Who is afraid of sanctions? The macroeconomic and distributional effects of the sanctions against Iran

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Abstract
The sanctions imposed on Iran at the beginning of 2012 have simultaneously limited the country's access to the international financial system, levied a strict boycott on Iran's oil and petrochemical exports, and limited imports of intermediate goods. This paper tries to quantify the aggregate and heterogeneous effects of these sanctions. Applying the synthetic control method, I show that the sanctions had persistent and significant effects on the Iranian economy. The cost reached its maximum of 19.1% of real gross domestic product 4 years after the application of the sanctions, and the economy has not fully recovered after their removal. I trace the poverty dynamics for different household groups after the sanctions by adopting a synthetic panel using Iran's household income and expenditure survey data. Inconsistently with the sanctions' initial goals, poverty dynamics suggest that households working in governmental sectors and educated households are unaffected by the sanctions. Instead, the sanctions condemn young, illiterate, rural, or religious minority households to poverty.

Keywords
heterogeneous poverty dynamics, sanction, synthetic control method, synthetic panel

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1 | INTRODUCTION

Sanctions are a popular political instrument that is used to force countries to comply with international agreements and laws. The usage of this instrument has increased significantly during the 20th century. Frank (2018), for example, documented that there were over 800 active sanctions in 2005. In recent years, several sanctions have been imposed on countries like Myanmar, North Korea, Iraq, Venezuela, and the Russian Federation. This paper will focus on the economic sanctions imposed on Iran in 2012, mostly by the European Union (EU) and the United States (US). These sanctions were very comprehensive and severe compared to the other sanctions imposed in the past decades. They restricted to a high degree the country’s access to international financial markets, levied a strict boycott on its oil exports, and limited the imports of intermediate goods to the country.

According to world bank reports, Iran is the second-largest economy in the Middle East and North Africa (MENA) region. Its economy is highly dependent on the oil sector, which accounts for over 20% of real gross domestic product (GDP) before the sanctions. In terms of crude oil and natural gas reserves, Iran ranks fourth and second in the world, respectively. After the 1979 Islamic revolution, Iran has experienced several rounds of sanctions mostly imposed by the United States and the European Union.

The most severe sanctions against Iran started in 2012. This wave of sanctions was drastically intensified twice. The first was in January 2012, when the US defined sanctions targeting the Iranian central bank, making it difficult for the government to receive dollars from its exports. The second was in July 2012, when the EU imposed a total ban on imports of Iran's crude oil. Since EU member states were the destination of about one-fifth of all Iran's oil exports, this new development had a massive effect on Iran's economy. Panel (b) of Figure 1 shows how Iran's oil export decreased about 800,000 barrels per day during this period. The sanction also banned EU member countries from establishing any investment by which involved technological transfers related to the oil and gas industry. This sanction affected Iran's oil production heavily; its oil supply decreased in 2012 by more than 680,000 barrels per day compared to its corresponding average of 4,200,000 in 2011 (Farzanegan, 2013).

In October 2012, the EU imposed a new financial sanction and prohibited any kind of financial transactions with the banks in Iran. This sanction forced Iran to sell its oil with a

![Figure 1](https://www.cbi.ir)

**FIGURE 1** (a) Exchange rate and (b) crude oil exports during sanction years. Data are reported quarterly and vertical lines show the first quarter after imposing sanctions and the first quarter after their removal. *Source: Central bank of Iran, www.cbi.ir [Color figure can be viewed at wileyonlinelibrary.com]*
significant discount and exchange it with other goods. This unexpected situation caused the Rial to lose about two-thirds of its value compared to the US dollar, to which it was previously pegged. Figure 1a shows the influence of the sanctions on the exchange rate. Finally, as a result of the sanctions, the country faced difficulties in purchasing intermediate goods.

In 2015, Iran reached a nuclear agreement with the EU and US, known as the Joint Comprehensive Plan of Action (JCPOA), which provided Iran a broad relief from the sanctions. After the agreement, Iran recovered its presanction share in the oil market, joined the international financial markets, and reaccessed the exchange reserve fund. However, in November 2018, the US decided to unilaterally leave the deal and impose most of those sanctions again.

