	Could you tell me how secure do you feel these days in your neighborhood? (4-point Likert scale from [0] "Not at all secure" to [3] "Very secure".)	1212	4.54	10.07	39.85	45.54	

Q20	Trust	Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?	1211	84.39	15.61		
Q21	Religiosity	Indicate how important is religion in your life? (4-point Likert scale from [0] "Not at all important" to [3] "Very important".)	1211	3.39	6.03	20.4	70.19
Q22	Location	Determined by phone number. (Here: [0] rural and [1] urban.)	1214	25.12	74.88		

Notes: The questions were originally asked in Persian language and not in the here presented order. If not otherwise mentioned, answer [0] refers to "No" and answer [1] refers to "Yes".

For practical reasons, several of the variables are rescaled in the analysis from 4-point Likert scale to binary variables, namely Q5, Q18, Q19, and Q21. In the first three questions the answers [3] and [4] will be rescaled to [1] and zero otherwise, and in question Q21 the answer [4] will be rescaled to [1] and zero otherwise. The variable Q13 will be used as continuous variable which measures the age of respondents in years.

The descriptive statistics presented in Table 17 already provides a first glimpse of the impact of the COVID-19 pandemic in Iran. After six waves of COVID-19, the direct health consequences of the pandemic are that 34.7% of the respondents have personally experienced a COVID-19 infection and 40% reported that they have lost a close relative or family member due to the virus. Related to the economic consequences, 17.3% of respondents have answered that they have experienced a fall in household income and 9.4% have lost their job because of the pandemic. Moreover, 39.9% of respondents have reported that the time spend with family has increased and 7.8% of respondent answered that the time spend in home office has increased compared to the time before the pandemic. In addition, the survey revealed that 15% of respondents have changed their fertility intentions as a consequence of the pandemic; more precisely, 9.6% have replied that they wanted children before, but now they are not planning to have children, and 5.4% have replied that they did not want children before, but now they are planning to have children. Table 18 reports the average marginal effects of the empirical investigation using logit regressions, where we study the determinants of marriage, child desire, and childbirth.

Referring to Hypothesis 1, we can see that the concern of the continuation of the pandemic is negatively associated with childbirth during the pandemic. More precisely, respondents who are concerned about the continuation of the pandemic have a 3.2 percentage points (pp) lower probability to have a child born in 2020 and 2021. This supports the community influence theory and empirical studies from other countries (Luppi, Arpino, and Rosina 2020; Aassve et al. 2021; Lima, Ferreira Soares, and Monteiro da Silva 2021; Afshari, Abedi, and Beheshtinasab 2022; Bailey, Currie, and Schwandt 2022; Pomar et al. 2022; Sobotka et al. 2022; Wang, Gozgor, and Lau 2022). For the other three dependent variables, we do not find a statistically significant association on conventional levels. The respondents' infection with COVID-19, which was discussed in Hypothesis2, does not show a statistically significant association with marriage, child desire, and childbirth in the full sample. However, the further analysis will reveal that there are significant effects in the subsamples of locations and social classes.

In reference to Hypothesis 3, we can see that the vaccination status of respondents shows a statistically significant and negative association with the respondents' childbirth behavior. According to the results, respondents who are vaccinated have a 4.7 pp lower probability to have a child born in 2020 and 2021. This finding is in contrast to previous studies such as Bujard and Andersson (2022) who argued that women postponed their pregnancies to after the vaccination. A possible explanation for the negative relationship is the skepticism about the side effects of the vaccination and especially misinformation about the danger for the unborn child (Sparks et al. 2022), which has convinced women to postpone pregnancy or not to get vaccinated. The other three dependent variables do not show a statistically significant association on conventional levels with the vaccination status.

With Hypothesis 4, we have studied the relationship between the experience of the life loss of a close relative or family member due to COVID-19 and the four dependent variables. We found that respondents who have experienced a life loss due to the pandemic have a 4.2 pp higher probability to change their willingness to have children, from wanting children before to not planning to have children. This can be explained with the community influence theory and especially the concerns about the capabilities of the health system during the pandemic which have been discussed by previous studies (Rodgers, St John, and Colemann 2005; Ameyaw et al. 2021; Chu et al. 2022). For the other three dependent variables, we do not find a statistically significant association on conventional levels.

Table 18: Determinants of marriage, child desire, and childbirth (marginal effects), full sample

	(18.1) Marriage	(18.2) Child desire decrease	(18.3) Child desire increase	(18.4) Childbirth
Concern	-0.022	0.016	-0.002	**-0.032****
	(-1.595)	(0.786)	(-0.150)	**(-2.389)**
Infection	-0.018	-0.027	-0.013	-0.022
	(-1.160)	(-1.355)	(-0.968)	(-1.508)
Vaccination	0.019	-0.006	-0.010	**-0.047*****
	(0.690)	(-0.192)	(-0.475)	**(-2.914)**
Loss	-0.024	**0.042****	0.001	0.007
	(-1.645)	**(2.368)**	(0.068)	(0.562)
Job	**0.042****	**0.089*****	-0.045	-0.040
	(2.254)	**(3.542)**	(-1.401)	(-1.210)
Family	0.001	0.017	**0.024****	0.011
	(0.113)	(0.935)	**(2.079)**	(0.834)
Home	0.012	0.001	0.013	0.027
	(0.440)	(0.015)	(0.588)	(1.101)
Income	0.024	0.024	-0.004	-0.012
	(1.345)	(1.009)	(-0.297)	(-0.600)
Female	0.008	0.012	0.006	**0.031****
	(0.518)	(0.614)	(0.482)	**(2.271)**
Age	**-0.004*****	**-0.003*****	**-0.001****	**-0.003*****
	(-5.599)	**(-3.838)**	**(-2.225)**	**(-4.202)**
Education (secondary)	0.016	-0.023	0.030	-0.012
	(0.386)	(-0.785)	(1.102)	(-0.514)
Education (tertiary)	0.052	-0.006	0.020	0.002
	(1.258)	(-0.179)	(0.657)	(0.093)
Lower class	0.012	0.031	**0.055****	0.003
	(0.466)	(0.816)	**(2.123)**	(0.088)
Working class	-0.009	0.044	0.030	0.017
	(-0.475)	(1.498)	(1.319)	(0.866)
Lower-middle class	-0.010	0.008	0.028	-0.001
	(-0.620)	(0.310)	(1.314)	(-0.064)
Job type (private sector)	0.005	0.022	0.011	0.005
	(0.273)	(1.003)	(0.804)	(0.411)
Job type (public sector)	-0.017	0.022	0.007	-0.031
	(-0.721)	(0.744)	(0.418)	(-1.310)
Life satisfaction	**0.028***	-0.028	0.009	**0.041****
	(1.923)	(-1.444)	(0.732)	**(2.518)**
Security	**-0.038****	**-0.060*****	0.013	-0.017
	(-2.449)	**(-2.766)**	(0.648)	(-0.976)
Trust	0.015	-0.021	-0.006	-0.021
	(0.989)	(-0.766)	(-0.420)	(-1.098)
Religiosity	0.012	-0.018	0.015	0.010
	(0.901)	(-0.984)	(1.055)	(0.678)
Urban	**-0.033****	-0.015	-0.018	-0.023
	(-2.132)	(-0.754)	(-1.349)	(-1.619)
Childbirth	0.008			
	(0.385)			
Marriage		-0.058	-0.018	-0.001
		(-1.614)	(-0.656)	(-0.035)
Observations	1130	1116	1116	1130
F-statistic	6.91***	3.59***	2.78***	5.11***
Estimator	Logit	Logit	Logit	Logit

*Notes: Linearized standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

Referring to Hypothesis 5, we can see that unemployment due to the pandemic is also an important determinant of marriage and child intentions. According to the results, respondents who became unemployed have an 8.9 pp higher probability to change their willingness to have children, from wanting children before to not planning to have children. This finding is in line with the discussed theory because children are associated with a financial burden in non-agrarian societies, which will lead to a reduction of child desires if the household income will be reduced due to unemployment. Previous empirical studies also support this argument (Abbasi-Shavazi, McDonald, and Hosseini-Chavoshi 2009; Schneider 2015; Alderotti et al. 2021; Matysiak, Sobotka, and Vignoli 2021; Kearney and Levine 2022). In addition, respondents who became unemployed due to the pandemic have a 4.2 pp higher probability to have married during the pandemic or are planning to do so. The further analysis will reveal that there are heterogenous effects, depending on gender, location, and social class. This supports empirical studies from other catastrophes which show that times of economic uncertainties facilitate marriages of women (Cetorelli 2014; Hill 2015; Das and Dasgupta 2022).

In reference to Hypothesis 6, we can see that more time spend with the family during the pandemic is positively associated with the willingness to have children. More precisely, respondents who have replied that the time spend with family has increased have a 2.4 pp higher probability that the willingness to have a child has increased. This supports the argument that spending more time with family brings married couples physically closer together and therefore increased the fertility intentions, which has also been discussed by other authors in the context of natural disasters (Ahmed and Tan 2022). For the other three dependent variables, we do not find a statistically significant association on conventional levels.

Finally, the variables *Home* and *Income*, which refer to Hypothesis 7 and Hypothesis 8, do not show any significant relationships on conventional levels with the four dependent variables in the full sample. As previously discussed, the effect of spending more time in home office on fertility intention is not clear, as it can either increase fertility intention due to an improved work-life balance (Powell and Craig 2015; H. Chung and Van der Horst 2018; H. Chung and Van der Lippe 2020), or it can facilitate the work-family conflict and thus reduce fertility intentions (Glavin and Schieman 2012; Kurowska 2020; Kurowska, Matysiak, and Osiewalska 2022). Our results suggest that none of these mechanisms dominates in the full sample, and thus the association is statistically insignificant on conventional levels. For the insignificant effects of *Income*, a possible explanation is that the main effect of income loss is already captured by the job loss variable. In addition, a study from Kenya also did not find a change in fertility desires due to COVID-19-related income loss (Zimmerman et al. 2022). This shows that the effect of the income loss might also be different depending on other factors.

In addition to our main variables of interest, we have also included other control variables, of which *Female*, *Age*, *Lower class*, *Life satisfaction*, *Security*, and *Urban* show statistically significant but mixed results. First, the respondents' gender shows a positive and statistically significant association with childbirth, which means that respondents who are female have a 3.1 pp higher probability to have a child born in 2020 and 2021. Second, the respondents' age shows a negative and statistically significant association with all four dependent variables. Third, the respondents who consider themselves as lower class have a 5.5 pp higher probability that the willingness to have a child has increased. Fourth, the respondents' life satisfaction shows a positive and statistically significant association with marriage and childbirth, which supports the community influence theory. Fifth, the respondents who feel secure have a 3.8 pp lower probability to having married during the pandemic, and they have a 6 pp lower probability of child desire decrease. Finally, respondents who are located in urban areas have a 3.3 pp lower probability of having married during the pandemic.

6.4.1 Heterogeneity across Genders

As previous results have suggested heterogenous effects depending on the respondents' gender, we have also estimated previous specifications for the subsamples of female and male respondents. From the full sample of 1214 respondents, there are 612 female respondents (50.4%) and 600 male respondents (49.4%). The reasoning behind this approach is that there are differences of the burden of childbirth on the female and male body, which is higher for women, and there are traditionally different roles within marriage for both genders. In addition, previous studies have not always included both genders, for example the discussed studies from low-income and lower-middle income countries that have only focused on the women's intentions (Tan, Ryan, and Lim-Soh 2021; Afshari, Abedi, and Beheshtinasab 2022; Akinyemi et al. 2022; T. Chen et al. 2022; Zimmerman et al. 2022).

The results of the empirical investigation using logit regressions are presented in Table 19 where we report the average marginal effects. When comparing the female and male subsamples, we can see different associations of the variables *Concern*, *Vaccination*, *Job*, *Family*, and *Income*, which refer to five of the eight hypotheses. According to the results, the relationships of the dependent variable *Childbirth* with the explanatory variables *Concern* and *Vaccination* are only statistically significant on conventional levels in the female subsample. This means that female respondents who are concerned about the continuation of the pandemic have a 6.5 pp lower probability to have a child born in 2020 and 2021, and that female respondents who are vaccinated have a 7.1 pp lower probability to have a child born during the pandemic. Moreover, the relationship of the dependent variable *Marriage* with the explanatory variable *Job* is only statistically significant on conventional levels in the female subsample. Thus, female respondents who became unemployed due to the pandemic have a 5.7 pp higher probability to have married during the pandemic or are planning to do so. This means that women who lost their job due to the pandemic compensated the income loss with marriage, which brings financial security for the bride and reduce the burden of her parents' household.

Table 19: Determinants of marriage, child desire, and childbirth (marginal effects), gender samples

	(19.1) Marriage (female)	(19.2) Marriage (male)	(19.3) Child desire decrease (female)	(19.4) Child desire decrease (male)	(19.5) Child desire increase (female)	(19.6) Child desire increase (male)	(19.7) Childbirth (female)	(19.8) Childbirth (male)
Concern	-0.023	-0.012	0.012	0.013	-0.029	0.023	**-0.065*****	-0.007
	(-1.052)	(-0.652)	(0.417)	(0.524)	(-1.523)	(0.978)	**(-2.893)**	(-0.567)
Infection	-0.035	0.005	-0.038	-0.021	-0.019	0.003	-0.035	-0.011
	(-1.533)	(0.209)	(-1.408)	(-0.831)	(-1.022)	(0.158)	(-1.482)	(-0.767)
Vaccination	0.005	0.046	-0.041	0.030	-0.008	0.002	**-0.071*****	0.005
	(0.132)	(0.996)	(-1.116)	(0.645)	(-0.294)	(0.067)	**(-3.090)**	(0.178)
Loss	-0.032	-0.016	**0.045***	**0.039***	0.013	-0.013	0.004	0.006
	(-1.490)	(-0.814)	**(1.791)**	**(1.759)**	(0.737)	(-0.747)	(0.217)	(0.570)
Job	**0.057****	0.034	**0.102*****	**0.079****		-0.032		-0.005
	(2.408)	(1.363)	**(2.670)**	**(2.372)**		(-0.805)		(-0.206)
Family	0.018	-0.018	0.007	0.021	**0.028***	0.023	0.021	-0.010
	(0.913)	(-0.883)	(0.298)	(0.907)	**(1.730)**	(1.317)	(1.075)	(-0.675)
Income	0.005	**0.039***	0.028	0.007	-0.032	0.013	0.007	-0.012
	(0.137)	**(1.761)**	(0.665)	(0.259)	(-0.834)	(0.623)	(0.199)	(-0.877)
Age	**-0.005*****	**-0.004*****	**-0.005*****	**-0.002****	**-0.003*****	-0.001	**-0.004*****	**-0.001*****
	(-3.858)	**(-4.524)**	**(-4.060)**	**(-2.265)**	**(-3.248)**	(-1.434)	**(-4.156)**	**(-3.036)**
Education (tertiary)	**0.039***	**0.046****	0.011	0.020	0.004	-0.025	0.000	0.018
	(1.814)	**(2.193)**	(0.383)	(0.733)	(0.194)	(-1.173)	(0.016)	(1.464)
Lower class	0.038	-0.010	0.085	-0.012	**0.083*****	0.023	-0.024	0.001
	(1.077)	(-0.256)	(1.476)	(-0.257)	**(2.615)**	(0.440)	(-0.484)	(0.063)
Working class	-0.006	-0.014	**0.090****	0.009	0.035	0.021	0.024	-0.001
	(-0.195)	(-0.522)	**(2.158)**	(0.239)	(1.179)	(0.467)	(0.826)	(-0.041)
Lower-middle class	0.004	-0.030	**0.066***	-0.035	0.023	0.044	-0.009	-0.006
	(0.180)	(-1.305)	**(1.826)**	(-0.996)	(0.902)	(1.016)	(-0.344)	(-0.352)
Job (private sector)	0.013	-0.023	-0.004	0.058	0.020	-0.027	-0.011	0.039
	(0.521)	(-0.697)	(-0.147)	(1.426)	(0.998)	(-0.783)	(-0.514)	(1.606)
Job (public sector)	0.009	-0.043	0.043	0.026	-0.007	-0.012	**-0.079***	0.022
	(0.274)	(-0.938)	(1.067)	(0.563)	(-0.210)	(-0.325)	**(-1.745)**	(0.811)
Life satisfaction	0.017	0.037	-0.030	-0.033	0.024	-0.001	**0.062****	0.008
	(0.840)	(1.499)	(-1.077)	(-1.276)	(1.216)	(-0.056)	**(2.532)**	(0.495)
Security	**-0.055****	-0.019	**-0.083*****	-0.032	0.010	0.029	-0.010	-0.009
	(-2.304)	(-0.835)	**(-2.843)**	(-1.123)	(0.337)	(0.750)	(-0.409)	(-0.567)
Trust	0.020	0.011	-0.023	-0.016	-0.003	-0.009	-0.015	-0.026

	(1.003)	(0.485)	(-0.607)	(-0.436)	(-0.152)	(-0.322)	(-0.546)	(-1.087)
Religiosity	**0.054****	-0.029	-0.010	-0.019	0.038	-0.004	0.014	0.003
	(2.327)	(-1.512)	(-0.392)	(-0.787)	(1.543)	(-0.162)	(0.706)	(0.176)
Urban	**-0.043***	-0.019	**0.071***	**-0.061****	-0.008	-0.029	-0.015	**-0.022***
	(-1.828)	(-0.939)	**(1.909)**	**(-2.318)**	(-0.434)	(-1.414)	(-0.695)	**(-1.664)**
Childbirth	0.020	-0.020						
	(0.761)	(-0.396)						
Marriage			-0.088	-0.032	-0.038	-0.005	0.009	-0.023
			(-1.580)	(-0.741)	(-1.029)	(-0.155)	(0.310)	(-0.811)
Observations	563	567	554	562	559	562	568	567
F-statistic	4.08***	4.89***	3.02***	2.7***	3.6***	2.48***	5.47***	3.93***
Estimator	Logit	Logit	Logit	Logit	Logit	Logit	Logit	Logit

*Notes: Linearized standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Some variables were dropped by the STATA software because they predict the failure perfectly.*

6.4.2 Heterogeneity across Locations

Another aspect which plays a role in the context of this study is the heterogeneity across locations, which refers to the respondents' type of settlement that means if respondents are located in urban or rural areas. From the full sample of 1214 respondents, there are 909 urban respondents (74.9%) and 305 rural respondents (25.1%). Thus, we have also estimated previous specifications for the subsamples of urban and rural respondents. The rationale for this approach is that there are historically different marriage and birth patterns in urban and rural areas in Iran (Abbasi-Shavazi, McDonald, and Hosseini-Chavoshi 2009). In addition, the theoretical considerations by Aassve et al. (2020) expect different effects of the COVID-19 pandemic on fertility in low- and middle-income countries, depending on the settlement type. Therefore, we expect different drivers of marriage and fertility in urban and rural areas.

The results of the empirical investigation using logit regressions are presented in Table 20 where we report the average marginal effects. When comparing the urban and rural subsamples, we can see different associations of the variables *Infection*, *Job*, *Family*, and *Income*, which refer to four of the eight hypotheses. According to the results, the association with *Infection* and the dependent variables is different in urban and rural areas. This means that rural respondents who were infected with COVID-19 have a 15.5 pp lower probability of having married during the pandemic or are planning to do so, while the association in the urban subsample is statistically insignificant on conventional levels. In the case of the urban subsample, we can see that respondents who were infected with COVID-19 have a 3.3 pp lower probability of having an increased child desire, and they have a 2.7 pp lower probability of having a child born during the pandemic or are planning to do so.

Moreover, the measurement of job loss also only shows a statistically significant association on conventional levels in the urban subsample. Accordingly, urban respondents who became unemployed due to the pandemic have a 4.2 pp higher probability to have married during the pandemic or are planning to do so, and they have a 10.3 pp higher probability to change their willingness to have children, from wanting children before to not planning to have children. In addition, urban respondents who have replied that the time spend with family has increased have a 3.3 pp higher probability that the willingness to have a child has increased. Last but not least, the variable of household income decrease (*Income*), which does not show statistically significant associations with the four dependent variables in the full sample, shows statistically significant associations with marriage and childbirth, when considering urban and rural subsamples.