This paper investigates the aggregate and heterogeneous effect of the sanctions on Iran's economy between 2012 and 2015 and the extent to which these effects were permanent. To compare the economic performance of Iran with its potential path in the absence of the sanctions, I adopt the synthetic control methodology (SCM) and construct a synthetic Iran as a weighted average of some other similar countries. In doing so, I match the GDP growth path, population, and the presanction averages of the rents from natural resources, international trade, industry, agriculture, and service production—all in GDP share—of the synthetic Iran with the actual Iran and I analyze how the dynamics of the Iranian economy changed relative to the synthetic economy after the sanctions. The result of this exercise suggests a considerable, severe, and persistent effect of the sanctions on the Iranian economy. During the 4 years after implementing the sanctions until the JCOPA agreement, Iran's real GDP dropped significantly relative to its counterfactual, reaching its maximum of 19.1% of GDP in 2015. The negative effect of sanctions persisted for 2 years after the removal of the sanctions and kept the Iranian economy more than 5% under its potential path.

Hence, results for the aggregate economy confirm that economic sanctions are indeed associated with considerable costs in terms of real GDP losses that are long-lived and can be considered as a credible punishment for countries under the sanction. Gharehgozli (2017) shows a similar result for the first 3 years after the implementation of the sanctions. However, from both an economic policy and sociological perspective, it is important to understand the distributional effects of the sanctions. One would expect that households with some access to political or economic resources and rents will normally suffer less by trying to use and redistribute the scarce resources in their favor. On the other hand, vulnerable groups might significantly suffer from any political and economic volatility caused by international sanctions due to their disadvantaged position in society and minimized access to the resources and rents.

Accordingly, the main contribution of the paper is to analyze the effects of sanctions on poverty mobility in different groups of households classified by households' head characteristics and their position in the income distribution. To compare the welfare change during this period, considering a simple poverty ratio will be misleading. Poverty mobility analysis is preferable since it allows us to assess the nature of these changes and distinguish the case of chronic poverty with that of more volatile poverty which is due to the reallocation of resources. Also, the policy implications for these chronic versus transitory changes in poverty are different.

In particular, I use the household income and expenditure survey (HIES) data provided by the Statistical Center of Iran. Each year, the survey is conducted for about 38,000 households and includes their social characteristics, living facilities, expenditures, and total income. The main shortcoming of this database is that the survey sample is updated each year and households cannot be directly compared in two different survey rounds. Using the methodology in Dang et al. (2014), I use households’ time-invariant characteristics to construct their
income dynamics and tackle the Iranian economy’s lack of panel data. According to the Iranian microdata, rural, young, and low-educated households, households not working in the public sector, religious minorities, and households belonging to the low-to-middle-income class are the most probable to become poor during the sanction period. Instead, households with occupations in the governmental sector and high-educated heads are suffering the least during the same period.

The effectiveness of sanctions as an instrument of deterrence of unethical policies as well as its consequences on the target countries attracted researchers’ interest in both economics and political science. The existing literature mostly tries to study the success or failure of the sanctions and their effects on the targeted economies. A large body of this literature studies the effects of sanctions on the bilateral and multilateral trade. Yang et al. (2009), Caruso (2003), and Frank (2018) find a significant negative effect of sanctions on trade, while Kohl and Klein Reesink (2019) cast doubts on the robustness of the latter authors’ results. Hinz (2017) studied the global effect of recent sanctions on Russia, Iran, and Myanmar and found that the overall cost of these sanctions in 2014 was about 50 billion dollars, which is equivalent to 0.4% of global trade. In another study, Crozet and Hinz (2018) find that the costs of the sanctions and counter-sanctions on Russia in 2014 were around 7.4% of its total exports. Rasoulinezhad (2017) and Haidar (2017) show that the international sanctions imposed on Iran after 2006 enormously changed its trade patterns, shifting trade flows from European toward Asian countries.

Another strand of literature tries to investigate the effects of sanctions on the target economy as a whole. Hufbauer et al. (2009) studying all economic sanctions imposed in the 20th century find that just one-third of them decreased economic activities. Faraji Dizaji and Van Bergeijk (2013) show that the impact of an oil boycott on Iran’s economy until 2012 was only significant in the first 2 years. Some papers study the effects of sanctions on a particular economic variable (Allen & Lektzian, 2013, on health outcomes and human capital; Farzanegan, 2013, on the informal economy; and Faraji Dizaji, 2014, on government expenditure). Madanizadeh et al. (2019), using Business Cycle Accounting methods and introducing five different wedges (efficiency, labor, investment, government, and trade) in a small open economy, try to explain the severe economic recession in Iran after the sanctions imposed in 2012. They find that a big part of the deviation of the Iranian economy can be explained by the efficiency and the investment wedges, while trade barriers had a relatively smaller explanatory power. More related to this study, Gharehgozli (2017) applying also the synthetic control method, studies the effect of the sanctions on Iran’s economy after 2012 and finds that they resulted in around 17% decrease in GDP during the first 3 years, with the highest negative effect of 12% drop happening in the first year. Compared to Gharehgozli (2017), I use a bigger pool of countries to construct the synthetic Iran and a longer time horizon. I also study the effects over the entire period of sanctions and assess their persistence after removing the sanctions by the JCPOA agreement.