Table 20: Determinants of marriage, child desire, and childbirth (marginal effects), location samples

	(20.1) Marriage (urban)	(20.2) Marriage (rural)	(20.3) Child desire decrease (urban)	(20.4) Child desire decrease (rural)	(20.5) Child desire increase (urban)	(20.6) Child desire increase (rural)	(20.7) Childbirth (urban)	(20.8) Childbirth (rural)
Concern	-0.015	-0.025	0.001	0.074	-0.013	0.044	**-0.026****	**-0.061***
	(-1.070)	(-0.731)	(0.058)	(1.606)	(-1.092)	(1.118)	**(-1.991)**	**(-1.946)**
Infection	0.007	**-0.155*****	-0.026	-0.069	**-0.033***	0.048	**-0.027***	0.003
	(0.423)	**(-3.322)**	(-1.216)	(-1.369)	**(-1.937)**	(1.357)	**(-1.700)**	(0.088)
Vaccination	0.016		-0.007	-0.080	-0.013		**-0.051*****	
	(0.725)		(-0.222)	(-1.036)	(-0.766)		**(-3.445)**	
Loss	-0.017	-0.038	**0.040****	**0.075****	**0.019***	**-0.064***	0.002	0.039
	(-1.099)	(-1.031)	**(1.994)**	**(2.107)**	**(1.720)**	**(-1.777)**	(0.145)	(1.356)
Job	**0.042****	0.044	**0.103*****	0.058	-0.032		-0.047	-0.010
	(1.968)	(1.088)	**(3.566)**	(1.128)	(-1.050)		(-1.113)	(-0.159)
Family	-0.001	0.012	0.022	-0.004	**0.033****	0.007	0.013	-0.005
	(-0.080)	(0.424)	(1.086)	(-0.101)	**(2.412)**	(0.303)	(0.960)	(-0.180)
Home	0.003		0.018		0.028		0.028	
	(0.109)		(0.515)		(1.570)		(1.245)	
Income	**0.046****	-0.018	0.026	-0.016	-0.012	0.044	**-0.071***	**0.094****
	(2.506)	(-0.469)	(0.893)	(-0.337)	(-0.783)	(1.309)	**(-1.820)**	**(2.304)**
Female	-0.016	**0.048***	**0.048****	**-0.100***	0.019	-0.033	**0.033****	-0.001
	(-0.904)	**(1.741)**	**(2.123)**	**(-1.944)**	(1.303)	(-1.184)	**(2.201)**	(-0.038)
Age	**-0.004*****	**-0.005*****	**-0.003*****	**-0.004****	**-0.002*****	0.000	**-0.002*****	**-0.004*****
	(-4.991)	**(-3.281)**	**(-3.162)**	**(-2.582)**	**(-3.516)**	(0.254)	**(-3.420)**	**(-2.972)**
Education (secondary)	-0.022	0.048	0.011	-0.060	-0.006	**0.117***	0.044	**-0.089***
	(-0.509)	(0.664)	(0.258)	(-1.210)	(-0.214)	**(1.845)**	(1.145)	**(-1.826)**
Education (tertiary)	0.009	**0.137***	0.027	-0.021	-0.017	0.087	0.055	-0.034
	(0.206)	**(1.826)**	(0.594)	(-0.360)	(-0.632)	(1.173)	(1.361)	(-0.669)
Lower class	-0.011	0.109	0.031	0.053	**0.060****	0.051	-0.006	-0.030
	(-0.370)	(1.482)	(0.687)	(0.547)	**(2.249)**	(0.722)	(-0.155)	(-0.557)
Working class	-0.005	0.032	**0.054***	0.062	0.027	0.022	0.029	-0.032
	(-0.224)	(0.548)	**(1.657)**	(0.741)	(1.227)	(0.361)	(1.319)	(-0.908)
Lower-middle class	-0.020	0.026	0.012	0.048	**0.036***	0.023	0.008	-0.031
	(-1.265)	(0.472)	(0.411)	(0.602)	**(1.810)**	(0.387)	(0.469)	(-0.828)
Job (private sector)	-0.017	**0.087****	0.012	0.068	0.024	**-0.071****	0.016	**-0.093****
	(-0.883)	**(2.259)**	(0.498)	(1.189)	(1.597)	**(-2.161)**	(1.176)	**(-2.181)**
Job (public sector)	**-0.048***	0.068	0.011	0.048	0.017	-0.050	-0.022	-0.085

	(-1.727)	(1.377)	(0.360)	(0.677)	(0.935)	(-1.107)	(-0.883)	(-1.236)
Life satisfaction	**0.043****	-0.000	-0.006	**-0.084****	0.006	0.012	**0.041****	0.048
	(2.434)	(-0.005)	(-0.260)	**(-2.133)**	(0.558)	(0.434)	**(2.472)**	(1.402)
Security	**-0.038****	**-0.108****	**-0.062*****	-0.063	0.008		-0.019	0.041
	(-2.343)	**(-2.238)**	**(-2.694)**	(-1.054)	(0.489)		(-1.226)	(0.639)
Trust	0.018	0.005	-0.044	0.047	0.000	-0.024	-0.018	-0.044
	(1.205)	(0.129)	(-1.346)	(0.861)	(0.009)	(-0.482)	(-0.928)	(-0.889)
Religiosity	-0.001	**0.107****	**-0.036***	0.087	**0.025****	0.006	0.009	-0.025
	(-0.059)	**(2.040)**	**(-1.695)**	(1.635)	**(2.087)**	(0.171)	(0.603)	(-0.744)
Childbirth	**0.037***	-0.027						
	(1.710)	(-0.389)						
Marriage			-0.048	-0.077	0.016		0.024	-0.048
			(-1.198)	(-1.052)	(0.817)		(1.148)	(-0.763)
Observations	844	286	832	284	832	284	844	286
F-statistic	5.55***	3.18***	3.09***	1.72**	4.24***	1.33	4.07***	2.89***
Estimator	Logit	Logit	Logit	Logit	Logit	Logit	Logit	Logit

*Notes: Linearized standard errors are reported in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Some variables were dropped by the STATA software because they predict the failure perfectly.*

According to the results, urban respondents who have reported a fall of household income due to the pandemic have a 4.6 pp higher probability to have married during the pandemic or are planning to do so. In the case of childbirth, we can find the opposite relationships in urban and rural samples. Urban respondents who have experienced a fall of household income have a 7.1 pp lower probability to have a child born during the pandemic or are planning to do so, and rural respondents have a 9.4 pp higher probability of childbirth. This can be explained by the theory of demographic transition which assumes that birth rates decline if the costs of an additional child exceed the benefits of having that child. This happens if there is a transition from an agrarian production to a modern knowledge-based economy. In our analysis, the rural sample represents the agrarian economy, in which an additional child is an economic asset during the pandemic, and the urban sample represents the modern economy, where an additional child is a burden for the household income.

6.4.3 Heterogeneity across Social Classes

As an additional step, we have also evaluated the heterogeneity across social classes, which are operationalized as a five-point Likert scale with the categories lower class, working class, lower-middle class, upper-middle class, and upper class. From the full sample of 1211 respondents, there are 127 lower-class respondents (10.5%), 318 working-class respondents (26.3%), 559 lower-middle class respondents (46.2%), 204 upper-middle class respondents (16.9%), and 3 upper-class respondents (0.2%). With the social classes, we cover differences of respondents in social norms and values, as well as income levels. The reasoning behind this approach is that previous studies on the consequences of the COVID-19 pandemic have already discussed differences among subgroups of the population, for example depending on the household income level or being part of an ethnic or another visible minority (Fostik and Galbraith 2021; Manning, Guzzo, and Kamp Dush 2021; Akinyemi et al. 2022; Bailey, Currie, and Schwandt 2022; Zimmerman et al. 2022). Moreover, several authors have provided evidence for different impacts of natural disasters on marriage and fertility intentions in low-income and high-income households, or differences depending on social attitudes and cultural values (Lin 2010; Davalos and Morales 2017; Sellers and Gray 2019; Boberg-Fazlic et al. 2021; Das and Dasgupta 2022). However, none of these studies have systematically investigated the role of social classes in the context of COVID-19 in Iran, which is one of our main contributions to the literature.

The results of the empirical investigation using logit regressions are presented in Table 21 to Table 24 where we report the average marginal effects. As our sample only includes 3 respondents that consider themselves as upper class, we do not include estimations for this case.

Table 21 presents the results for the dependent variable *Marriage* which refers to the answer of the question that asked if the respondents have married during the pandemic in the years 2020 and 2021or have the plans to get married within the next 6 months. In the full sample, the only hypothesis-related variable that shows a statistically significant association with the dependent variable is the job loss variable (*Job*), but the effect is driven by the working class, as the estimation with the working-class sample reveals. It shows that working-class respondents who became unemployed due to the pandemic have a 9.9 pp higher probability to have married during the pandemic or are planning to do so. In addition, working-class respondents who have personally experienced a COVID-19 infection have a 6.5 pp lower probability to have married. Another variable that only is statistically significant in one social class is the concern about the continuation of the pandemic (*Concern*). Accordingly, lower-class respondents who are concerned about the pandemic have a 14.5 pp lower probability to have married during the pandemic. In the upper-middle class sample, we can see statistically significant associations with the life loss variable (*Loss*) and the income loss variable (*Income*). We can see that upper-middle class respondents who have experienced a life loss due to the pandemic have a 7.6 pp lower probability to have married, and upper-middle class respondents who have experienced a fall in household income have a 12 pp higher probability to have married during the pandemic. Table 22 shows the results for the dependent variable *Child desire decrease* which refers to the answer of the question that asked if the willingness to have children has changed since the start of the pandemic, from wanting children before to not planning to have children. In the full sample, the only two hypothesis-related variables that shows a statistically significant association with the dependent variable are the life loss (*Loss*) and job loss (*Job*) variables. We can see that this effect is mainly driven by working-class and lower-middle class respondents. In the case of the life loss variable, the results suggest that it impacted the child desire of working-class respondents stronger. According to the results, working-class respondents who have experienced a life loss due to the pandemic have an 8.8 pp higher probability to change their willingness to have children, from wanting children before to not planning to have children, and lower-middle class respondents have a 4.2 pp higher probability. In the case of the job loss variable, we can see similar associations in the full sample, and in the working-class and lower-middle class subsamples.

Table 21: Determinants of marriage (marginal effects), social class samples

	(21.1) Marriage (full sample)	(21.2) Marriage (lower class)	(21.3) Marriage (working class)	(21.4) Marriage (lower-middle class)	(21.5) Marriage (upper-middle class)
Concern	-0.021	**-0.145****	0.008	-0.022	-0.002
	(-1.590)	**(-1.989)**	(0.323)	(-1.197)	(-0.046)
Infection	-0.019	-0.001	**-0.065***	-0.020	0.020
	(-1.228)	(-0.016)	**(-1.688)**	(-0.935)	(0.709)
Vaccination	0.020			0.013	-0.015
	(0.758)			(0.400)	(-0.312)
Loss	-0.024	-0.045	-0.021	-0.011	**-0.076****
	(-1.644)	(-0.580)	(-0.591)	(-0.575)	**(-2.328)**
Job	**0.041****		**0.099*****	-0.000	0.027
	(2.241)		**(4.078)**	(-0.015)	(0.355)
Family	0.002	0.023	0.008	-0.005	0.006
	(0.173)	(0.441)	(0.251)	(-0.300)	(0.248)
Home	0.011		0.056	0.010	0.018
	(0.397)		(1.479)	(0.313)	(0.275)
Income	0.024	-0.048	0.024	-0.017	**0.120*****
	(1.336)	(-0.563)	(0.888)	(-0.655)	**(2.901)**
Female	0.008	0.071	0.011	0.010	0.026
	(0.534)	(1.051)	(0.452)	(0.467)	(0.864)
Age	**-0.004*****	**-0.010*****	**-0.004****	**-0.004*****	**-0.005*****
	(-5.552)	**(-2.836)**	**(-2.278)**	**(-3.560)**	**(-3.942)**
Education (secondary)	0.013		0.024	-0.039	
	(0.328)		(0.380)	(-0.770)	
Education (tertiary)	0.048	-0.018	0.026	0.011	0.028
	(1.231)	(-0.196)	(0.434)	(0.229)	(0.900)
Job (private sector)	0.004			0.003	0.001
	(0.259)			(0.143)	(0.051)
Job (public sector)	-0.017			-0.017	0.009
	(-0.716)			(-0.549)	(0.184)
Life satisfaction	**0.028***	0.015	0.048	0.015	-0.004
	(1.900)	(0.288)	(1.367)	(0.714)	(-0.105)
Security	**-0.039****		**-0.045***	-0.033	0.027
	(-2.507)		**(-1.807)**	(-1.301)	(0.565)
Trust	0.016	0.022	-0.004	-0.058	**0.085*****
	(1.009)	(0.426)	(-0.116)	(-1.389)	**(2.901)**
Religiosity	0.013	0.028	-0.003	0.010	0.017
	(0.914)	(0.660)	(-0.135)	(0.507)	(0.550)
Urban	**-0.033****	-0.030	-0.006	**-0.037***	-0.014
	(-2.160)	(-0.791)	(-0.262)	**(-1.809)**	(-0.298)
Childbirth	0.009	0.018		0.018	0.013
	(0.419)	(0.253)		(0.670)	(0.259)
Observations	1132	122	308	524	192
F-statistic	7.86***	2.07**	5.56***	3.71***	2.21***
Estimator	Logit	Logit	Logit	Logit	Logit

*Notes: Linearized standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Some variables were dropped by the STATA software because they predict the failure perfectly.*

Table 22: Determinants of child desire decrease (marginal effects), social class samples

	(22.1) Child desire decrease (full sample)	(22.2) Child desire decrease (lower class)	(22.3) Child desire decrease (working class)	(22.4) Child desire decrease (lower-middle class)	(22.5) Child desire decrease (upper-middle class)
Concern	0.016	-0.033	0.038	-0.002	0.054
	(0.771)	(-0.471)	(0.958)	(-0.080)	(0.979)
Infection	-0.026	-0.047	-0.031	-0.015	-0.053
	(-1.307)	(-0.614)	(-0.656)	(-0.584)	(-1.068)
Vaccination	-0.009		0.008	**-0.064****	
	(-0.302)		(0.130)	**(-2.053)**	
Loss	**0.042****	0.025	**0.088****	**0.042***	0.023
	(2.392)	(0.390)	**(2.319)**	**(1.781)**	(0.642)
Job	**0.093*****	0.062	**0.094***	**0.109*****	0.055
	(3.752)	(0.787)	**(1.699)**	**(3.164)**	(0.575)
Family	0.014	0.077	0.007	**0.044***	-0.043
	(0.788)	(1.142)	(0.162)	**(1.746)**	(-0.989)
Home	0.001		0.019	0.029	-0.021
	(0.017)		(0.277)	(0.731)	(-0.293)
Income	0.025	-0.011	0.031	0.004	0.022
	(1.029)	(-0.110)	(0.642)	(0.107)	(0.480)
Female	0.009	-0.042	-0.021	**0.047***	-0.048
	(0.471)	(-0.571)	(-0.519)	**(1.688)**	(-1.312)
Age	**-0.003*****	**-0.005***	**-0.004***	**-0.002****	-0.003
	(-3.920)	**(-1.765)**	**(-1.892)**	**(-2.085)**	(-1.504)
Education (secondary)	-0.028	-0.027	-0.049	-0.016	-0.067
	(-0.969)	(-0.399)	(-1.069)	(-0.309)	(-0.660)
Education (tertiary)	-0.020	-0.093	0.038	0.014	-0.062
	(-0.630)	(-0.741)	(0.525)	(0.262)	(-0.637)
Job (private sector)	0.021	0.004	0.032	-0.001	0.096
	(0.946)	(0.051)	(0.678)	(-0.040)	(1.639)
Job (public sector)	0.018	0.109	-0.083	0.031	0.090
	(0.624)	(0.965)	(-1.126)	(0.866)	(1.352)
Life satisfaction	-0.032	-0.052	**-0.133*****	0.022	0.009
	(-1.613)	(-0.939)	**(-3.080)**	(0.811)	(0.166)
Security	**-0.058*****	0.033	-0.028	**-0.089*****	-0.055
	(-2.689)	(0.319)	(-0.492)	**(-3.272)**	(-1.172)
Trust	-0.021	**0.157****	0.061	**-0.094***	
	(-0.770)	**(2.221)**	(1.187)	**(-1.787)**	
Religiosity	-0.015	-0.075	**0.085***	-0.031	**-0.082****
	(-0.788)	(-1.107)	**(1.843)**	(-1.182)	**(-2.205)**
Urban	-0.020	-0.005	0.005	-0.030	0.046
	(-0.997)	(-0.103)	(0.113)	(-0.975)	(0.807)
Marriage	-0.054		0.002	-0.035	
	(-1.522)		(0.023)	(-0.851)	
Observations	1118	114	295	515	190
F-statistic	4.0***	1.43	2.38***	2.54***	1.6*
Estimator	Logit	Logit	Logit	Logit	Logit

*Notes: Linearized standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Some variables were dropped by the STATA software because they predict the failure perfectly.*

The other two explanatory variables that show a statistically significant association with *Child desire decrease* are *Vaccination* and *Family* which are only significant in the lower-middle class sample. Accordingly, lower-middle class respondents who are vaccinated have a 6.4 pp lower probability to change their willingness to have children, from wanting children before to not planning to have children, and lower-middle class respondents who have spent more time with the family during the pandemic have a 4.4 pp higher probability of decreased child desire.

Table 23 presents the results for the dependent variable *Child desire increase* which refers to the answer of the question that asked if the willingness to have children has changed since the start of the pandemic, from not wanting children before to planning to have children. In the full sample, the only hypothesis-related variable that shows a statistically significant association with the dependent variable is the increase of time spend with family during the pandemic (*Family*). When considering the social classes, we can see different effects in the lower-class sample and in the lower-middle class sample. More precisely, lower-class respondents who have spent more time with the family during the pandemic have a 11.4 pp lower probability of an increased child desire, while lower-middle class respondents have a 5.8 pp higher probability. This supports previous findings that spending more time at home or with family during the pandemic can either increase or decrease the child desire, depending on the circumstances of the family. The concern about the continuation of the pandemic (*Concern*) also shows a statistically significant association in the upper-middle class sample, so that the upper-middle class respondents who are concerned about the pandemic have a 4 pp lower probability of an increased child desire.

Table 24 shows the results for the dependent variable *Childbirth* which refers to the answer of the question that asked if a child that was born in 2020 or 2021 or if it is expected that a child will be born in the next 6 months. In the full sample, the only two hypothesis-related variables that show a statistically significant association with the dependent variable are the variables *Concern* and *Vaccination*. The concern about the continuation of the pandemic shows a statistically and negative association with childbirth in all samples, except for the working-class sample. In addition, the vaccination status shows only in the lower-middle class sample a statistically significant associations with the dependent variable. Accordingly, lower-middle class respondents who are vaccinated have a 6.7 pp lower probability to have a child born during the pandemic or are expecting to do so.

Table 23: Determinants of child desire increase (marginal effects), social class samples

	(23.1) Child desire increase (full sample)	(23.2) Child desire increase (lower class)	(23.3) Child desire increase (working class)	(23.4) Child desire increase (lower-middle class)	(23.5) Child desire increase (upper-middle class)
Concern	-0.002	0.101	0.014	-0.007	**-0.040***
	(-0.184)	(1.086)	(0.519)	(-0.406)	**(-1.789)**
Infection	-0.012	-0.025	-0.009	-0.002	
	(-0.875)	(-0.292)	(-0.403)	(-0.098)	
Vaccination	-0.009			-0.027	
	(-0.425)			(-0.983)	
Loss	0.001	-0.004	-0.031	0.015	0.050
	(0.117)	(-0.047)	(-1.157)	(0.858)	(0.958)
Job	-0.041			-0.024	
	(-1.289)			(-0.737)	
Family	**0.023****	**-0.114*****	0.031	**0.058*****	
	(2.039)	**(-2.663)**	(1.227)	**(2.619)**	
Home	0.013			0.011	0.044
	(0.615)			(0.421)	(1.167)
Income	-0.004	0.073	-0.011	-0.009	0.005
	(-0.266)	(1.476)	(-0.365)	(-0.457)	(0.243)
Female	0.004	**0.117****	0.010	-0.009	**0.042***
	(0.279)	**(2.031)**	(0.473)	(-0.372)	**(1.760)**
Age	**-0.001****	**-0.007***	**-0.001***	**-0.002****	0.002
	(-2.150)	**(-1.957)**	**(-1.653)**	**(-2.054)**	(1.132)
Education (secondary)	0.024		0.026	-0.006	
	(0.939)		(0.722)	(-0.124)	
Education (tertiary)	0.010		-0.003	-0.006	0.020
	(0.324)		(-0.050)	(-0.118)	(1.485)
Job (private sector)	0.008		-0.004	0.023	
	(0.603)		(-0.171)	(0.881)	
Job (public sector)	0.003		0.004	0.019	
	(0.176)		(0.119)	(0.664)	
Life satisfaction	0.005	0.031	0.027	0.017	**-0.054***
	(0.426)	(0.450)	(1.340)	(0.858)	**(-1.766)**
Security	0.013	0.048		-0.000	
	(0.680)	(1.078)		(-0.006)	
Trust	-0.007	0.002		0.010	0.008
	(-0.474)	(0.027)		(0.464)	(0.452)
Religiosity	0.016	**0.099***	0.033	0.011	0.015
	(1.079)	**(1.674)**	(1.103)	(0.515)	(0.695)
Urban	**-0.022***	0.033	-0.019	-0.025	-0.082
	(-1.674)	(0.585)	(-1.022)	(-1.146)	(-1.349)
Marriage	-0.016	0.088		-0.014	
	(-0.589)	(0.980)		(-0.280)	
Observations	1118	120	297	515	201
F-statistic	3.22***	2.15**	3.29***	4.03***	4.68***
Estimator	Logit	Logit	Logit	Logit	Logit

*Notes: Linearized standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Some variables were dropped by the STATA software because they predict the failure perfectly.*

Table 24: Determinants of childbirth (marginal effects), social class samples

	(24.1) Childbirth (full sample)	(24.2) Childbirth (lower class)	(24.3) Childbirth (working class)	(24.4) Childbirth (lower-middle class)	(24.5) Childbirth (upper-middle class)
Concern	**-0.033****	**-0.080***	-0.010	**-0.030***	**-0.049****
	(-2.473)	**(-1.716)**	(-0.337)	**(-1.832)**	**(-2.042)**
Infection	-0.023	0.063	-0.033	-0.014	-0.072
	(-1.547)	(0.756)	(-0.874)	(-0.822)	(-1.377)
Vaccination	**-0.047*****		0.028	**-0.067*****	-0.034
	(-2.966)		(0.461)	**(-3.671)**	(-0.727)
Loss	0.007		-0.014	0.021	0.036
	(0.529)		(-0.505)	(1.520)	(1.034)
Job	-0.038		-0.030	-0.016	
	(-1.160)		(-0.590)	(-0.397)	
Family	0.011	0.006	**0.063****	-0.006	-0.011
	(0.856)	(0.121)	**(2.015)**	(-0.332)	(-0.333)
Home	0.027		0.066	0.042	
	(1.101)		(0.943)	(1.508)	
Income	-0.011	**0.120****	-0.057	-0.004	-0.054
	(-0.580)	**(2.332)**	(-0.956)	(-0.164)	(-1.464)
Female	**0.030****	0.102	**0.058***	0.023	0.038
	(2.219)	(1.004)	**(1.859)**	(1.180)	(1.034)
Age	**-0.002*****	-0.009	**-0.004*****	**-0.002*****	**-0.002***
	(-4.293)	(-1.155)	**(-2.906)**	**(-2.722)**	**(-1.857)**
Education (secondary)	-0.012		-0.042	0.019	-0.054
	(-0.530)		(-0.947)	(0.554)	(-1.246)
Education (tertiary)	-0.002		-0.046	0.043	-0.018
	(-0.064)		(-0.886)	(1.232)	(-0.416)
Job (private sector)	0.005			-0.010	0.032
	(0.407)			(-0.539)	(0.772)
Job (public sector)	-0.033			-0.015	-0.032
	(-1.366)			(-0.565)	(-0.563)
Life satisfaction	**0.040****	0.033	0.025	**0.073****	0.045
	(2.459)	(0.809)	(0.716)	**(2.360)**	(1.538)
Security	-0.015		-0.012	-0.015	-0.017
	(-0.898)		(-0.211)	(-0.619)	(-0.563)
Trust	-0.021		-0.022	-0.052	-0.010
	(-1.094)		(-0.517)	(-1.433)	(-0.279)
Religiosity	0.012		0.018	0.005	-0.016
	(0.800)		(0.502)	(0.278)	(-0.436)
Urban	**-0.024***	-0.017	0.001	-0.029	**-0.060***
	(-1.757)	(-0.548)	(0.043)	(-1.427)	**(-1.687)**
Marriage	-0.002			-0.004	0.027
	(-0.086)			(-0.210)	(0.581)
Observations	1132	123	308	524	195
F-statistic	5.5***	2.51**	2.68***	3.13***	2.93***
Estimator	Logit	Logit	Logit	Logit	Logit

*Notes: Linearized standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Some variables were dropped by the STATA software because they predict the failure perfectly.*

The other two explanatory variables that show a statistically significant association with *Childbirth* are *Family* and *Income* which are only significant in the working-class sample and in the lower-class sample, respectively. First, working-class respondents who have spent more time with the family during the pandemic have a 6.3 pp higher probability of childbirth during the pandemic. Second, lower-class respondents who have experienced a fall of household income have a 12 pp higher probability of childbirth. Overall, we can see that there are differences of the associations of the hypothesis-related variables and the four dependent variables, depending on the social class. Several associations are only statistically significant in specific subsamples.