Few existing papers discuss the heterogeneous effects of sanctions on the target countries. Hufbauer et al. (2009), document that the reduction in the foreign aid received by countries under sanctions can have a huge welfare cost, which mostly affects vulnerable groups. Drury and Peksen (2014) discuss the high vulnerability and economic sensitivity of women during the period of economic sanctions. Ali and Shah (2000) show that as a result of the United Nations sanctions on Iraq, the mortality rate for infants and kids doubled. Some papers try to discuss the impacts of sanctions on income distribution. Neuenkirch and Neumeier (2015) found out that poor populations are enduring the highest welfare cost in the countries under the US economic sanctions. In another study, Afesorgborac and Mahadevan (2016) by using 68 target
states, analyzed the sanction costs for different income groups from 1960 to 2008. They show that imposing sanctions on those countries changed the shape of income distribution and increased inequality. Yet, relatively to the current study, those studies use cross-country data to draw conclusions on inequality. Most importantly, to the best of my knowledge, this is the first paper investigating the heterogeneous economic impacts of sanctions on a country using national households survey data.

The rest of the paper is organized as follows: Section 2 explores the costs imposed by the sanction on the aggregate economy. Section 3 discusses the synthetic panel method and its application to assess the heterogeneous poverty dynamics using the HIES data. Section 4 highlights the effect of sanctions on poverty mobility, and Section 5 concludes.

## 2 AGGREGATE EFFECT OF SANCTIONS

In this section, I briefly discuss how strongly the sanctions affected Iran’s economy between 2012 and 2015 and the extent to which these effects were persistent. Figure 2 shows that real GDP and the oil sector dropped considerably during the sanction period. Industrial production was also dampened, albeit to a lesser extent, since this sector is highly dependent on imported intermediate goods.

It is very difficult to compare the economic performance of Iran with its potential path in the absence of the sanctions, since one should consider the global GDP growth fall in 2012 by almost 1% and also the significant oil price drop in 2014 (about 60%), which could have affected Iran’s economy even without those sanctions (see Figure 3). For that reason, I adopt the synthetic control methodology to measure the effect of the 2012–2015 sanctions on Iran’s economy by comparing it with a counterfactual benchmark. Following Abadie and Gardeazabal (2003), I will compare the economic evolution of Iran during the period under the sanctions with that of a weighted combination of similar countries chosen to resemble the characteristics of Iran’s economy before sanctions. I name this weighted average of other similar countries as “Synthetic Iran” and compare its growth with actual Iran after the

![Figure 2](https://www.cbi.ir)
sanction. The identifying assumption here is that Iran’s actual economy without sanctions would have growth similar to the synthetic country.

Let \( J \) be the number of countries in the control group, and \( W = (w_1, ..., w_J) \) be a \((J \times 1)\) vector of nonnegative weights (summing to one) that shows the weight of each country \( j \) in constructing the synthetic Iran. Define \( X(K \times 1) \) a vector of presanction values for \( K \) different economic variables of Iran. Here \( X \) includes values for the log-deviation of Iran’s real GDP (in PPP constant US dollars) from 1990 to 2011 as well as the presanction average of a number of country characteristics such as GDP share of rents from natural resources, the GDP share of imports of goods and services, industrial production, agricultural production, and services to total production, and the population. Also, \( X_0(K \times J) \) is a matrix of the values of the same indicators for the \( J = 46 \) control countries. Moreover, define \( V \) as a diagonal matrix with non-negative values. Following Abadie and Gardeazabal (2003) and Abadie et al. (2010), \( V \) is chosen so that the mean squared prediction error (MSPE) of the outcome variable is minimized for the period before the sanction. Then the synthetic Iran is constructed by choosing optimal weights \( W^* \) that minimize the following expression:

\[
(X - X_0W)V(X - X_0W)'
\]

such that \( w_j \geq 0 \) for \((j = 1, ..., J)\) and \( w_1 + \cdots + w_J = 1 \).

Table 1 presents the countries that contribute to construct synthetic Iran. Unsurprisingly, the fundamental characteristics of Saudi Arabia’s economy can explain around half of the dynamics of Iran’s economy. Real GDP, exports, and government income in both countries are highly dependent on oil income and also both countries are located in the same geopolitical region and face similar political and economic uncertainty. Along with countries like Nigeria, Sudan, and Algeria, about 80% of Iran’s real GDP path and economic characteristics can be explained by other oil exporter countries. The remaining 20% is explained by countries such as Greece 10%, South Korea 8%, and China 2%. Table 2 shows that the GDP share presanction averages of the synthetic Iran are matched well with the corresponding covariates in the Iranian economy. This implies that the synthetic Iran may be a reliable counterfactual, and we can quantitatively analyze the change in the Iranian economic activity after the sanctions.
Figure 4 depicts the real GDP path from 1990 for both Iran (solid blue line) and synthetic Iran (dashed red line). Around the dashed line, I plot one SD for the difference of the two time series before the sanctions. One can notice that both time series before starting the sanctions in 2012 have a high level of comovement. In the first year after the treatment, Iran's real GDP drops 7.74%, which considering more than 4.5% growth for our synthetic economy, results in 12.5% cost in terms of real GDP for Iran. This huge cost in the first year mostly comes from the significant drop in Iran's oil exports. While the synthetic economy during the sanction years is slowly growing, the economy under treatment is either shrinking or, at best, experiencing a very slow recovery after 2013. At the end of 2015, which was the last year of the oil boycott and most financial sanctions, the total GDP cost for Iran relative to the synthetic Iran exceeds 19.1%.

Gharehgozli (2017) using the same method estimated a 12% drop in real GDP in the first year and a total cost of around 17% of real GDP for the 2012 sanctions, focusing only on the first 3 years after the implementation of the sanctions. Relative to Gharehgozli (2017), I extend the period of analysis and show that the effect of sanctions is persistent. Moreover, I am using the growth rate of per capita real GDP for a longer period to construct the synthetic Iran, while Gharehgozli (2017) uses real value of GDP in levels to construct the weights. Also, in this paper, all economic sectoral activities are in GDP share while she uses levels for agricultural and services, and GDP share for industrial production and, as a result, finds a different composition of the synthetic country.

It is important to evaluate the persistency of the sanctions effect, which has been ignored in the existing literature (see Gharehgozli, 2017). As shown in Figure 3, the total crude oil exports of Iran after the JCOPA agreement started to recover to their pre-sanctions level and, at the end of 2016, even exceeded it. Nevertheless, after 2 years of the agreement, Iran's real GDP was still

| Country       | Weight | Country   | Weight |
|---------------|--------|-----------|--------|
| Saudi Arabia  | 0.53   | Sudan     | 0.07   |
| Nigeria       | 0.12   | Algeria   | 0.05   |
| Greece        | 0.1    | China     | 0.02   |
| Korea, Rep.   | 0.08   |           |        |

*Note: Other countries have either a weight of zero or less than 10^−4.*

| Covariate                  | Iran | Synthetic Iran |
|----------------------------|------|----------------|
| Natural resource rent (% GDP) | 28   | 28             |
| Import of goods and services (% GDP) | 22   | 27             |
| Industry added value (% GDP)   | 45   | 44             |
| Agriculture added value (% GDP) | 7    | 8              |
| Population (millions)           | 70.8 | 70.8           |

*Note: Means are calculated from 2000 until 2011 due to data availability. Also, the mean for shares of service sector has almost zero weight in the matching and as a result, is not used in the matching exercise.*
5% below the level of the synthetic Iran. The impact of exchange rate depreciation on intermediate goods' imports besides frictions in the financial markets triggered a long-lasting effect of the sanctions. It is worth noting that the magnitude of this effect should be interpreted with caution since synthetic control estimates may be less reliable when extrapolating further into the future.

An important question here is whether the gap between the two time series in Figure 4 comes from the sanctions or is just because of the inability of the method to match the growth path after the sanctions. To answer this question, I perform different exercises that I report in Appendix C. These include "Placebo studies" to assess how the results depend on a special treatment date, control country, or different treatment countries. As shown in more detail in Appendix C, the results are robust in all cases and show a huge, significant, and long-lasting effect of the sanctions.