6.5 Conclusion

With our results, we provide new empirical evidence for the impact of the COVID-19 pandemic on marriage and fertility behavior in Iran. We used logistic regressions and the responses from our representative survey to investigate through which channels the pandemic affected the four dependent variables. The main findings are that the concern about the continuation of the pandemic (*Concern*) and the respondents' vaccination status (*Vaccination*) show negative associations with childbirth during the pandemic, and the experience of unemployment due to the pandemic (*Job*) is positively associated with marriage during the pandemic. The experiences of life loss and job loss are positively associated with a decrease of the respondents' child desire, while spending more time with the family (*Family*) is positively associated with an increase of the respondents' child desire. Moreover, the further analysis revealed heterogenous effects depending on the respondents' gender, location, and social class.

According to the results, the associations with *Concern*, *Vaccination*, and *Family* are only statistically significant in the female subsample, while the association of fall in household income (*Income*) and marriage is only statistically significant in the male subsample. Based on the location, we found that an infection with COVID-19 only shows a statistically significant and negative association with marriage in the rural subsample. The variables *Job*, *Family*, and *Income* only show statistically significant associations in the urban subsample. Within the subsamples based on social classes, we found diverse associations. This means that the direct and indirect effects of the pandemic did not show statistically significant associations with marriage and fertility intentions in all social classes, for example the infection with COVID-19 shows only a statistically significant and negative association with marriage during the pandemic in the working-class subsample. Another example is the vaccination status, which is only statistically significant in the lower-middle class subsample and shows a negative association with child desires and childbirth. In addition, the job loss variable is only statistically significant in the working class and lower-middle class samples.

Based on these finding, we have learned that the impact of the COVID-19 pandemic on the marriage and fertility decisions in Iran, and thus also on the marriage and fertility rates, is very complex and the pandemic affects members of subgroups of the population differently. Therefore, policies that are aimed at changing the behavior of respondents need to be carefully designed and need to consider the gender, location, and social class. We are assuming in this context that the government wants to increase marriage and fertility rates, which is an agenda of the past years. As marriage is a pre-condition for childbirth in Iran, one policy needs to aim at the pandemic-related factors that reduce the marriage intentions, for example the COVID-19 infections in rural areas and among working-class respondents. This can be achieved by the improvement of healthcare infrastructure in rural and working-class areas, as well as information campaigns. Our findings can also be a lesson for natural disaster management in general and make these areas more resilient to similar disasters in the future.

Other policies need to aim at the factors that reduce child desires and childbirth, for example the concern about the pandemic and misinformation about vaccinations which show negative associations with childbirth during the pandemic in the female subsample. In this case, information campaigns and healthcare services especially targeted at women can be helpful. Another factor that is associated with a reduction in child desire is the loss of employment due to the pandemic, which is statistically significant in the full sample, especially in urban areas, and among respondents from working-class and lower-middle class households. This situation can be improved if the government designs policies that help respondents to come back into employment and create incentives for childbirth, such as transfer payments for couples who are willing to have children, which can compensate the income loss of the disaster.

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Appendix

Appendix A

Table A 1: Description and data sources of used variables

Variable	Definition	Sources
Disaster	Dummy variable that takes the value 1 if a natural disaster happened 6 months before.	EM-DAT (2020).
Earthquake	Dummy variable that takes the value 1 if a disastrous earthquake happened 6 months before.	EM-DAT (2020).
Flood	Dummy variable that takes the value 1 if a disastrous flood happened 6 months before.	EM-DAT (2020).
Ln(GDP per capita)	Natural logarithm of GDP per capita in IRR.	MEFA (2020).
ΔLn(GDP per capita)	First difference of the natural logarithm of the Gross Domestic Product (GDP) per capita in Iranian Rial (IRR).	MEFA (2020).
Ln(Population)	Natural logarithm of the population size.	MEFA (2020).
CPI	Consumer Price Index (CPI), base year 1395.	MEFA (2020) and SCI (2020).
Expenditures	The sum of current expenditures of provincial governmental organizations and province's acquisition of capital assets as percent of GDP.	MEFA (2020).
Trade	Trade (Imports + Exports) as percent of GDP.	MEFA (2020) and CBI (2020).
FDI inflows	Foreign direct investment (FDI) inflows as percent of GDP.	MEFA (2020) and CBI (2020).

Table A 2: Unit root tests of used variables

Variable	LLC	LLC (Intercept)	LLC (Trend)	IPS (Intercept)	IPS (Trend)	HAD (Intercept)	HAD (Trend)
Disasters	−4.0293***	−13.5646***	−16.0372***	−12.8014***	−13.453***	0.2742	−0.1653
Ln(GDP p.c.)	−0.0006	−5.1009***	−5.9324***	−5.556***	−5.4484***	2.9546***	4.3091***
ΔLn(GDP p.c.)	−1.5275*	−6.7229***	−7.4795***	−11.1844***	−11.6937***	−0.7421	−0.834
Ln(Population)	−0.2223	−3.8015***	−4.4569***	−5.2724***	−5.2505***	3.308***	3.6951***
CPI	−0.4715	−53.1493***	−61.6659***	−63.2394***	−69.2038***	−0.9417	−1.377
Expenditures	−1.8297**	−0.2271	0.1346	−3.5492***	−3.3827***	1.7411**	1.4677*
Trade	−4.916***	−3.7431***	−4.2794***	−4.8067***	−4.7924***	4.0187***	4.1673***
FDI inflows	−6.9575***	−6.8853***	−6.3354***	−6.8068***	−6.4235***	5.1481***	3.1753***

*Notes: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The above table reports the test statistics of the Levin–Lin–Chu unit-root test (LLC), Im–Pesaran–Shin unit-root test (IPS), and Hadri test for stationarity (HAD). The lag length is determined by Akaike information criterion (AIC) with maximum length of 5, except for the case of the HAD test. The null hypothesis for the LLC and IPS tests is that a unit root exists, and for the HAD test the null hypothesis assumes the existence of stationarity. Overall, we can reject the null hypothesis in most LLC and IPS tests, while the HAD test provides mixed results (Hadri 2000; Im, Pesaran, and Shin 2003; Levin, Lin, and Chu 2002).*

Table A 3: Likelihood-ratio (LR) tests for different used spatial panel models

Likelihood-ratio test	**LR χ^2**	**p-value**	**Better fit**
SDM nested in GNS	1.14	0.2858	SDM
SDEM nested in GNS	5.02**	0.0251	GNS
SAC nested in GNS	28.94***	0.0007	GNS
SAR nested in GNS	39.10***	0.0000	GNS
SEM nested in GNS	31.21***	0.0005	GNS
SAC nested in SDM	27.80***	0.0005	SDM
SAR nested in SDM	37.96***	0.0000	SDM
SEM nested in SDM	30.07***	0.0004	SDM
SAC nested in SDEM	23.92***	0.0024	SDEM
SAR nested in SDEM	34.08***	0.0001	SDEM
SEM nested in SDEM	26.19***	0.0019	SDEM
SAR nested in SAC	10.16***	0.0014	SAC
SEM nested in SAC	2.27	0.1315	SEM

*Notes: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The abbreviations refer to different spatial panel models using the ML estimator that are reported in Tables A6 and A7 of Appendix A. GNS refers to the general nesting spatial model, SDM refers to the spatial Durbin model, SDEM refers to the spatial Durbin error model, SAC refers to the Cliff-Ord type spatial model, SAR refers to the spatial autoregressive model, and SEM refers to the spatial error model, as presented in Elhorst (2014).*

Table A 4: Moran's I and Geary's C of used variables

Variable	Year	Moran's I	Geary's C	Variable	Year	Moran's I	Geary's C
Disasters	1389	−0.0297	1.0623	CPI	1389	−0.2079	1.1343
Disasters	1390	−0.0992	1.2128	CPI	1390	−0.2187	1.1555
Disasters	1391	−0.0538	0.8951	CPI	1391	−0.2218	1.1459
Disasters	1392	0.0136	0.9518	CPI	1392	−0.2334	1.167
Disasters	1393	0.3784***	0.5912**	CPI	1393	−0.2412	1.1978
Disasters	1394	0.3109***	0.6752***	CPI	1394	−0.2513	1.2494
Disasters	1395	0.2294***	0.7463**	CPI	1395	−0.2495	1.2255
Ln(GDP p.c.)	1389	0.2546***	0.6901***	Expenditures	1389	0.0454	0.9644
Ln(GDP p.c.)	1390	0.3401***	0.6057***	Expenditures	1390	0.0915	0.9046
Ln(GDP p.c.)	1391	0.3202***	0.6291***	Expenditures	1391	0.0617	0.9419
Ln(GDP p.c.)	1392	0.3309***	0.6056***	Expenditures	1392	0.063	0.9415
Ln(GDP p.c.)	1393	0.3054***	0.6259***	Expenditures	1393	0.0934	0.9197
Ln(GDP p.c.)	1394	0.266***	0.6593***	Expenditures	1394	0.0601	0.9327
Ln(GDP p.c.)	1395	0.2668***	0.661***	Expenditures	1395	0.0576	0.9461
ΔLn(GDP p.c.)	1389	0.178**	0.7434**	Trade	1389	0.0407**	0.9046
ΔLn(GDP p.c.)	1390	0.4648***	0.5188***	Trade	1390	0.0405**	0.9046
ΔLn(GDP p.c.)	1391	0.188**	0.6942**	Trade	1391	0.0346**	0.9112
ΔLn(GDP p.c.)	1392	−0.178	1.0968	Trade	1392	0.0356**	0.9105
ΔLn(GDP p.c.)	1393	0.1295*	0.8103*	Trade	1393	0.043***	0.9034
ΔLn(GDP p.c.)	1394	0.3524***	0.6088***	Trade	1394	0.0847**	0.8615
ΔLn(GDP p.c.)	1395	0.1544**	0.7482**	Trade	1395	0.0752***	0.8716
Ln(Population)	1389	−0.3578	1.3449	FDI inflows	1389	0.1801***	0.7184**
Ln(Population)	1390	−0.3574	1.3446	FDI inflows	1390	0.0034	0.9147
Ln(Population)	1391	−0.3557	1.3424	FDI inflows	1391	0.0563**	0.8313
Ln(Population)	1392	−0.3539	1.34	FDI inflows	1392	0.0029	1.0635
Ln(Population)	1393	−0.3519	1.3376	FDI inflows	1393	0.1498**	0.9517
Ln(Population)	1394	−0.3497	1.3348	FDI inflows	1394	−0.0581	1.1936
Ln(Population)	1395	−0.3474	1.3319	FDI inflows	1395	0.1089**	0.8959

*Notes: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The above table reports the spatial autocorrelation coefficients Moran's I and Geary's C which are calculated using a spatial weights matrix that is a row-standardized contiguity matrix. Therefore, Moran's I ranges from –1 to 1, where –1 is a strong negative spatial autocorrelation and 1 a strong positive spatial autocorrelation. In the case of Geary's C, the range $0 \leq C < 1$ means positive spatial autocorrelation and the range $1 < C \leq 2$ means negative spatial autocorrelation (Anselin 1988, 101–5; Moran 1948; Geary 1954).*

Table A 5: Correlation matrix of used variables (including spatial lags)

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
(1) Disaster	1.000															
(2) Ln(GDP p.c.)	0.068	1.000														
(3) ΔLn(GDP p.c.)	−0.091	−0.039	1.000													
(4) Ln(Population)	0.116*	−0.108	−0.027	1.000												
(5) CPI	0.188*	0.542*	−0.354*	0.034	1.000											
(6) Expenditures	−0.087	−0.734*	0.098	−0.225*	−0.679*	1.000										
(7) Trade	0.193*	0.099	0.001	0.008	0.009	−0.057	1.000									
(8) FDI inflows	−0.030	0.143*	0.275*	−0.031	−0.197*	0.020	0.168*	1.000								
(9) W*Disaster	0.399*	0.104	−0.130*	0.046	0.275*	−0.076	0.129*	−0.014	1.000							
(10) W*Ln(GDP p.c.)	0.125*	0.740*	−0.161*	−0.026	0.771*	−0.666*	0.079	0.011	0.159*	1.000						
(11) W*ΔLn(GDP p.c.)	−0.117*	−0.146*	0.760*	−0.007	−0.459*	0.210*	0.059	0.243*	−0.208*	−0.226*	1.000					
(12) W*Ln(Population)	−0.054	0.167*	0.003	−0.776*	0.070	0.080	0.222*	0.028	−0.021	0.155*	−0.010	1.000				
(13) W*CPI	0.183*	0.545*	−0.358*	0.036	0.999*	−0.685*	0.007	−0.205*	0.274*	0.771*	−0.458*	0.074	1.000			
(14) W*Expenditures	−0.067	−0.607*	0.212*	0.120*	−0.844*	0.705*	−0.008	0.078	−0.098	−0.860*	0.263*	−0.254*	−0.845*	1.000		
(15) W*Trade	0.151*	0.088	0.104	0.178*	0.012	0.040	0.113	0.276*	0.239*	0.158*	−0.010	0.079	0.009	0.005	1.000	
(16) W*FDI inflows	−0.050	−0.007	0.381*	0.005	−0.417*	0.161*	0.284*	0.319*	−0.147*	−0.168*	0.409*	0.099	−0.414*	0.295*	0.159*	1.000

*Notes: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Table A 6: Comparison of different spatial panel models (OLS, SLX, and SAR)

Dependent variable: ΔLn(GDP per capita)	**(A6.1) Pooled**	**(A6.2) FE**	**(A6.3) SLX**	**(A6.4) SLX**	**(A6.5) SAR**	**(A6.6) SAR**
Disaster	0.002	0.029	0.01	0.012	0.007	0.014
	(0.023)	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)
Disaster $_{t-1}$	0.021	0.034	0.031	0.021	0.038	0.037
	(0.031)	(0.03)	(0.027)	(0.02)	(0.024)	(0.025)
Disaster $_{t-2}$	−0.012	0.033*	0.039**	0.004	0.029	0.03*
	(0.023)	(0.017)	(0.018)	(0.019)	(0.02)	(0.018)
Ln(Population)	−0.038**	−0.701	−0.419	−0.05**	−0.489	−0.553
	(0.019)	(0.511)	(0.443)	(0.021)	(0.36)	(0.376)
CPI	−0.003***	−0.008	−0.006	0.008	−0.002	−0.004
	(0.001)	(0.01)	(0.008)	(0.007)	(0.008)	(0.008)
Expenditures	−0.061***	−0.044**	−0.041**	−0.053***	−0.038**	−0.04**
	(0.016)	(0.021)	(0.016)	(0.011)	(0.015)	(0.016)
FDI inflows	0.03***	−0.017*	−0.024***	0.015**	−0.023***	−0.021***
	(0.01)	(0.01)	(0.009)	(0.007)	(0.008)	(0.008)
Trade	0.000	−0.002	−0.002	0.000	−0.001*	−0.001*
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Ln(GDP p.c.)$_{t-1}$	−0.091**	−0.693***	−0.733***	−0.077***	−0.585***	−0.617***
	(0.036)	(0.066)	(0.084)	(0.02)	(0.083)	(0.07)
W*Disaster			0.129***	0.107***		
			(0.044)	(0.035)		
W*Disaster$_{t-1}$			0.048	−0.055		
			(0.048)	(0.037)		
W*Disaster$_{t-2}$			−0.005	−0.058		
			(0.038)	(0.039)		
W*Ln(Population)			−1.905*	−0.036		
			(1.004)	(0.047)		
W*CPI			−0.053*	−0.013		
			(0.027)	(0.017)		
W*Expenditures			0.008	−0.012		
			(0.032)	(0.024)		
W*FDI inflows			0.028*	0.055***		
			(0.015)	(0.016)		
W*Trade			−0.004**	0.001*		
			(0.002)	(0.000)		
W*Ln(GDP p.c.)$_{t-1}$			−0.081	−0.005		
			(0.096)	(0.043)		
W*ΔLn(GDP p.c.)					0.667***	0.466***
					(0.168)	(0.082)
Observations	203	203	203	203	203	203
R^2	0.274	0.725	0.783		0.79	0.09
Hausman test	No	FE	FE	FE	FE	FE
Year dummies	No	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	ML	OLS	ML

*Notes: Robust standard errors are reported in parentheses. A constant was included in the estimations but not reported. Coefficient estimates are obtained using the 'xsmle' Stata syntax outlined in Belotti et al. (2017). SLX refers to the spatial lag of X model and SAR refers to the spatial autoregressive model, as presented in Elhorst (2014). Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

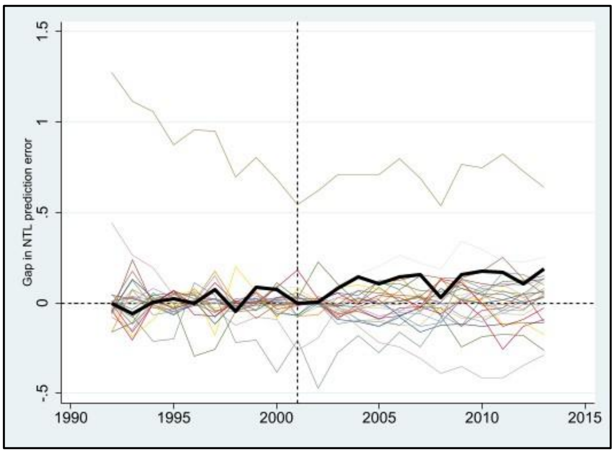
Table A 7: Comparison of different spatial panel models (SDM, SEM, SDEM, SAC, and GNS)