3 | HETEROGENEOUS EFFECTS OF SANCTIONS

This section analyzes how different groups of households in Iran are affected during the years of the sanctions. To compare the welfare change during this period, considering a simple poverty ratio will be misleading. Poverty mobility analysis is preferable since it allows us to assess the nature of these changes and distinguish the case of chronic poverty with that of more volatile poverty which is due to the reallocation of resources. Also, the policy implications for these chronic versus transitory changes in poverty are different. For transitory poverty, policymakers prefer to implement strong social protection programs, while for chronic poverty, investment in infrastructures and human capital seems more vital. To study poverty mobility, I use the data from the Statistical Center of Iran, which conducts the HIES every year and publishes detailed data of households' members' characteristics as well as their income and expenditures. The main focus of the analysis in this section will be on the poverty dynamics in Iran as a result of imposing the sanctions. I will trace each poor and Nonpoor household in the
last year before sanctions (1390 in the Iranian calendar year [2011–2012]) until the last year before the JCPOA agreement (1393 [2014–2015]) to evaluate their poverty status 3 years after the sanction’s application.

To trace each household’s poverty status, one needs to have households data for income or expenditure in both the initial and the final year under investigation. Since the household budget survey in Iran in these 2 years is from random and independent samples, first, I need to construct the panel equivalent of these two cross-sections. To this end, I use the recent methodology proposed by Dang et al. (2014) and Dang and Lanjouw (2013) and construct a synthetic panel.

### 3.1 Synthetic panel method and poverty mobility

Let's define \( x_{it} \) as a vector of the time-invariant characteristics for household \( i \) in the survey round \( t \). We assume that two rounds of surveys are available, so \( t = 1 \) or 2. These time-invariant characteristics should be available or easy to compute in both rounds. Also, let's define \( y_{it} \) to be the per capita expenditure of household \( i \) being surveyed in period \( t \). Then the linear projection of household expenditure on its characteristics for each of the two rounds is defined by:

\[
y_{it} = \beta_i'x_{it} + \epsilon_{it}
\]

(2)

where \( \epsilon_{it} \) captures both the error terms and the time-variant determinants of the household expenditure. Given that in the current study I am interested in estimating poverty dynamics, if \( z_t \) is the poverty line in round \( t \), the percentage of poor household in Period 1 which are not poor in the second period will be:

\[
P(y_{i1} < z_1, y_{i2} \geq z_2)
\]

(3)

and the percentage of nonpoor household in Period 1 which become poor in the second round is:

\[
P(y_{i1} \geq z_1, y_{i2} < z_2)
\]

(4)

These probabilities give us the gross poverty change between the two periods which is more informative than a simple comparison of the average poverty rate. These dynamics can be directly estimated if we have access to actual panel data. Yet, in the absence of panel data, we can construct a synthetic panel for households in period \( t = 2 \) to estimate their expenditure in period \( t = 1 \) (which I define as \( y_{i1}^2 \)) using the \( \beta_i \)'s and \( \epsilon_i \)'s and then study poverty mobility.

The probabilities in Equations (3) and (4) cannot be estimated without imposing further structure on the data generating process. Although, we can still obtain upper and lower bounds for these probabilities. To see this, notice that the probability in Equation (3) can be written as follows:

\[
P(\epsilon_{i1} < z_1 - \beta_1'x_{i1}, \epsilon_{i2} \geq z_2 - \beta_2'x_{i2})
\]

(5)
This probability depends on the joint distribution of $\epsilon_{i1}$ and $\epsilon_{i2}$, which are part of the household expenditures that we cannot explain by time-invariant characteristics. It follows from the definitions of those residuals that mobility between two periods is higher when the correlation between $\epsilon_{i1}$ and $\epsilon_{i2}$ is lower.