Dependent variable: ΔLn(GDP per capita)	**(A7.1) SDM**	**(A7.2) SDM**	**(A7.3) SEM**	**(A7.4) SDEM**	**(A7.5) SAC**	**(A7.6) GNS**
Disaster	−0.015	−0.003	−0.012	0.009	−0.008	0.000
	(0.015)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
Disaster_{t-1}	0.024	−0.027	−0.02	−0.035*	0.025	0.029
	(0.022)	(0.022)	(0.027)	(0.021)	(0.028)	(0.022)
Disaster_{t-2}	0.039*	0.039**	0.037**	0.037**	0.037**	0.039**
	(0.019)	(0.017)	(0.015)	(0.016)	(0.016)	(0.017)
Ln(Population)	0.036	−0.18	−0.122	−0.368	−0.218	−0.223
	(0.335)	(0.323)	(0.349)	(0.306)	(0.360)	(0.309)
CPI	0.003	−0.001	0.004	−0.003	0.003	−0.002
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)
Expenditures	−0.043***	−0.042***	−0.047***	−0.037**	−0.046***	−0.041***
	(0.014)	(0.014)	(0.016)	(0.015)	(0.016)	(0.014)
FDI inflows	−0.028***	−0.026***	−0.027***	−0.023***	−0.027***	−0.026***
	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)
Trade	−0.001	−0.001	−0.001	−0.002*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\text{Ln(GDP p.c.)}_{t-1}$	−0.718***	−0.725***	−0.704***	−0.727***	−0.703***	−0.725***
	(0.092)	(0.082)	(0.084)	(0.083)	(0.086)	(0.083)
W*Disaster	0.055*	0.09***		0.104***		0.094***
	(0.028)	(0.035)		(0.04)		(0.034)
W*Disaster_{t-1}	0.000	0.022		0.052		0.030
	(0.039)	(0.038)		(0.045)		(0.040)
W*Disaster_{t-2}	−0.046	−0.027		−0.018		−0.026
	(0.041)	(0.036)		(0.037)		(0.037)
W*Ln(Population)	−0.499	−1.165		−1.486		−1.272
	(0.841)	(0.821)		(1.026)		(0.874)
W*CPI	−0.025	−0.038*		−0.037		−0.038*
	(0.017)	(0.021)		(0.024)		(0.022)
W*Expenditures	0.051*	0.031		0.025		0.030
	(0.026)	(0.025)		(0.031)		(0.027)
W*FDI inflows	0.043***	0.036***		0.032**		0.036***
	(0.014)	(0.012)		(0.016)		(0.013)
W*Trade	−0.001	−0.002		−0.003**		−0.003*
	(0.002)	(0.001)		(0.002)		(0.002)
$\text{W*Ln(GDP p.c.)}_{t-1}$	0.575***	0.264***		−0.093		0.181
	(0.18)	(0.101)		(0.08)		(0.128)
W*ΔLn(GDP p.c.)	0.921***	0.484***			0.193**	0.375***
	(0.246)	(0.096)			(0.088)	(0.126)
λ			0.637***	0.493***	0.517***	0.188*
			(0.086)	(0.092)	(0.115)	(0.109)
σ^2_e		0.004***	0.004***	0.004***	0.005***	0.004***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	203	203	203	203	203	203
R^2	0.833	0.119	0.035	0.109	0.044	0.116
Hausman test	FE	FE	FE	FE	FE	FE
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	ML	ML	ML	ML	ML

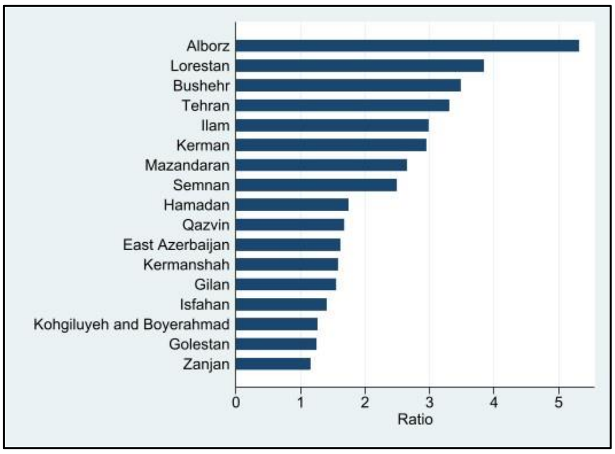
*Notes: Robust standard errors are reported in parentheses. A constant was included in the estimations but not reported. Coefficient estimates are obtained using the "xsmle" Stata syntax outlined in Belotti et al. (2017). SDM refers to the spatial Durbin model, SEM refers to the spatial error model, SDEM refers to the spatial Durbin error model, SAC refers to the Cliff-Ord type spatial model, and GNS refers to the general nesting spatial model, as presented in Elhorst (2014). Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

Appendix B

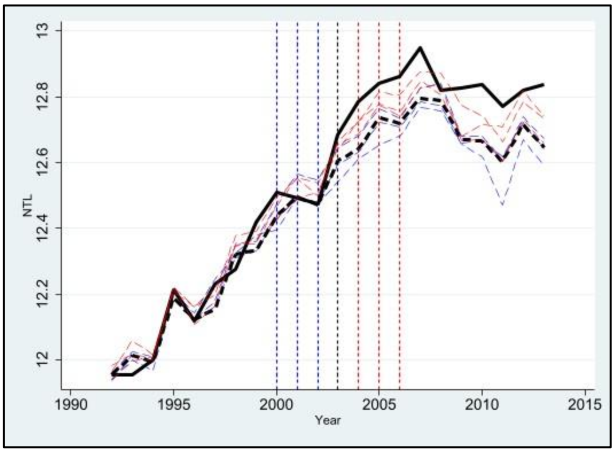
Figure B 1: Placebo tests for the SCM analysis of Kerman Province



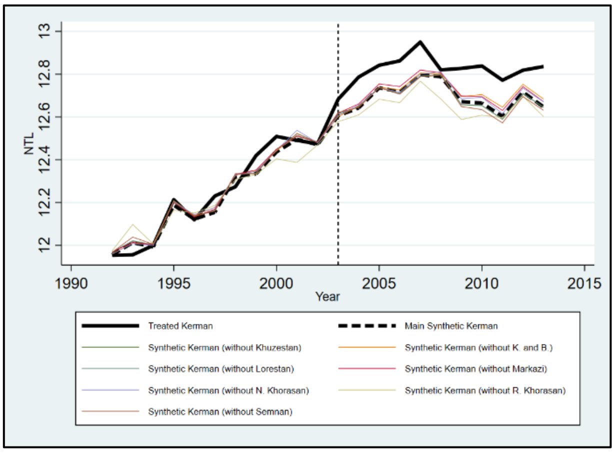
(a) In-space placebo test.



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

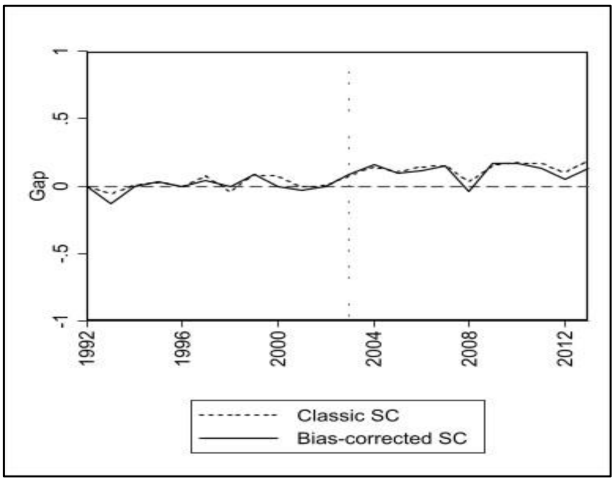


(c) In-time placebo test.

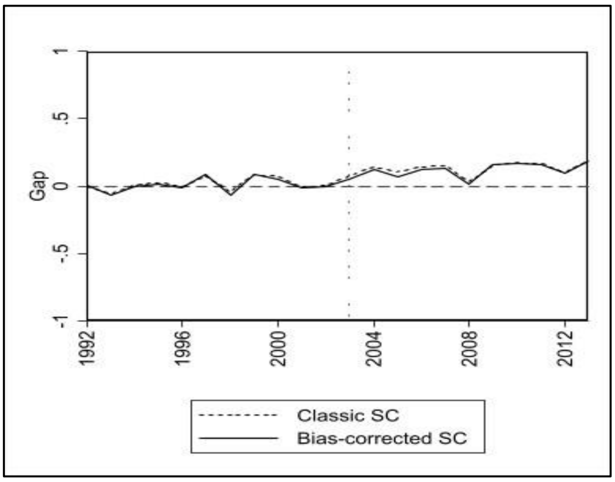


(d) Leave-one-out test.

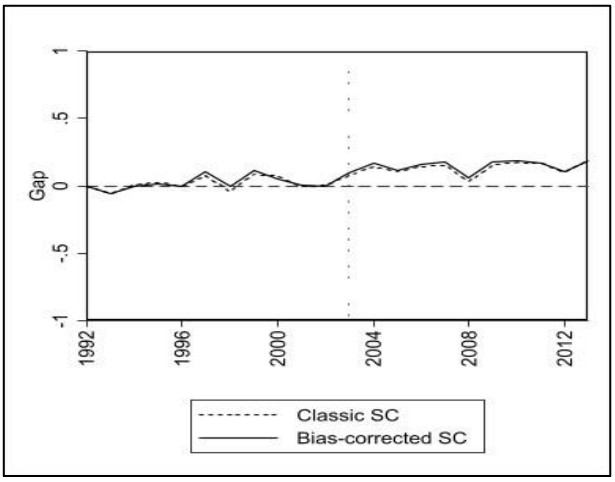
Figure B 2: Comparison of gaps in the classic and bias-corrected synthetic controls for the analysis of Kerman Province



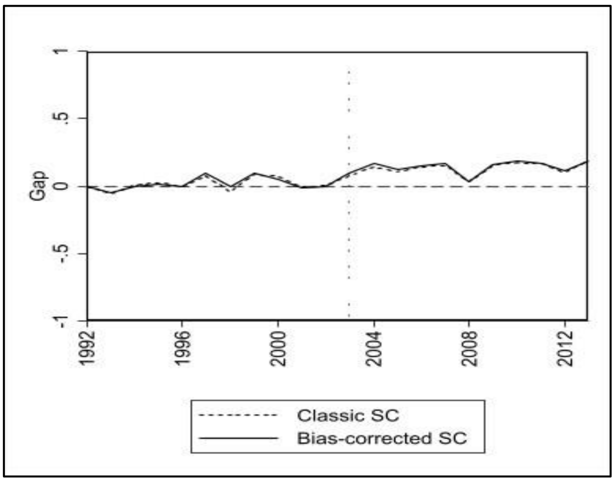
(a) Bias-corrected synthetic control (SC) based on OLS regression.



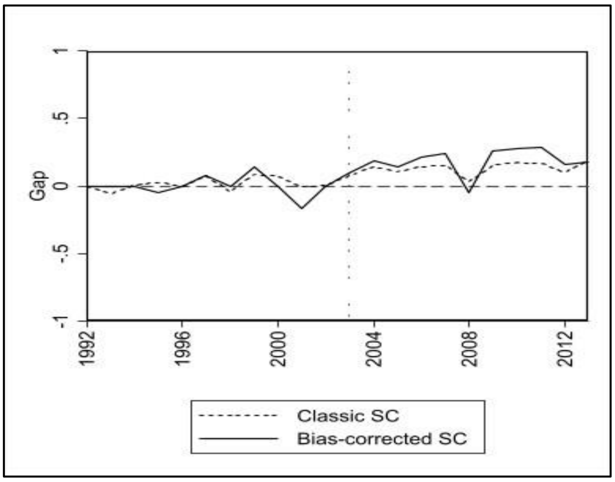
(b) Bias-corrected synthetic control (SC) based on Ridge regression.



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

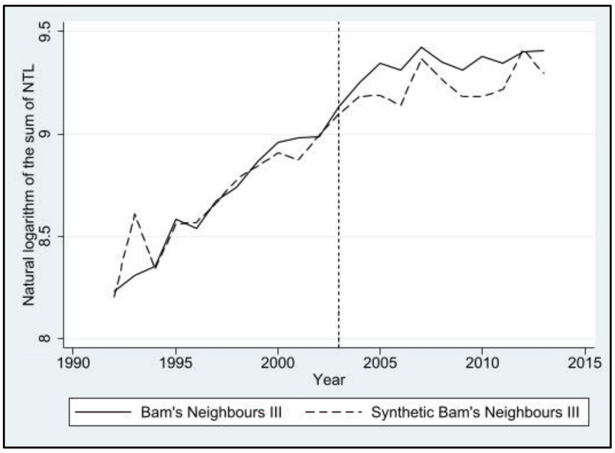


(d) Bias-corrected synthetic control (SC) based on elastic net regression.

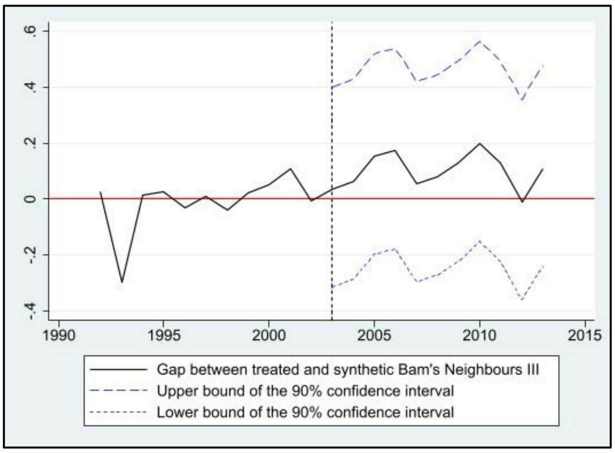


(e) Bias-corrected synthetic control (SC) based on OLS regression with only those donor pool units for which the synthetic-control-estimated weights are strictly positive.

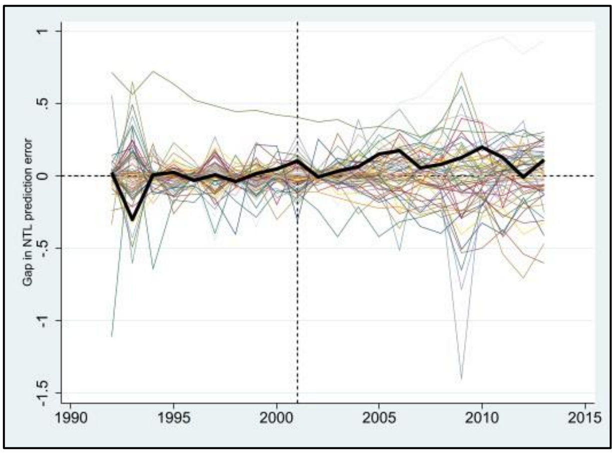
Figure B 3: SCM analysis and placebo tests for Bam County's neighbors of third order



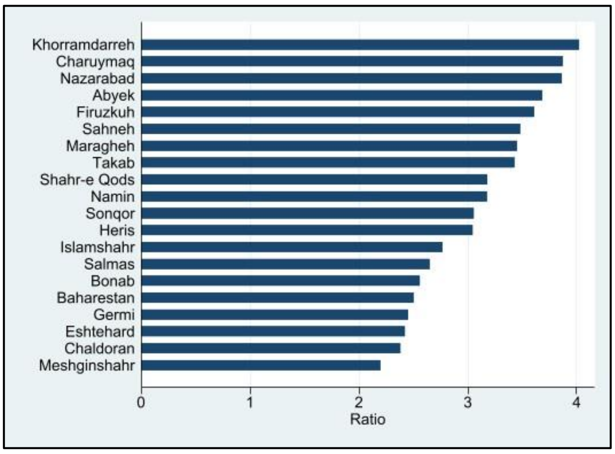
(a) Trajectories of treated and synthetic Bam's neighbors of third order.



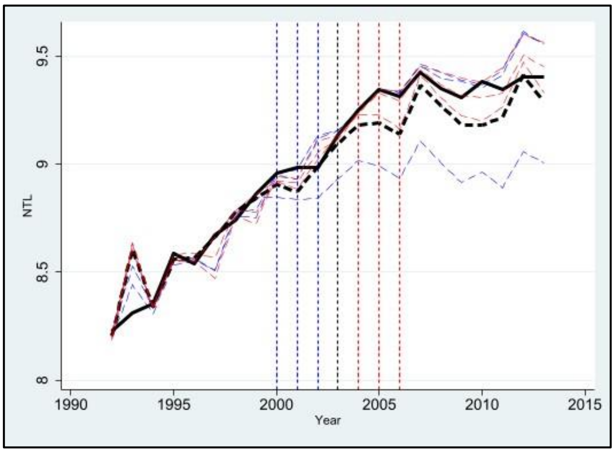
(b) Gap of treated and synthetic Bam's neighbors of third order including confidence sets.



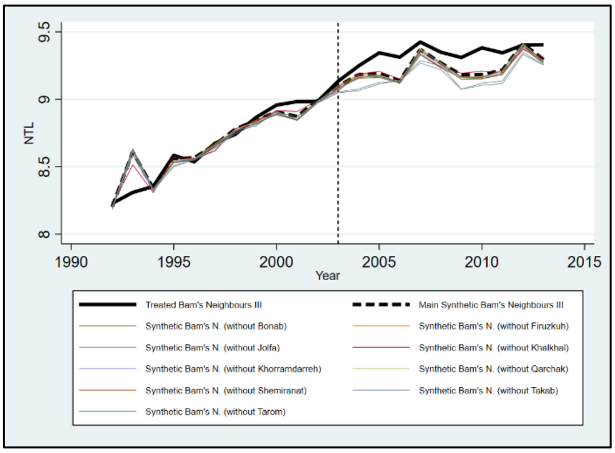
(c) In-space placebo test.



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

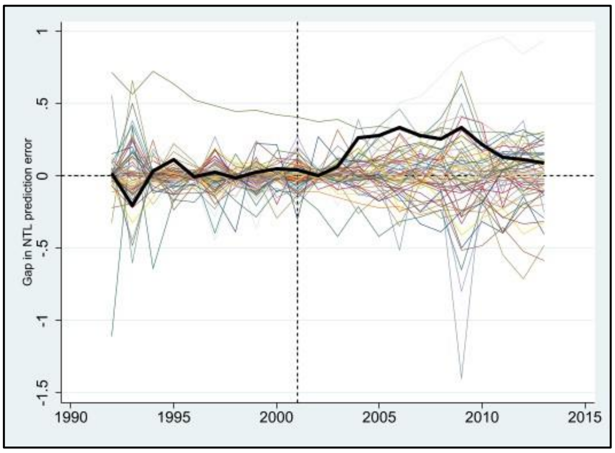


(e) In-time placebo test.

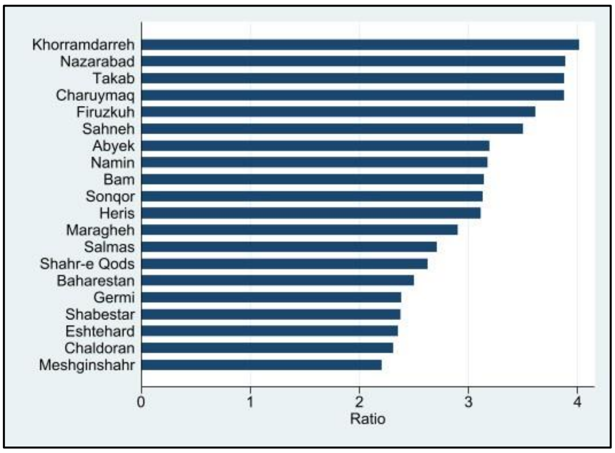


(f) Leave-one-out test.

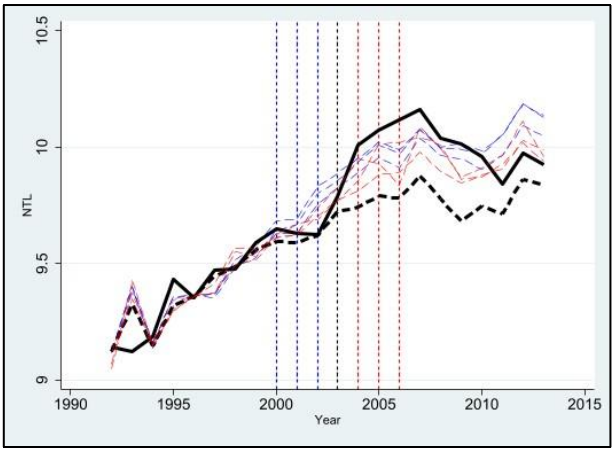
Figure B 4: Placebo tests for the SCM analysis of Bam County



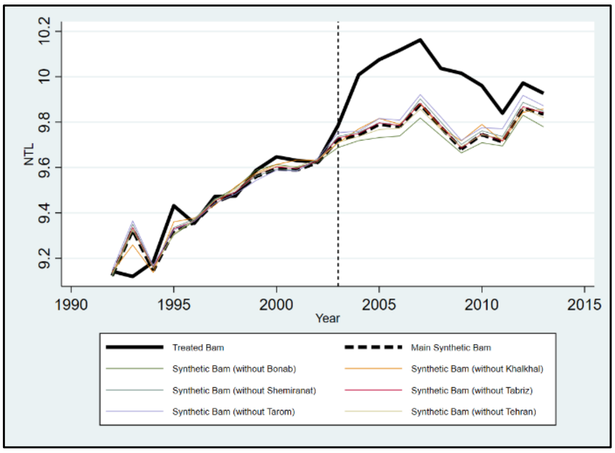
(a) In-space placebo test.



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

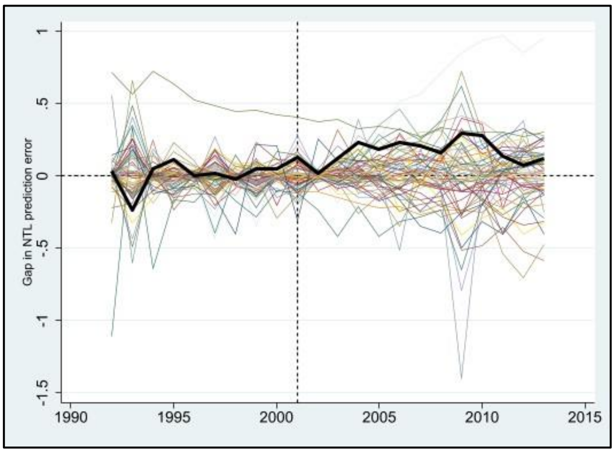


(c) In-time placebo test.

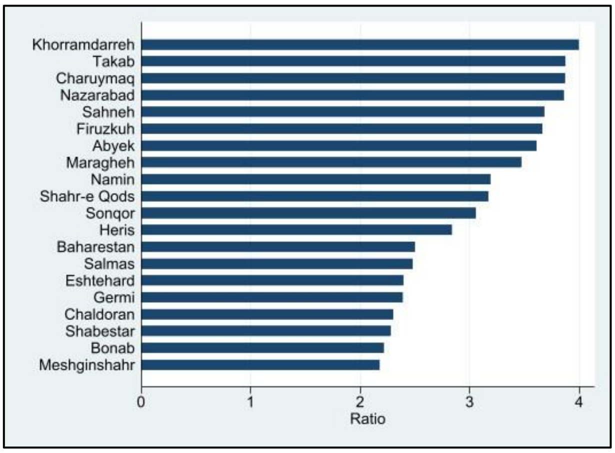


(d) Leave-one-out test.

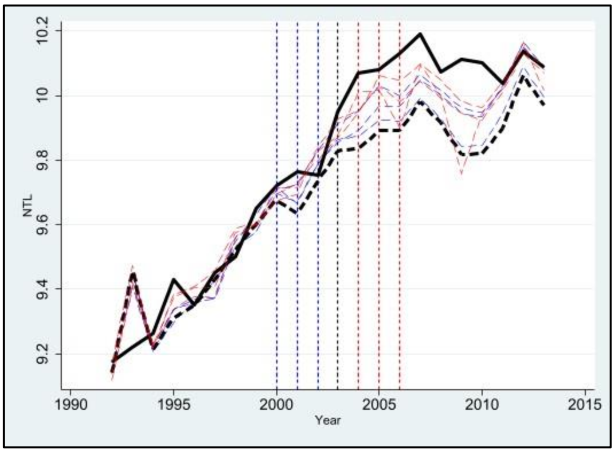
Figure B 5: Placebo tests for the SCM analysis of Bam County's neighbors of first order



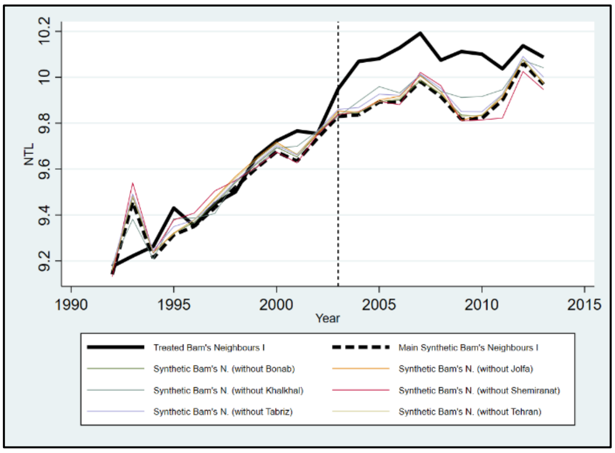
(a) In-space placebo test.



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

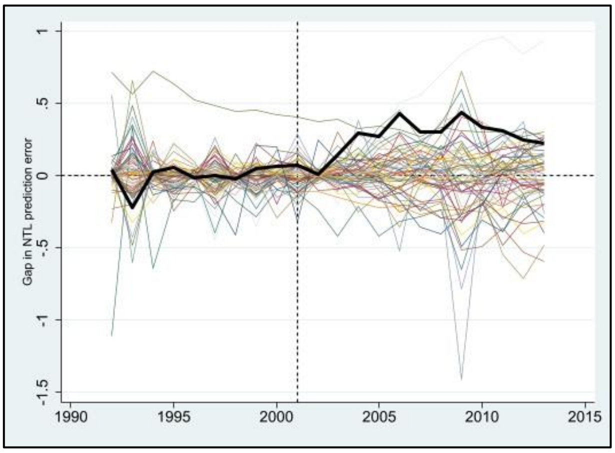


(c) In-time placebo test.

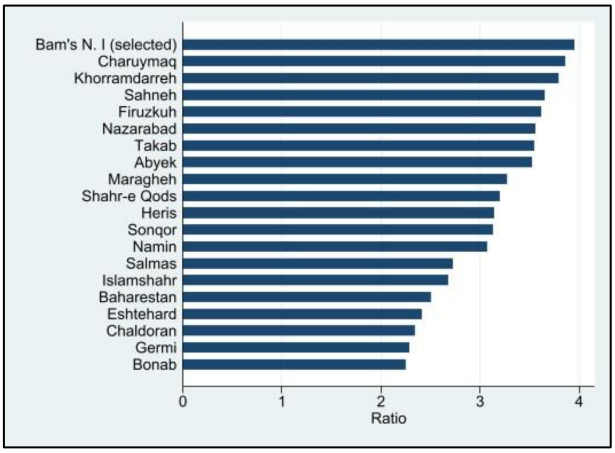


(d) Leave-one-out test.

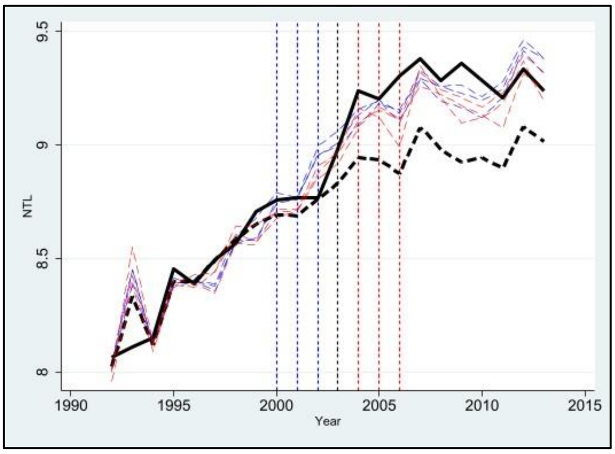
Figure B 6: Placebo tests for the SCM analysis of Bam County's selected neighbors of first order (excluding Kerman and Jiroft counties)



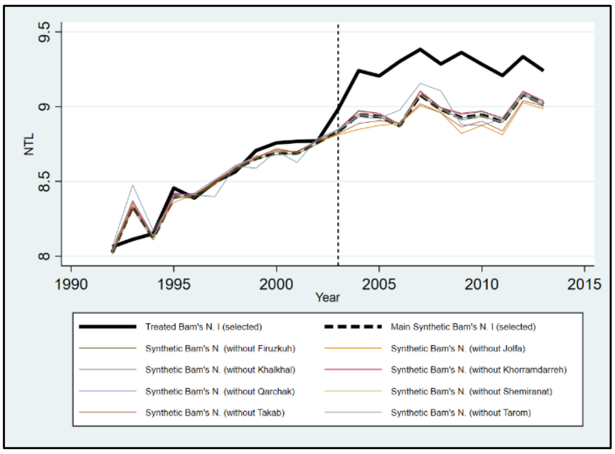
(a) In-space placebo test.



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

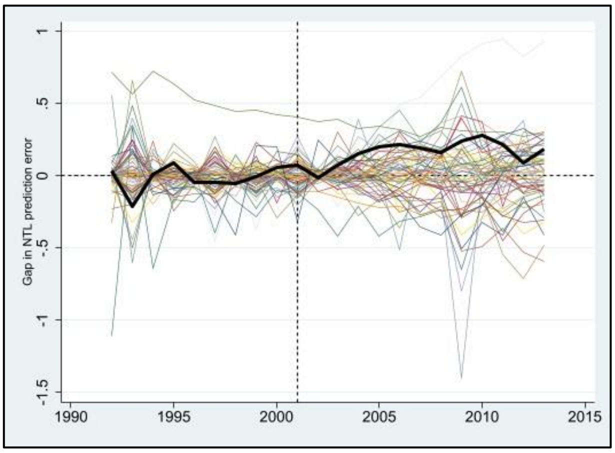


(c) In-time placebo test.

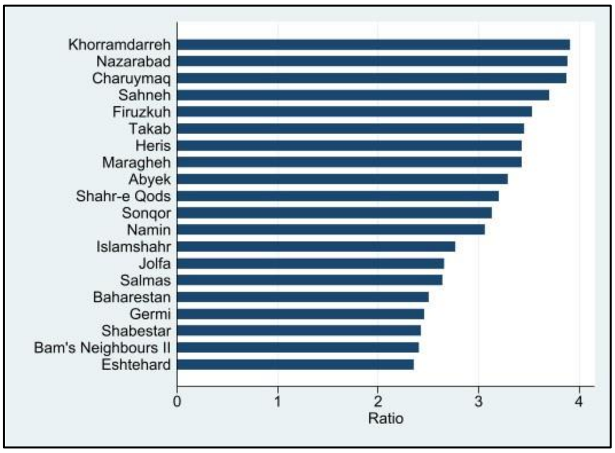


(d) Leave-one-out test.

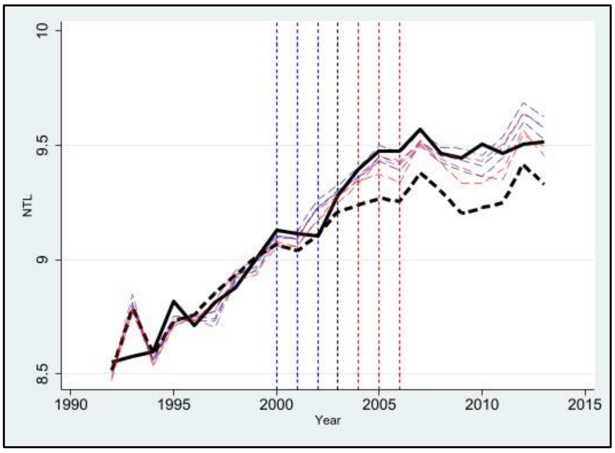
Figure B 7: Placebo tests for the SCM analysis of Bam County's neighbors of second order



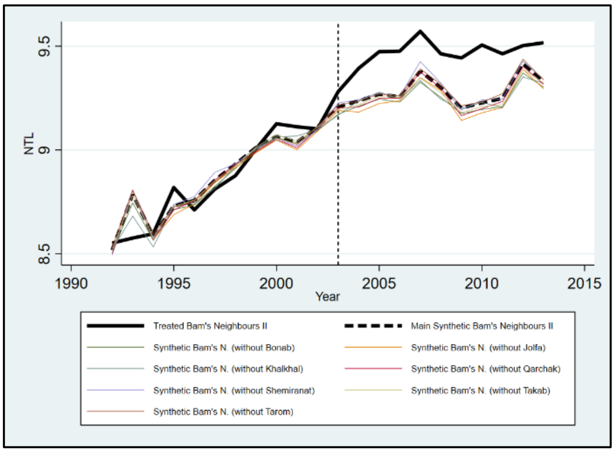
(a) In-space placebo test.



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

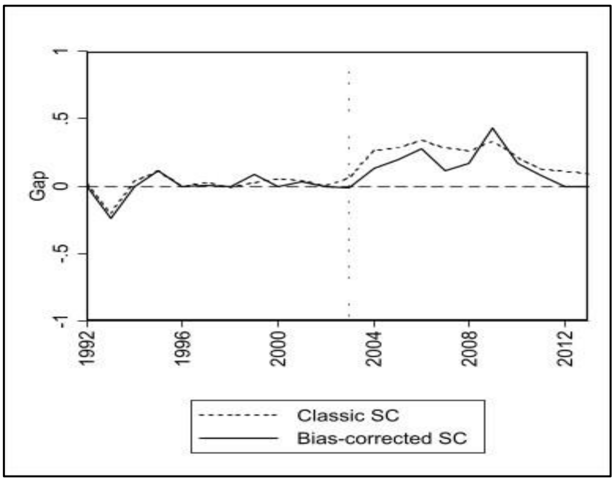


(c) In-time placebo test.

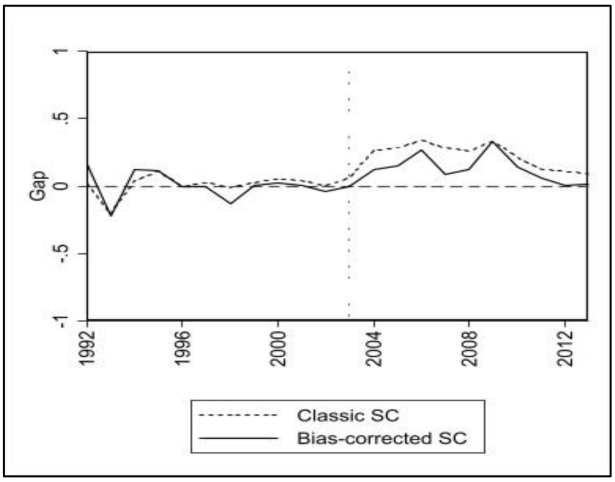


(d) Leave-one-out test

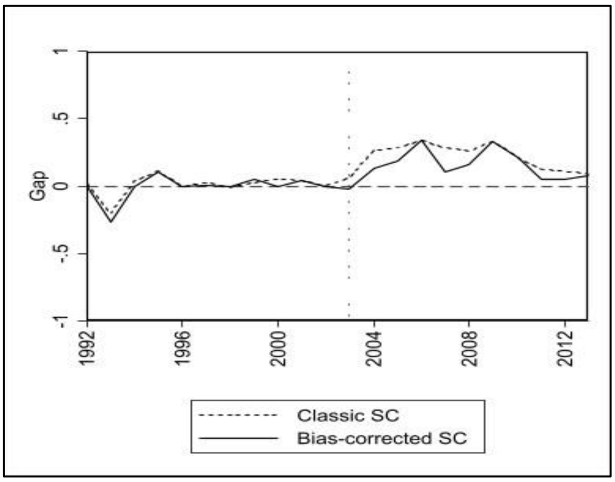
Figure B 8: Comparison of gaps in the classic and bias-corrected synthetic controls for the analysis of Bam County



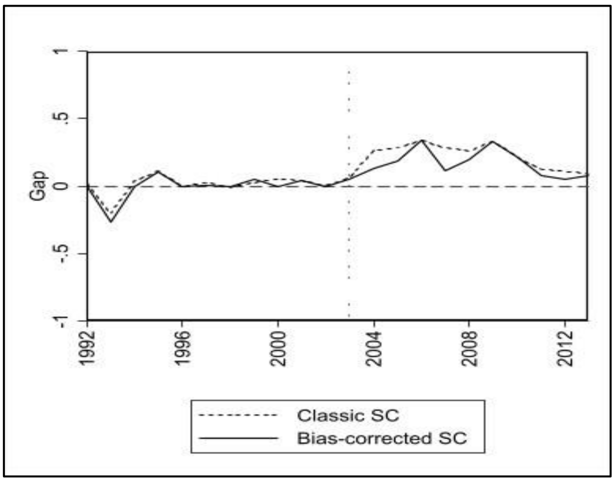
(a) Bias-corrected synthetic control (SC) based on OLS regression.



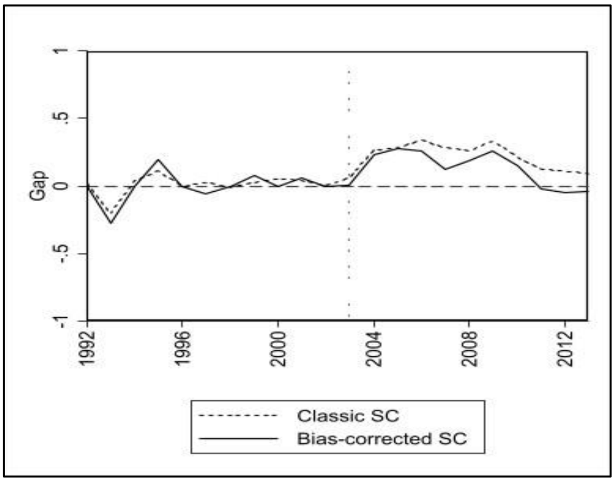
(b) Bias-corrected synthetic control (SC) based on Ridge regression.



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

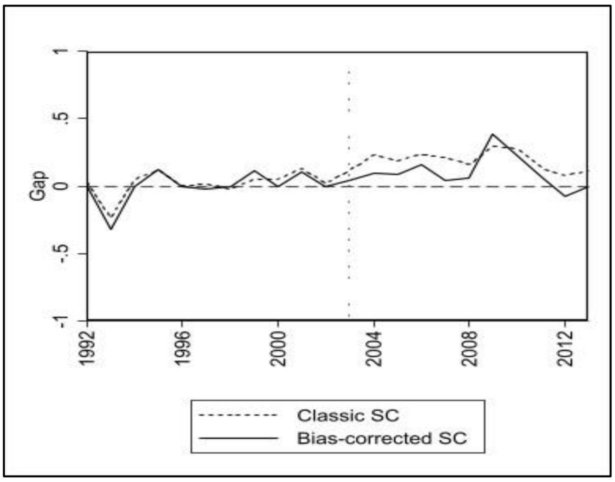


(d) Bias-corrected synthetic control (SC) based on elastic net regression.

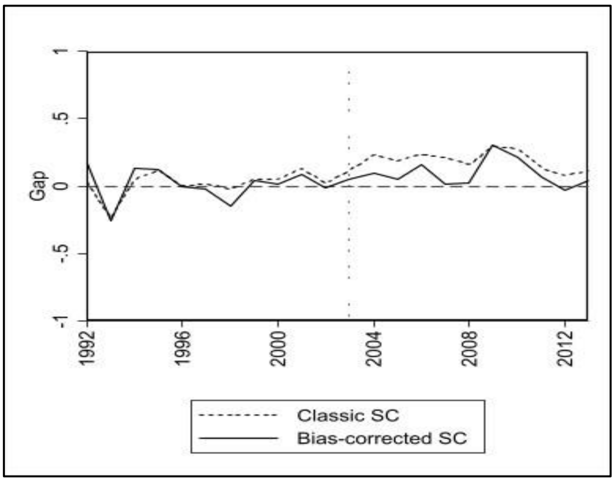


(e) Bias-corrected synthetic control (SC) based on OLS regression with only those donor pool units for which the synthetic-control-estimated weights are strictly positive.

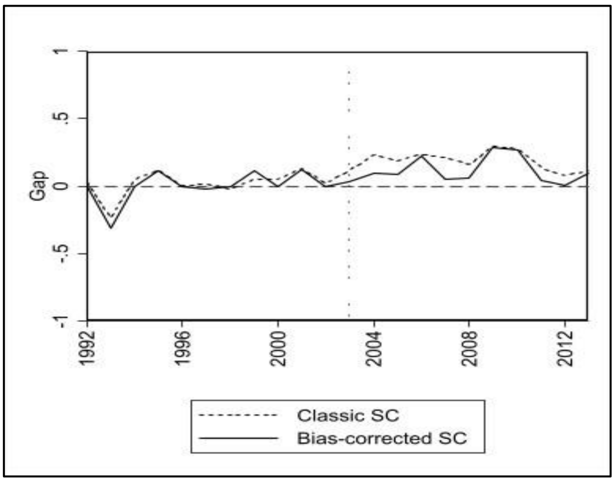
Figure B 9: Comparison of gaps in the classic and bias-corrected synthetic controls for the analysis of Bam County's neighbors of first order



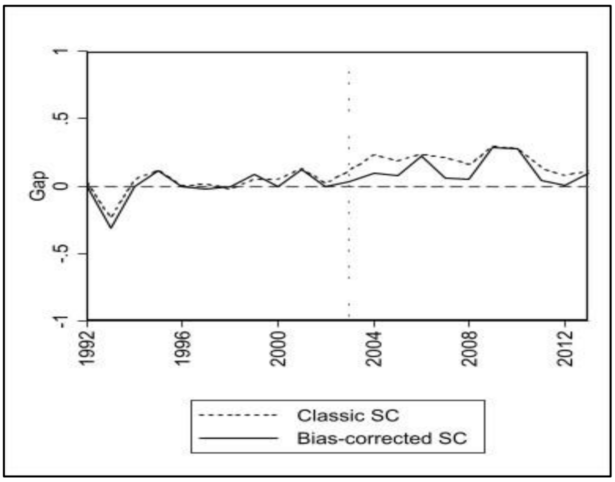
(a) Bias-corrected synthetic control (SC) based on OLS regression.



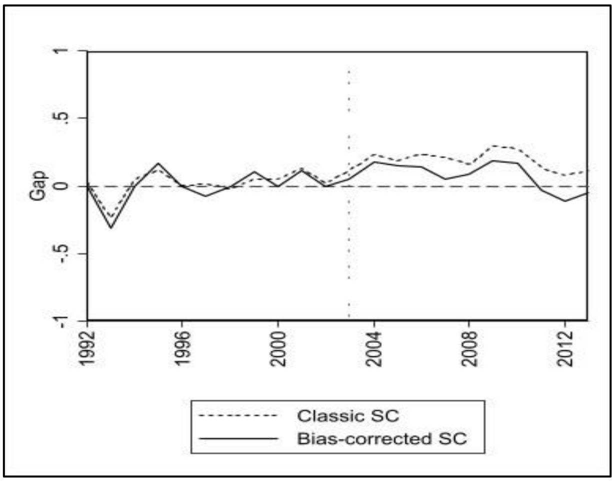
(b) Bias-corrected synthetic control (SC) based on Ridge regression.