To estimate the probability in Equation (5), I make two assumptions regarding the household survey data: (a) I assume that some characteristics of households ($x_i$ in this case) are time-invariant and do not change between the two survey rounds. This assumption implies that these characteristics can help us to connect two rounds of survey data and construct our synthetic panel, (b) I assume that the two error terms $\epsilon_{i1}$ and $\epsilon_{i2}$ are positive quadrant dependent which implies that their correlation is nonnegative. Some studies provide robust evidence for the second assumption.6

Without imposing more parametric structure on the error terms and assuming that the two assumptions mentioned above are satisfied, I can estimate the lower and upper bound for poverty mobility. To get the upper bound of mobility, I consider the case in Equation (5) for which the two error terms of the different rounds are totally independent (correlation $(\epsilon_{i1}, \epsilon_{i2}) = 0$), which results in the following probabilities for the movement out of and into poverty, respectively.

$$P\left(y_{i1}^{2U} < z_1, y_{i2} \geq z_2\right) = P\left(\epsilon_{i1} < z_1 - \beta_1'x_{i1}\right) P\left(\epsilon_{i2} \geq z_2 - \beta_2'x_{i2}\right)$$  \hspace{1cm} (6)

$$P\left(y_{i1}^{2U} \geq z_1, y_{i2} < z_2\right) = P\left(\epsilon_{i1} \geq z_1 - \beta_1'x_{i1}\right) P\left(\epsilon_{i2} < z_2 - \beta_2'x_{i2}\right)$$  \hspace{1cm} (7)

where $y_{i1}^{2U} = \hat{\beta}_1'x_{i2} + \epsilon_{i1}$ stands for the upper bound of Period 1 estimated expenditure for household being sampled in period 2.7

Therefore, although $\epsilon_{i1}$ and $\epsilon_{i2}$ are unknown for any household in Period 2, I can use the independence of error terms and applying random draws with replacement of $\epsilon_{i1}$, along with $\beta_1$, construct their expenditure in Period 1. On the other hand, when the two error terms are totally dependent (correlation $(\epsilon_{i1}, \epsilon_{i2}) = 1$), I can get the lower bound estimation for poverty mobility. Specifically, the lower bound estimates of movement out of and into poverty, respectively, will be:

$$P\left(y_{i1}^{2L} < z_1, y_{i2} \geq z_2\right) = P\left(\gamma\epsilon_{i2} < z_1 - \beta_1'x_{i1}\right) - P\left(\epsilon_{i2} \geq z_2 - \beta_2'x_{i2}\right)$$  \hspace{1cm} (8)

$$P\left(y_{i1}^{2L} \geq z_1, y_{i2} < z_2\right) = P\left(\epsilon_{i1} < z_1 - \beta_1'x_{i1}\right) - P\left(\gamma\epsilon_{i2} \leq z_1 - \beta_1'x_{i1}\right)$$  \hspace{1cm} (9)

where $\gamma = \sqrt{\frac{\text{Var}(\epsilon_{i1})}{\text{Var}(\epsilon_{i2})}}$.

The advantage of this nonparametric method is that it needs just few assumptions and can produce reasonable bounds for mobility, but the sharpness of the bound can highly depend on the set of regressors. Here I will also follow a parametric approach to estimate the narrower bounds by imposing some structure on the distribution of the error terms. For this purpose, I will augment assumption (b) and assume that error terms $\epsilon_{i1}$ and $\epsilon_{i2}$ are jointly distributed by a bivariate normal distribution with correlation coefficient $\rho > 0$ and with SDs $\sigma_{i1}$ and $\sigma_{i2}$. Then the estimation of the upper bound and lower bound of poverty mobility will depend on the minimum and maximum possible values for $\rho$, respectively. Given assumption (a) and
augmented assumption (b), for each household in round 2 the parametric estimates of poverty mobility is

$$\hat{P}(y_{i1} < z_i, y_{i2} \geq z_2) = \Phi_2\left(\frac{z_i - \hat{\beta}'_{1}x_{i12}}{\hat{\sigma}_1}, \frac{z_2 - \hat{\beta}'_{2}x_{i12}}{\hat{\sigma}_2}, -\rho\right)$$

(10)

for households movements out of poverty, and

$$\hat{P}(y_{i1} \geq z_i, y_{i2} < z_2) = \Phi_2\left(-\frac{z_i - \hat{\beta}'_{1}x_{i12}}{\hat{\sigma}_1}, \frac{z_2 - \hat{\beta}'_{2}x_{i12}}{\hat{\sigma}_2}, -\rho\right)$$

(11)

for their movements into poverty; where $\Phi_2$ refers to the cumulative density function of a binormal distribution. Lower-bound (upper bound) estimates of poverty mobility can be obtained by using the maximum (minimum) possible value of $\rho$ in Equations (10) and (11). If the true value for $\rho$ is known, then this bound will be actually a point estimate. This method has two main differences with the pseudo-panel literature: (i) even two surveys of repeated cross-section are enough to construct a synthetic panel, and (ii) compare to pseudo panels, they are at a more disaggregated level. Some of the recent studies applied the method and verified that it compares well to the real panel data.  