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

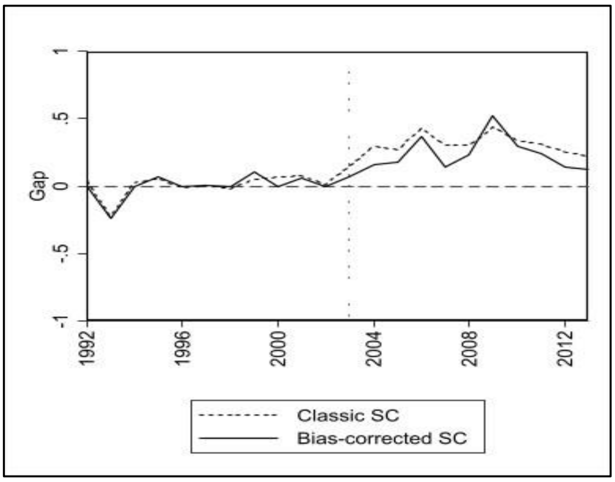


(d) Bias-corrected synthetic control (SC) based on elastic net regression.

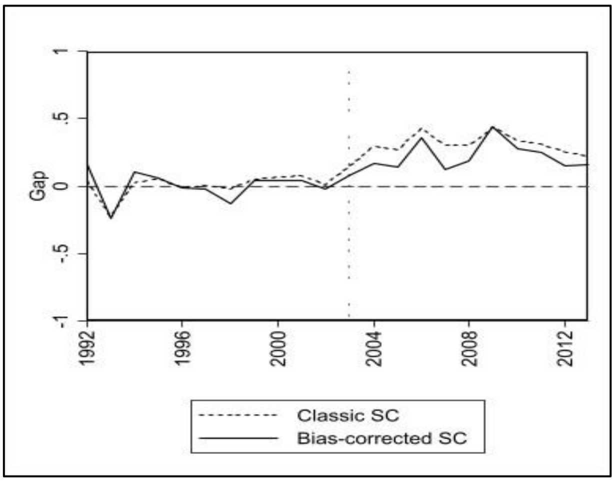


(e) Bias-corrected synthetic control (SC) based on OLS regression with only those donor pool units for which the synthetic-control-estimated weights are strictly positive.

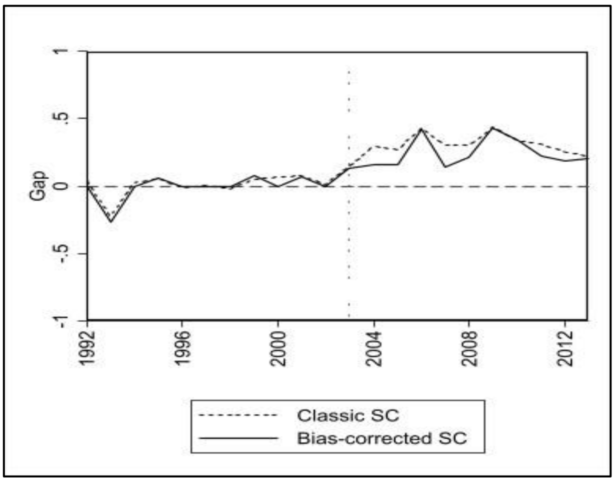
Figure B 10: Comparison of gaps in the classic and bias-corrected synthetic controls for the analysis of Bam County's selected neighbors of first order (excluding Jiroft and Kerman)



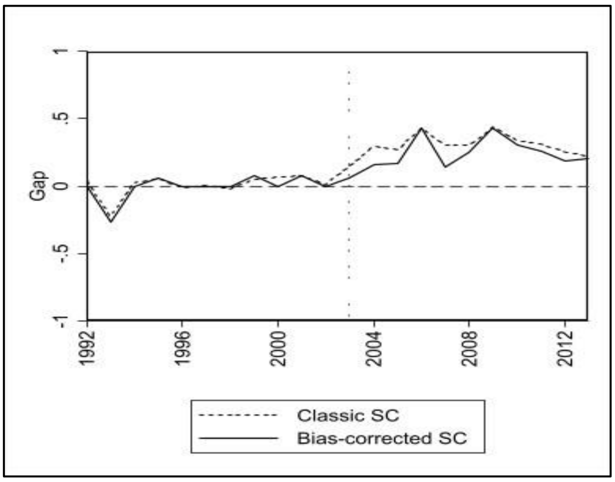
(a) Bias-corrected synthetic control (SC) based on OLS regression.



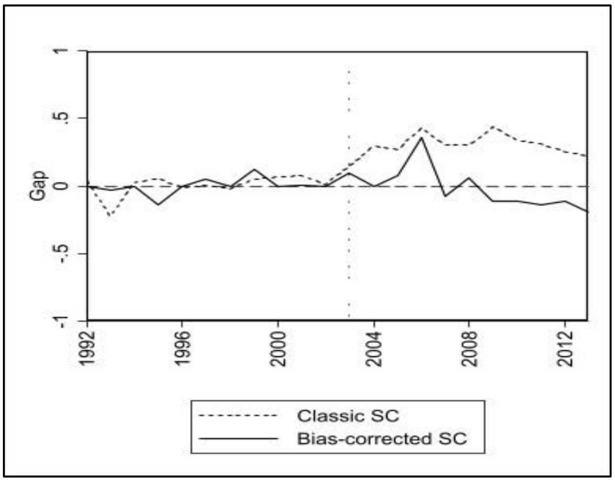
(b) Bias-corrected synthetic control (SC) based on Ridge regression.



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

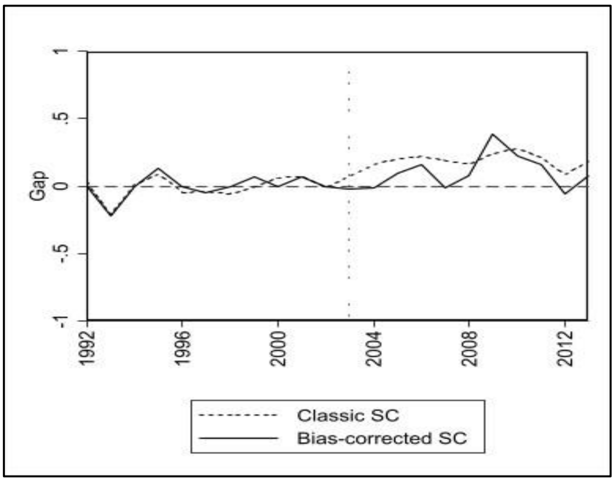


(d) Bias-corrected synthetic control (SC) based on elastic net regression.

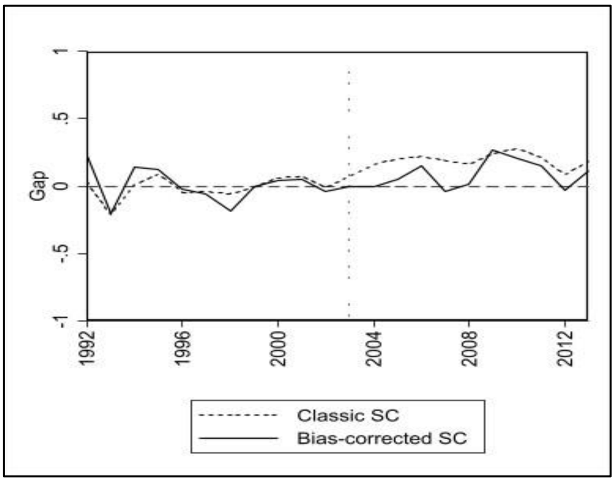


(e) Bias-corrected synthetic control (SC) based on OLS regression with only those donor pool units for which the synthetic-control-estimated weights are strictly positive.

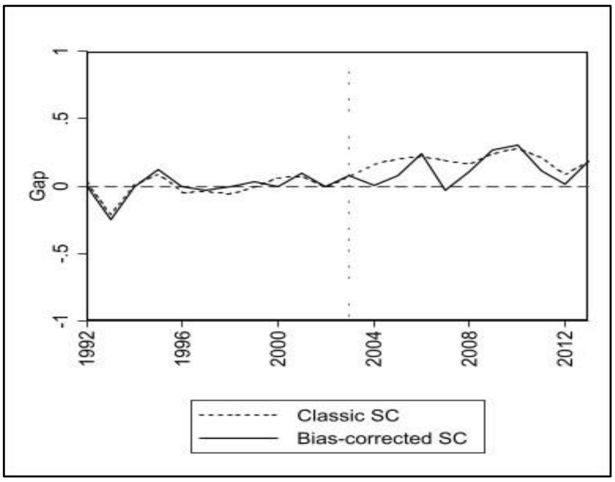
Figure B 11: Comparison of gaps in the classic and bias-corrected synthetic controls for the analysis of Bam County's neighbors of second order



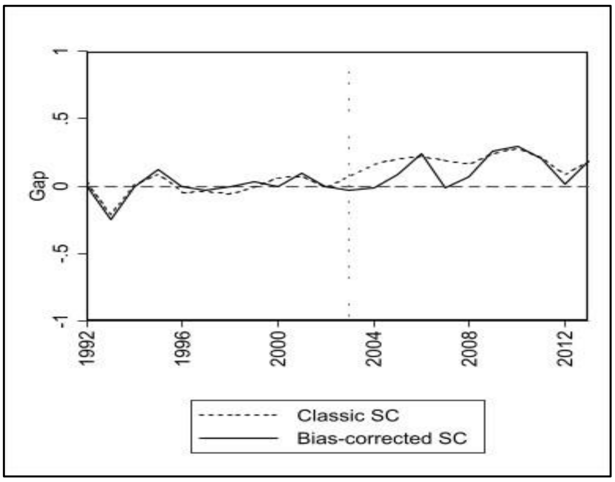
(a) Bias-corrected synthetic control (SC) based on OLS regression.



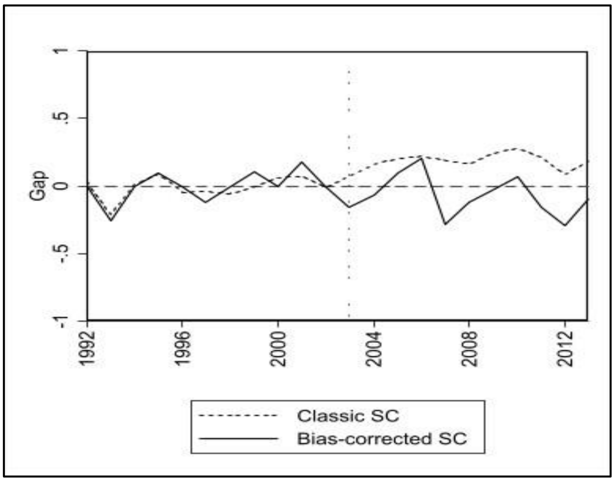
(b) Bias-corrected synthetic control (SC) based on Ridge regression.



(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.

Table B 1: Large-scale natural disasters in Iran, 1992-2020

No.	Year	Provinces (2017 borders)	Coordinates	Magnitude (Richter scale)	Affected area (km^2)	Disaster type	Total deaths	Total affected	Total damage (in million US$, infl.-adjusted)
1	1992	Golestan			1,100	Flood	63	20,000	5,476
2	1993	Bushehr, Chaharmahal and Bakhtiari, Fars, Hormozgan, Ilam, Isfahan, Kerman, Khuzestan, Kohgiluyeh and Boyerahmad, Lorestan, North Khorasan, Razavi Khorasan, South Khorasan, Yazd			625,200	Flood	407	484,728	1,792
3	1997	South Khorasan	33.825 N, 59.809 E	7.3		Earthquake	1,568	74,600	161
4	1997	Ardabil	38.075 N, 48.050 E	6		Earthquake	1,100	38,600	123
5	1999-2001	Fars, Bushehr, Kerman, Yazd, Sistan and Baluchestan, Kohguliyeh and Boyerahmad, Hormozgan, Khuzestan				Drought		37,000,000	5,127
6	2001	North Khorasan, Razavi Khorasan, South Khorasan, Golestan, Semnan			77,940	Flood	412	1,200,200	115
7	2002	Hamadan, Qazvin, Zanjan	35.626 N, 49.047 E	6.5		Earthquake	227	111,300	432
8	2002	North Khorasan, Razavi Khorasan, South Khorasan, Golestan, Semnan			9,720	Flood	39	200,000	6
9	2003	Kerman	28.995 N, 58.311 E	6.6		Earthquake	26,796	267,628	703
10	2006	Lorestan	33.5 N, 48.78 E	6.1		Earthquake	63	161,418	54
11	2007	Kerman, Sistan and Baluchestan, Hormozgan				Storm	12	185,009	
12	2014	North Khorasan, Razavi Khorasan, South Khorasan, Golestan, Mazandaran, Semnan			305,525	Flood	37	440,000	54
13	2017	Kermanshah, Ilam	34.911 N, 45.959 E	7.3		Earthquake	444	209,000	781
14	2019	Chaharmahal and Bakhtiari, Fars, Qom, Gilan, Golestan, Hamadan, Kermanshah, Khuzestan, Kohgiluyeh and Boyerahmad, Kurdestan, Lorestan, Markazi, Mazandaran, Semnan, Sistan and Baluchestan, Yazd, North Khorasan				Flood	70	10,001,076	2,531
15	2020	Bushehr, Fars, Hormozgan, Khuzestan, Lorestan, Sistan and Baluchestan, Qom				Flood	21	22	1,500
16	2020	Hormozgan, Kerman, Sistan and Baluchestan				Flood	4	196,152	808

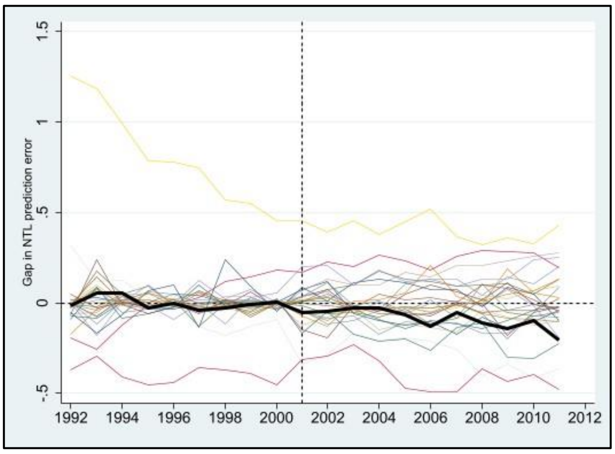
(Source: Authors' illustration using data from EM-DAT (2021))

Table B 2: Counties in the donor pool after excluding disaster-affected counties

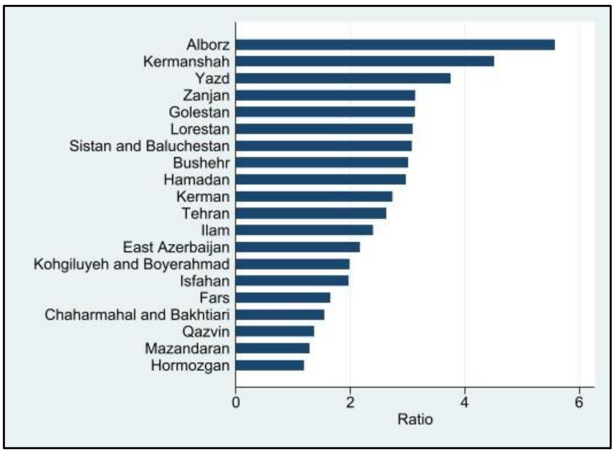
Number	**County**	**Number**	**County**	**Number**	**County**
1	Abyek	22	Kangavar	43	Qazvin
2	Ahar	23	Karaj	44	Ravansar
3	Alborz	24	Khalkhal	45	Sahneh
4	Baharestan	25	Khodaafarin	46	Salmas
5	Bilasavar	26	Khorramdarreh	47	Sardasht
6	Bonab	27	Khoy	48	Savojbolagh
7	Bukan	28	Mahneshan	49	Shabestar
8	Chaldoran	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

Appendix C

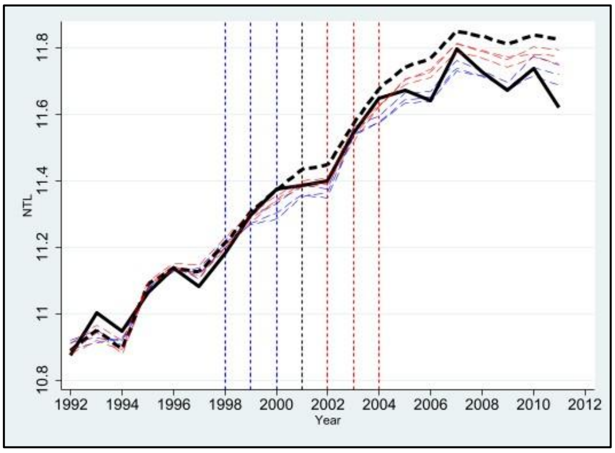
Figure C 1: Placebo tests for the SCM analysis of Golestan Province



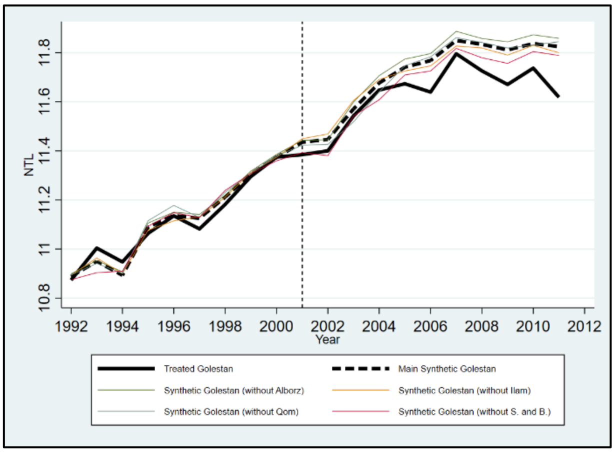
(a) In-space placebo test.



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

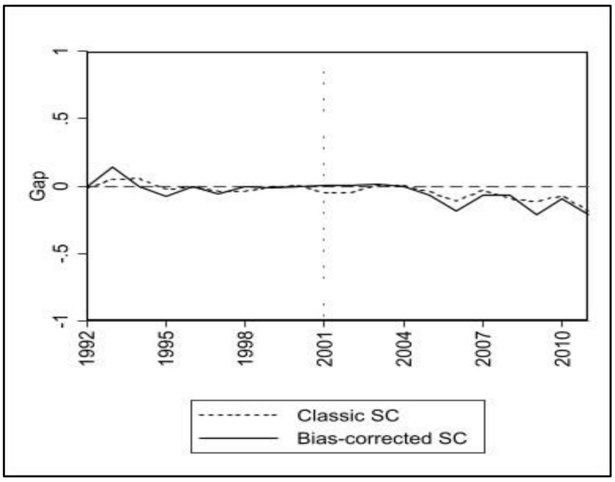


(c) In-time placebo test.

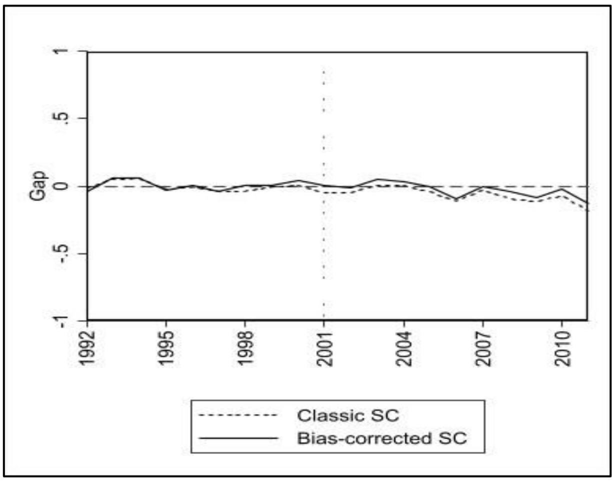


(d) Leave-one-out test.

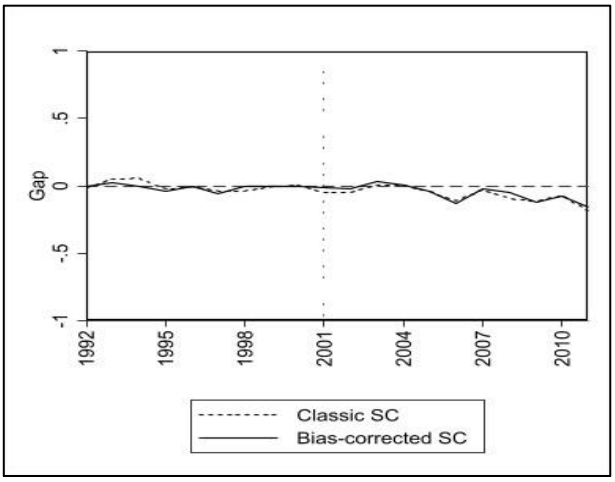
Figure C 2: Comparison of gaps in the classic and bias-corrected synthetic controls for the analysis of Golestan Province



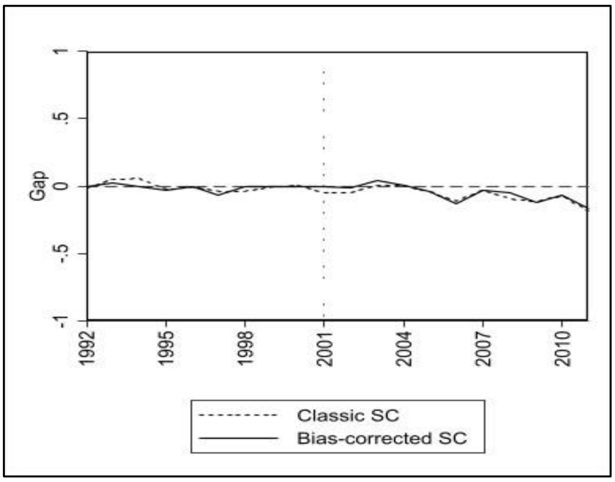
(a) Bias-corrected synthetic control (SC) based on OLS regression.



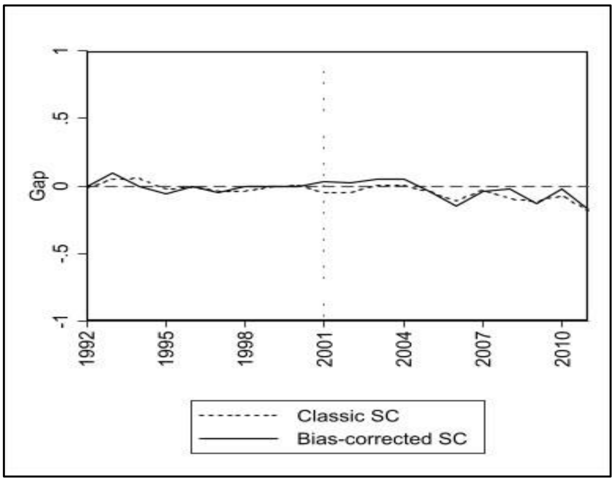
(b) Bias-corrected synthetic control (SC) based on Ridge regression.



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

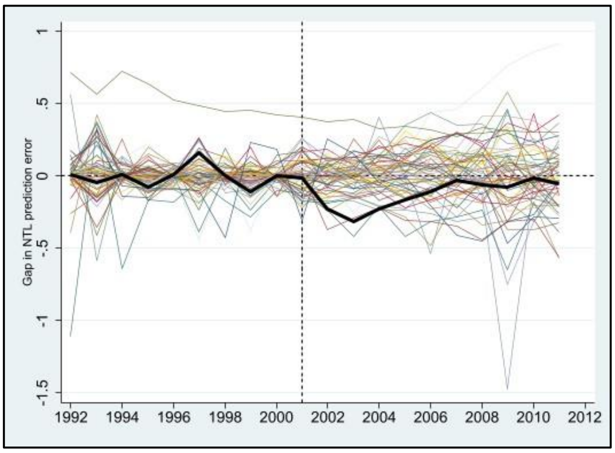


(d) Bias-corrected synthetic control (SC) based on elastic net regression.

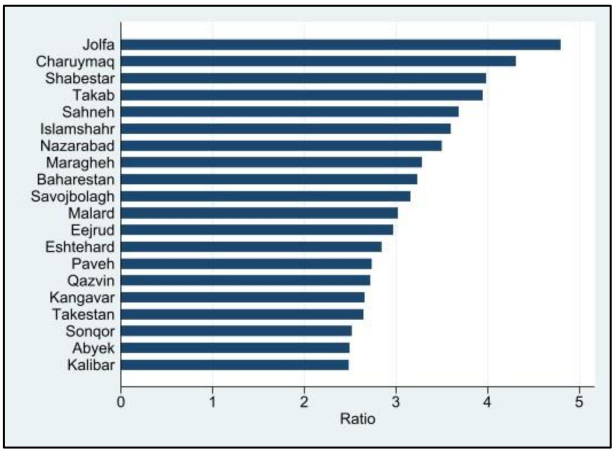


(e) Bias-corrected synthetic control (SC) based on OLS regression with only those donor pool units for which the synthetic-control-estimated weights are strictly positive.

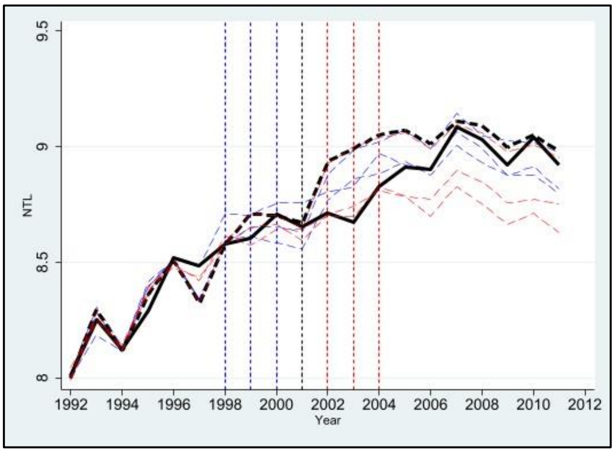
Figure C 3: Placebo tests for the SCM analysis of Azadshahr County



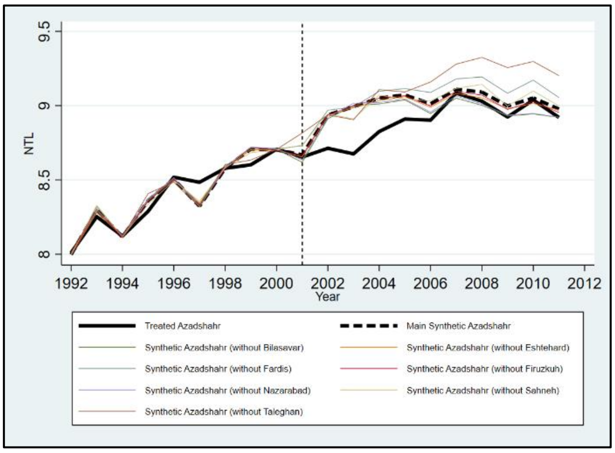
(a) In-space placebo test.



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

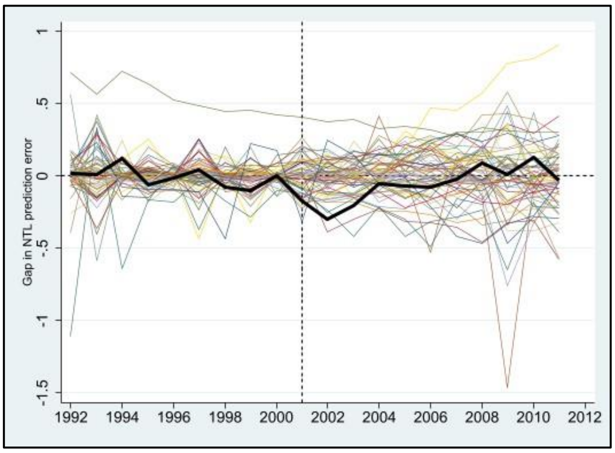


(c) In-time placebo test.

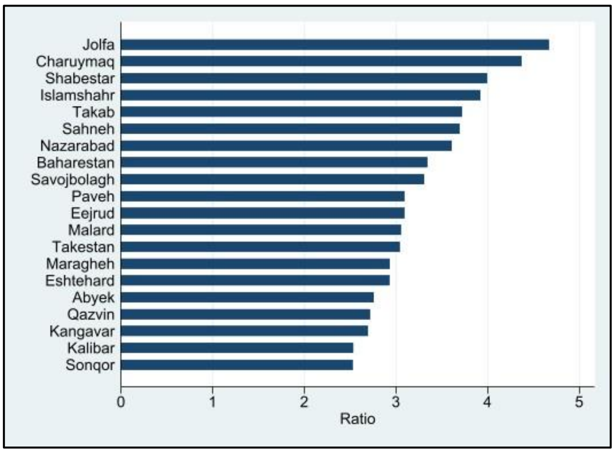


(d) Leave-one-out test.

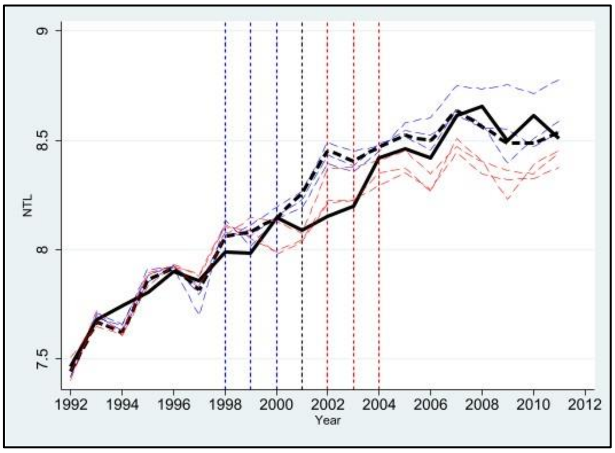
Figure C 4: Placebo tests for the SCM analysis of Galikash County



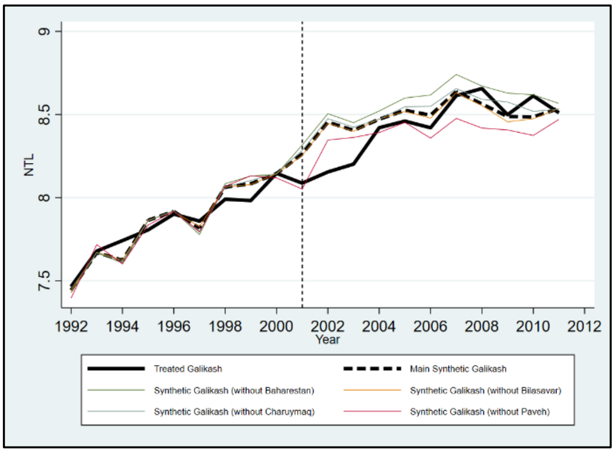
(a) In-space placebo test.



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

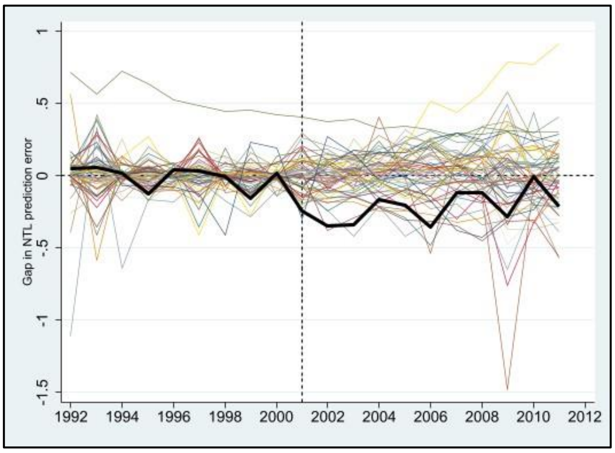


(c) In-time placebo test.

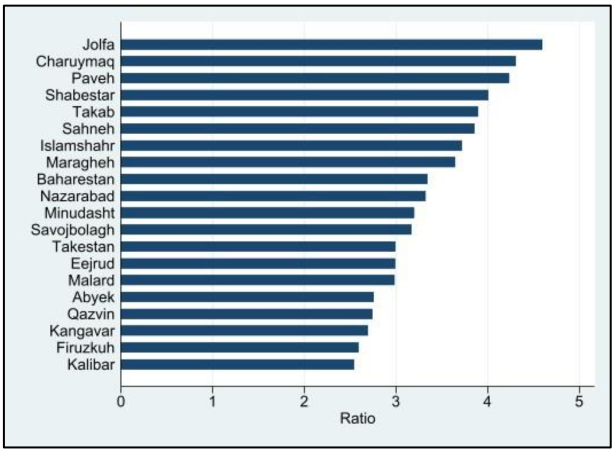


(d) Leave-one-out test.

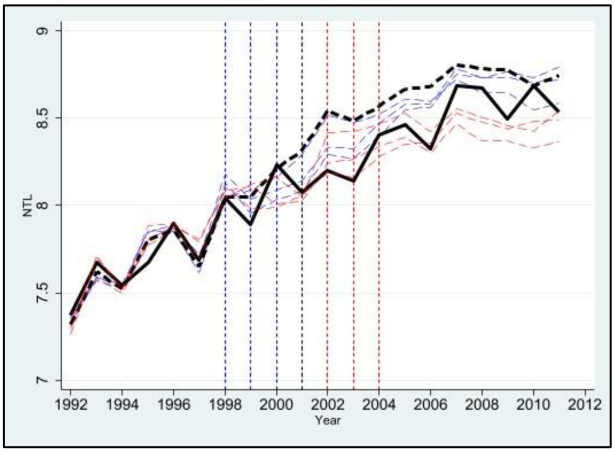
Figure C 5: Placebo tests for the SCM analysis of Minudasht County



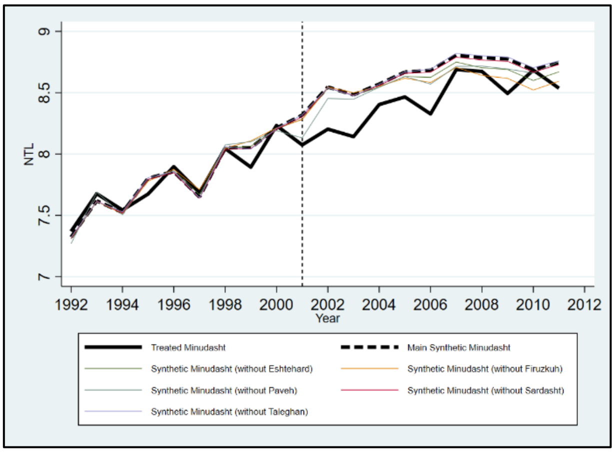
(a) In-space placebo test.



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

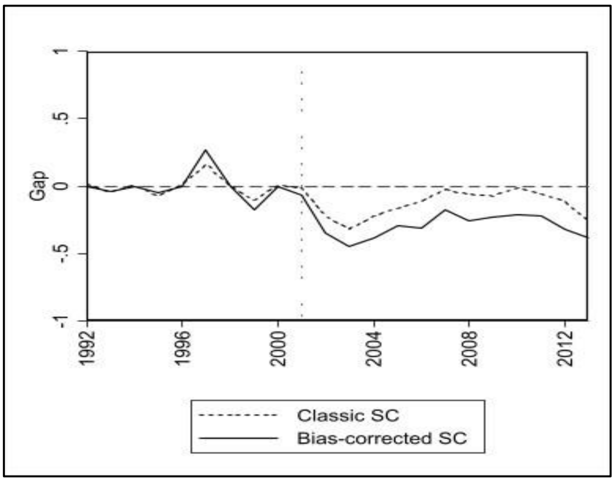


(c) In-time placebo test.

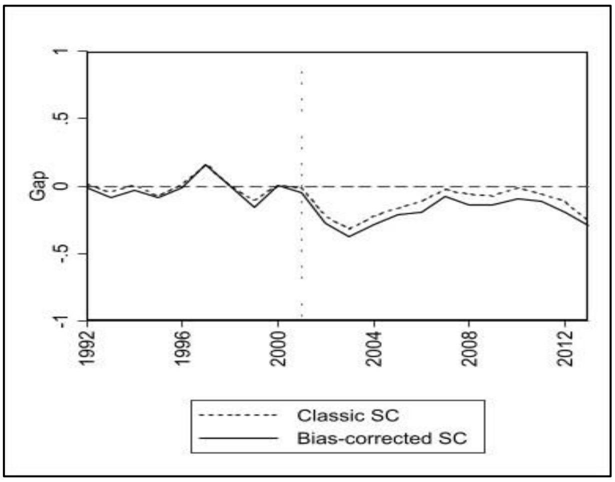


(d) Leave-one-out test.

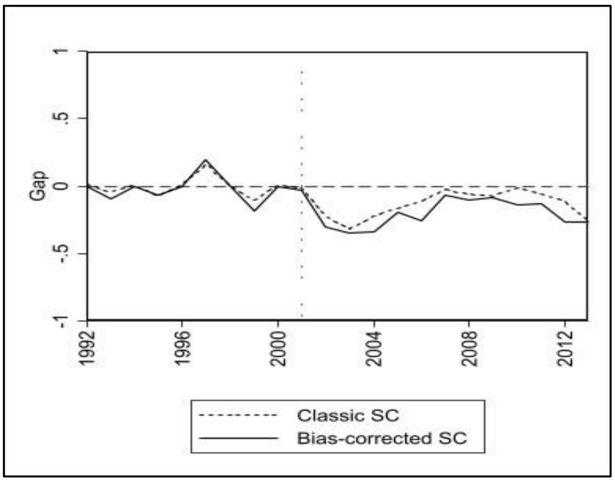
Figure C 6: Comparison of gaps in the classic and bias-corrected synthetic controls for the analysis of Azadshahr County



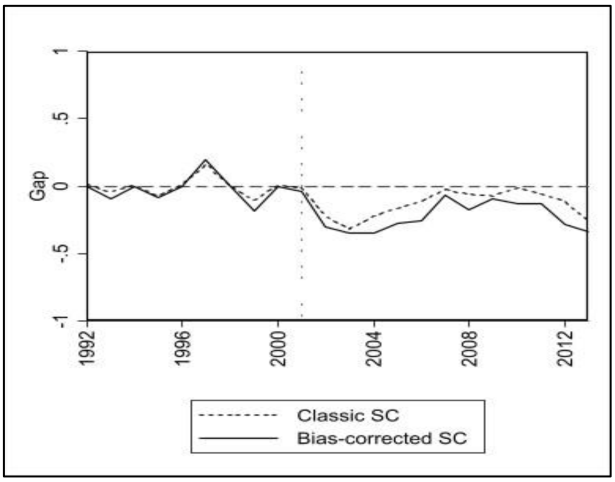
(a) Bias-corrected synthetic control (SC) based on OLS regression.



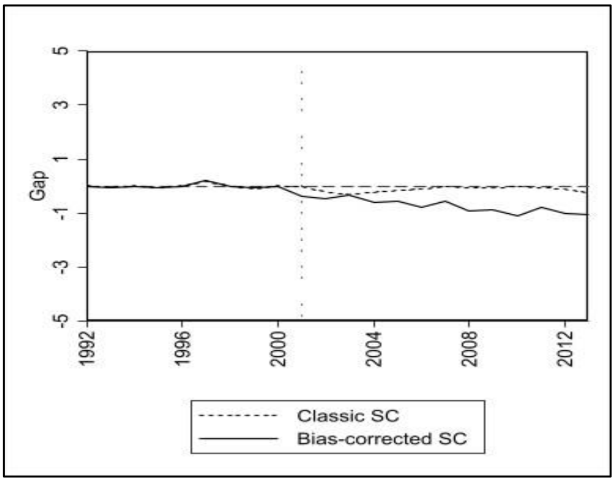
(b) Bias-corrected synthetic control (SC) based on Ridge regression.



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

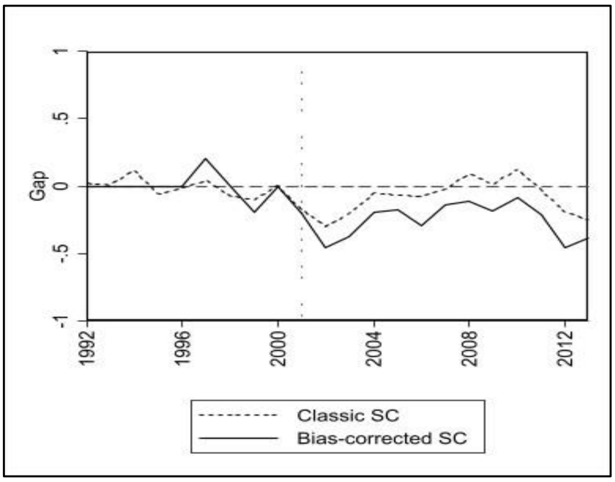


(d) Bias-corrected synthetic control (SC) based on elastic net regression.

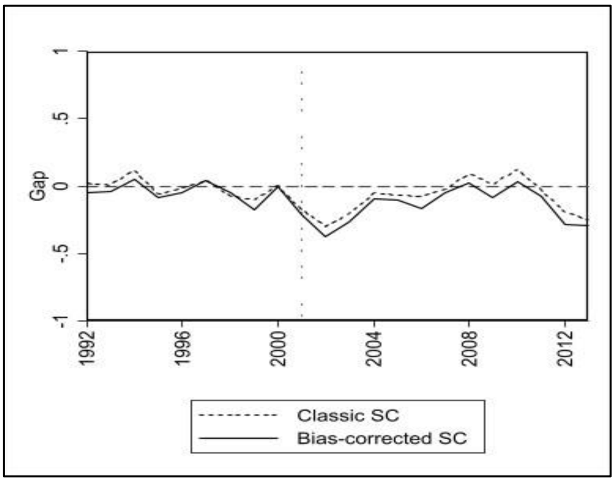


(e) Bias-corrected synthetic control (SC) based on OLS regression with only those donor pool units for which the synthetic-control-estimated weights are strictly positive.

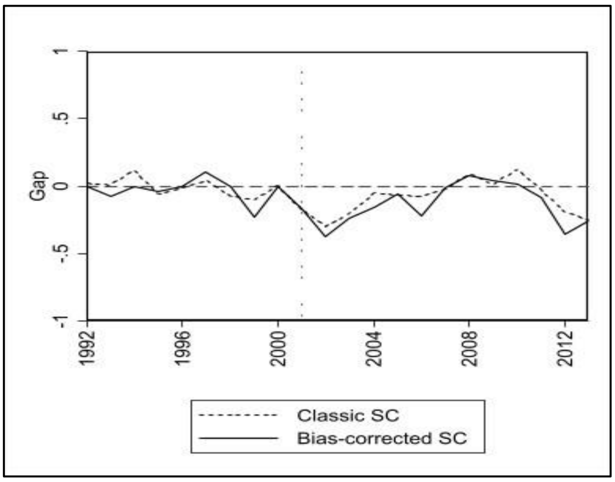
Figure C 7: Comparison of gaps in the classic and bias-corrected synthetic controls for the analysis of Galikash County



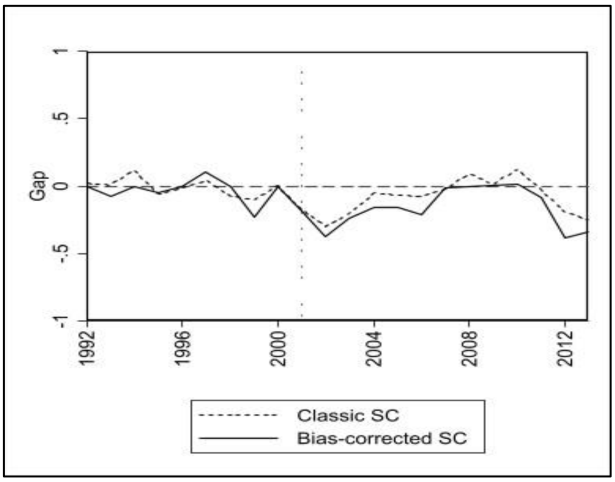
(a) Bias-corrected synthetic control (SC) based on OLS regression.



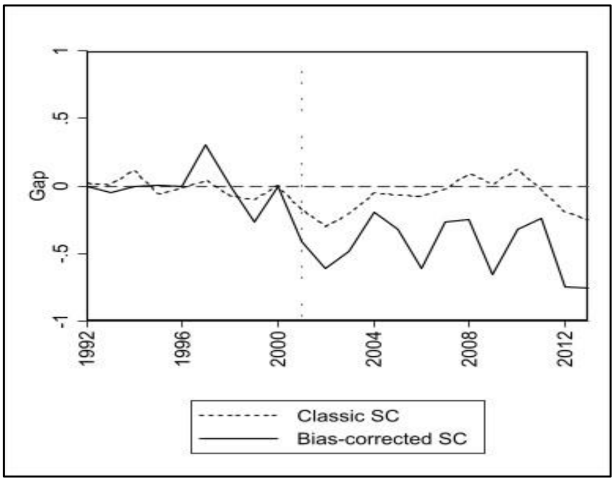
(b) Bias-corrected synthetic control (SC) based on Ridge regression.



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

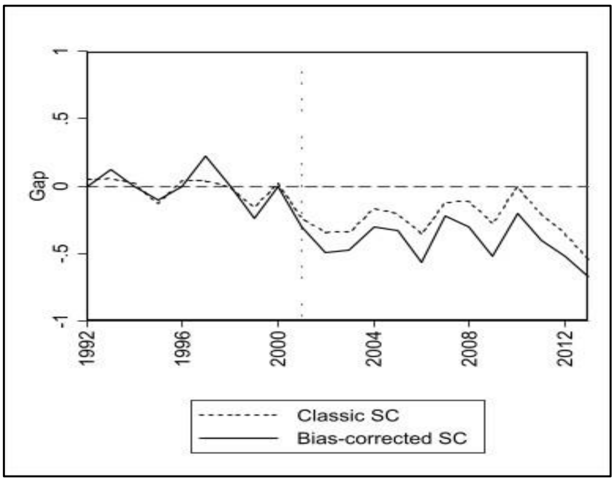


(d) Bias-corrected synthetic control (SC) based on elastic net regression.

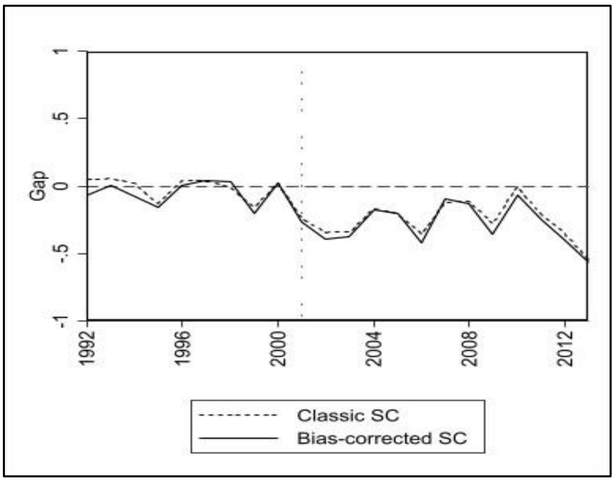


(e) Bias-corrected synthetic control (SC) based on OLS regression with only those donor pool units for which the synthetic-control-estimated weights are strictly positive.

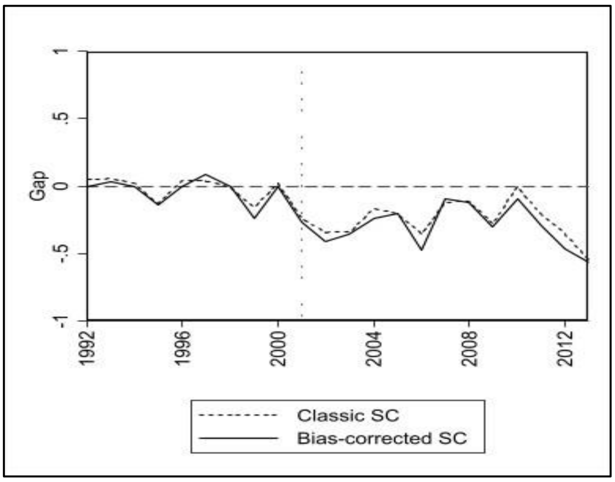
Figure C 8: Comparison of gaps in the classic and bias-corrected synthetic controls for the analysis of Minudasht County



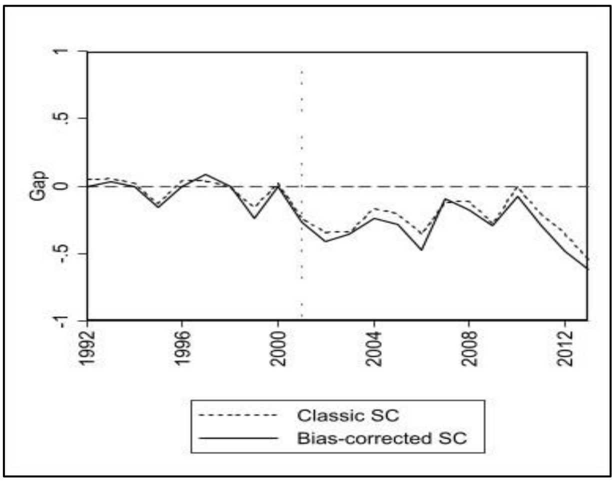
(a) Bias-corrected synthetic control (SC) based on OLS regression.



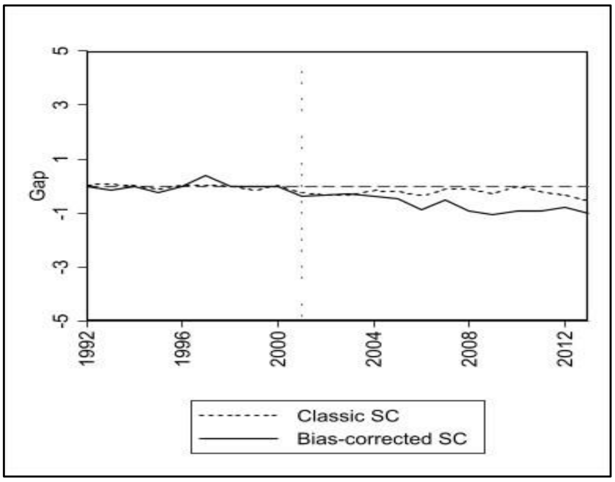
(b) Bias-corrected synthetic control (SC) based on Ridge regression.



(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.

Table C 1: Estimated costs of the Golestan flood (based on classic SC)

	Azadshahr		**Galikash**		**Minudasht**	
Year	IRR (billion)	US$ (million)	IRR (billion)	US$ (million)	IRR (billion)	US$ (million)
2001	18.29	10.42	121.77	69.39	171.73	97.85
2002	297.20	37.51	236.81	29.89	291.76	36.82
2003	426.82	52.41	160.25	19.68	272.25	33.43
2004	335.13	39.38	46.13	5.42	157.86	18.55
2005	253.88	28.60			207.84	23.41
2006	166.08	18.16			343.33	37.54
Sum	**1,497.39**	**186.47**	**564.97**	**124.37**	**1,444.78**	**247.61**

Table C 2: Estimated costs of the Golestan flood (based on penalized SC)

	Azadshahr		**Galikash**		**Minudasht**	
Year	IRR (billion)	US$ (million)	IRR (billion)	US$ (million)	IRR (billion)	US$ (million)
2001	81.16	46.25	145.58	82.95	217.49	123.92
2002	494.12	62.36	392.92	49.59	454.52	57.36
2003	646.43	79.37	320.71	39.38	405.83	49.83
2004	623.42	73.26	188.39	22.14	306.01	35.96
2005	500.24	56.35			356.33	40.14
2006	529.03	57.85			615.81	67.34
Sum	**2,874.40**	**375.44**	**1047.60**	**194.05**	**2,355.98**	**374.55**

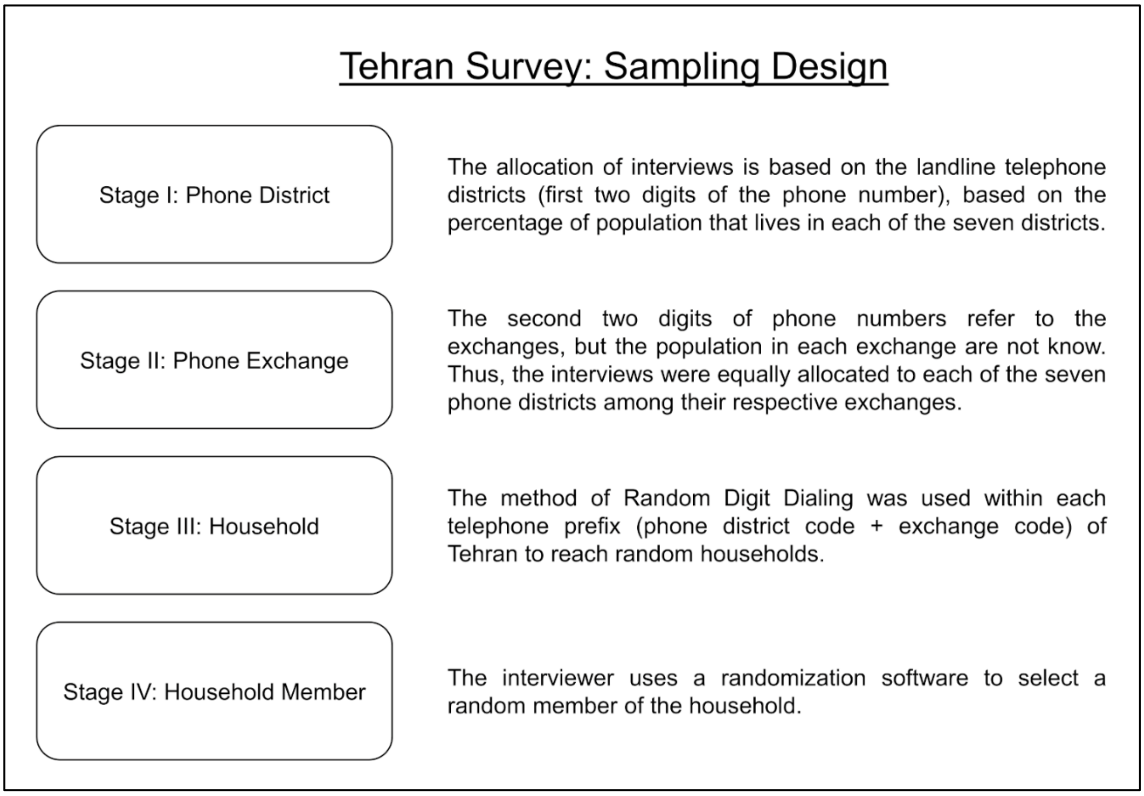
Appendix D

Table D 1: Characteristics of respondents in the survey sample compared to characteristics of the official Iranian 2016 Census (shares in percent)

		Census 2016 (N = 6,909,972)	**Survey 2020/21 (n = 502)**	**Survey 2020/21 (n = 418)**
Age	18–34	38.6	23.9	24.6
	35–51	33.9	35.46	38
	52–68	20.1	28.69	28.7
	69–85	6.8	10.76	8.4
	86–100+	0.7	0.6	0.3
Gender	Female	50.6	48.6	49.3
	Male	49.4	51.4	50.7
Marital status	Married	68.3	70.1	71.1
	Never married	22.7	19.3	19.6
	Divorced/widowed	8.4	10.6	9.3
Education	Illiterate	5.7	4.6	2.9
	Primary education	10.3	16.5	16.5
	Secondary education	45.8	42.4	43.5
	Tertiary education	37.5	36.5	37.1
Employment	Employed	58.7	33.1	35.9
	Jobless	23.3	20.9	19.6
	Homemaker/student	10.6	45	44.5

Notes: The Census 2016 data are from Statistical Centre of Iran (SCI) and refer to the population aged 18 years or older of Tehran County (SCI 2018).

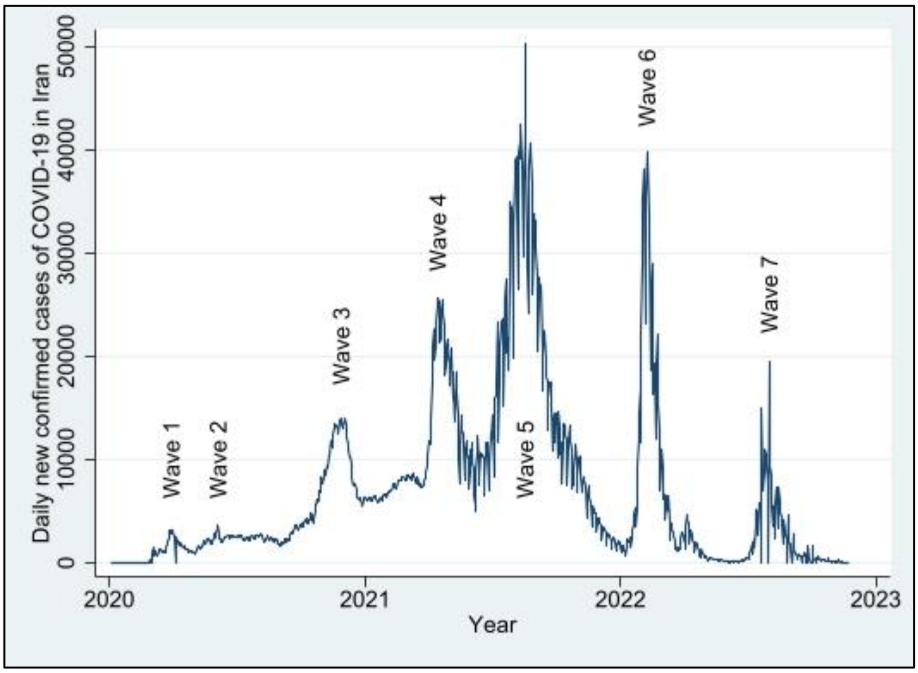
Figure D 1: Overview of the survey's multi-stage cluster sampling (Tehran)



(Source: Authors' illustration based on the technical report of IranPoll)

Appendix E

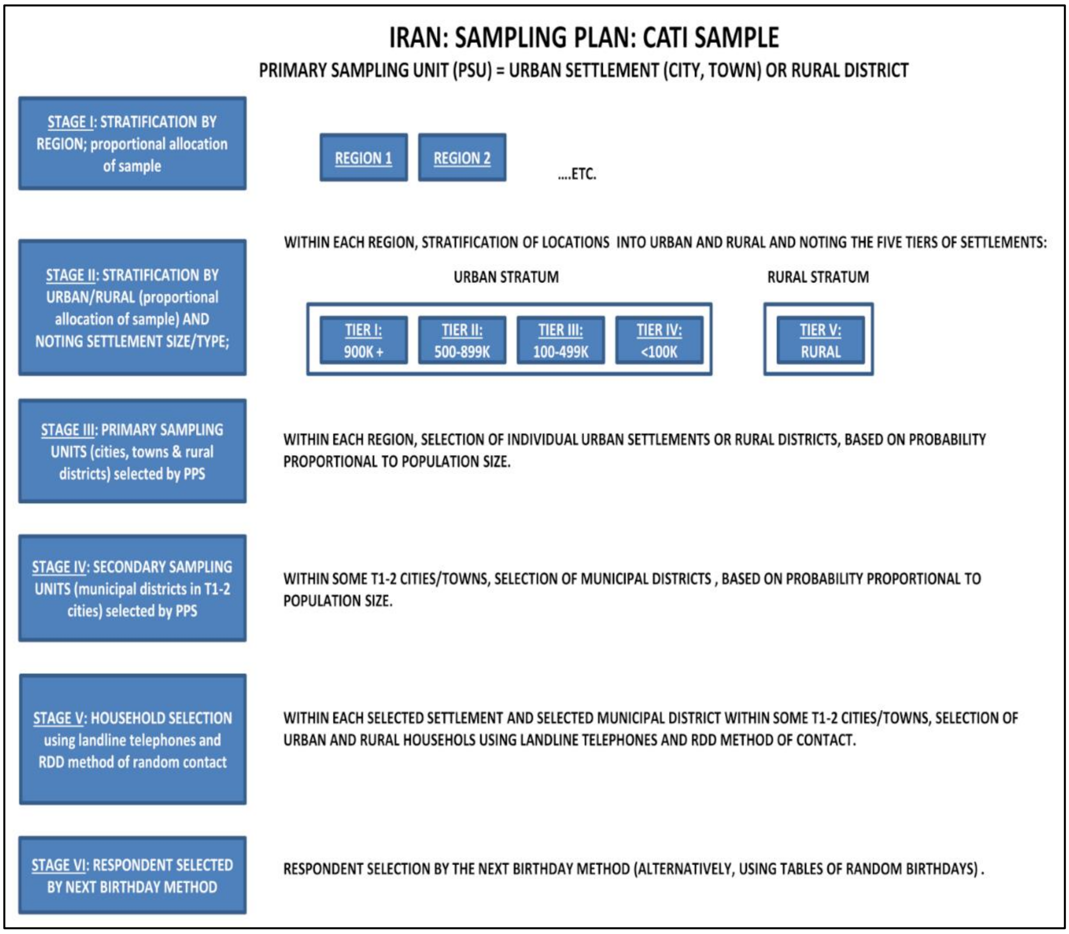
Figure E 1: COVID-19 waves in Iran



Notes: The figure shows the seven waves of COVID-19 infections in Iran from February 2020 to November 2022. The peak of the first wave was on 30 March 2020 (with 3186 new cases) and it was followed by a second wave with a peak on 5 June 2020 (with 3574 new cases). The third wave peaked on 28 November 2020 (with 14051 new cases). The peak of the fourth wave was on 15 April 2021 (with 25582 cases) and it was followed by a fifth wave with a peak on 18 August 2021 (with 50228 new cases). The latter is also the single day with the highest number of new confirmed cases during the whole pandemic. The sixth wave peaked on 8 February 2022 (with 39819 new cases), and the latest seventh wave peaked on 2 August 2022 (with 19426 new cases).

(Source: Authors' illustration using data from WHO (2022))

Figure E 2: Overview of the survey's multi-stage cluster sampling (Iran)



(Source: Technical report of R-Research)

Table E 1: Sample distribution of completed interviews

Region	Provinces	Share of population			Completed interviews		
		Region	**Urban**	**Rural**	**Region**	**Urban**	**Rural**
1. North	Gilan, Golestan, Mazandaran	10%	59%	41%	119 (9.8%)	71 (59.7%)	48 (40.3%)
2. Tehran	Tehran, Alborz, Semnan, Qazvin, Qom, Markazi, Hamadan	28%	89%	11%	335 (27.6%)	305 (91%)	30 (9%)
3. Centre	Isfahan, Chaharmahal and Bakhtiari, Yazd	9%	84%	16%	104 (8.6%)	89 (85.6%)	15 (14.4%)
4. North-West	West Azerbaijan, East Azerbaijan, Ardabil, Zanjan	12%	69%	31%	149 (12.3%)	104 (69.8%)	45 (30.2%)
5. North-East	Razavi Khorasan, North Khorasan, South Khorasan	10%	70%	30%	120 (9.9%)	90 (75%)	30 (25%)
6. South-West	Khuzestan, Lorestan	8%	73%	27%	94 (7.7%)	63 (67%)	31 (33%)
7. South	Fars, Kohgiluyeh and Boyerahmad, Bushehr, Hormozgan	11%	66%	34%	125 (10.3%)	80 (64%)	45 (36%)
8. West	Ilam, Kurdistan, Kermanshah	5%	73%	27%	75 (6.2%)	59 (78.7%)	16 (21.3%)
9. South-East	Sistan and Baluchestan, Kerman	7%	54%	46%	93 (7.7%)	48 (51.6%)	45 (48.4%)
Total		**100%**	**74%**	**26%**	**1214 (100%)**	**909 (74.9%)**	**305 (25.1%)**

Notes: The share of population in the nine regions and the share of urban and rural population within each region are based on the official Iranian 2016 Census (SCI 2018) as presented in the technical report of R-Research.

Table E 2: Characteristics of respondents in the survey sample compared to the general population

		Target (in %)	Achieved (in %)
Age	18–24	15	12.8
	25–49	59	50.4
	50–59	13	23.7
	60–65	4	12.9
Gender	Female	49.6	50.6
	Male	50.4	49.4
Education	Illiterate	15	8.4
	Primary school	18	12
	(Partial) middle school	14	10.2
	Partial high school	7	2.4
	High school diploma	22	31
	Tertiary education	24	36

Notes: The target is based on the official Iranian 2016 Census (SCI 2018) as presented in the technical report of R-Research.