### 3.2 Households income and expenditure survey (HIES) data

Statistical Center of Iran has provided different microlevel databases throughout the years for researchers and policymakers. The HIES is one of these, which has been taken in rural areas since 1963 and in urban areas as of 1968. A three-stage cluster sampling method with strata is used in the HIES. At the first stage, the census areas are classified and selected. In the second stage, the urban and rural blocks are selected, and the selection of sample households is made at the third stage. To obtain more representative estimations of the whole year, the samples are evenly distributed between the months of the year (Statistical Center of Iran, 2010 HIES report).

The HIES includes four different main categories of household data: (i) social characteristics of household members (ii) assets, housing characteristics, and living facilities (iii) total household expenditures, and (iv) total household income. Social characteristics include household members’ age, sex, location, education, activity, and marital status. The questionnaire for the expenditure part includes 14 different sections for all food and nonfood expenditures. For their income, households are asked for their salary, transfers, and any other kind of income they may have. The survey sample is updated each year.

I use the microdata set of the HIES for two different years, 1390 (2011–2012) and 1393 (2014–2015), that correspond to the last year before the sanctions were imposed to the last year of the sanctions period, respectively. The HIES includes 38,111 households in 1390 and 37,849 households in 1393, of which I have excluded the top and lowest 1% of the expenditure distribution in each year. I am interested in the dynamics of the total expenditure of households in per-capita terms.

As mentioned in the previous section, a fundamental assumption in using synthetic income panel is that the underlying population sampled is the same in the two survey rounds. This
assumption implies that the time-invariant characteristics can be used to connect them and construct a synthetic panel. This assumption would not be satisfied if the underlying population had changed following a major event (Dang et al., 2014). Figure 5 shows the total number of births, deaths, and migrants in Iran during the sanction years. There is no considerable change in any of the variables describing the demographic dynamics due to the economic sanction. Moreover, in Appendix E, Figure E1 and Table E1 compare the distribution of time-invariant characteristics of the households between the two survey rounds. All characteristics have very similar distributions, and according to the \( t \) test results for equality of means, all of them (except education groups) have the same mean with 95% confidence interval.

### 3.3 Poverty mobility results

This section discusses the nonparametric and parametric synthetic panel estimation for Iranian data and results obtained for the corresponding poverty mobility. At the first stage, I fit the logarithm of per capita real expenditure of households on a set of their time-invariant characteristics. One can always question the extent that these features are time-invariant, but how the distribution of the estimated data fits the actual data at Period 1 can give us a simple criterion for choosing the characteristics. I use different model specifications, with variables that are all time-invariant to an acceptable degree, and check the sensibility of the selection criteria I use.

The first specification includes only the household head's characteristics such as birth year, gender, location (urban/rural), educational achievements, and his/her sector of economic activity. Another specification adds some family characteristics like household size and marital status. Finally, the last and most general specification includes some important households asset components such as house ownership and controls for their house's area. This is the most preferred specification. All specifications control for state fixed effects and just focus on the steadiest set of households, considering households which their head is between 25 and 65 years old in 2011 (28–68 years old in 2014). Appendix D reports the estimation results.

![Figure 5](wileyonlinelibrary.com)
Figure 6 presents the distribution of the fitted value for the logarithm of per capita real expenditure at \( t = 1 \) for households surveyed at \( t = 2 \). The distribution looks very similar to the actual distribution of per capita real expenditure for households surveyed at \( t = 1 \). The plotted distributions in Figure 6 warrant that the synthetic panel method works quite well and that the assumption of unchanged households’ characteristics is justified.

Using the fitted value of these households at \( t = 1 \), I can estimate the nonparametric upper bound for poverty mobility. For each household in Period 2, I take a random draw with replacement from the residuals of Period 1 (\( \hat{\epsilon}_i \)) and estimate its expenditure in the first round (\( y_{i1}^{2U} = \hat{\beta}_i x_{i2} + \hat{\epsilon}_i \)). Since the poverty line is not officially reported in Iran, I define the 20th percentile of real expenditure per capita distribution in Period 1 as the poverty line and the same standard of living is set for the second round. Then I compute the mobility probabilities in Equations (5) and (6). Repeating these steps 1000 times and getting the average of probabilities, I obtain the nonparametric upper bound of mobility. For the lower bound, since the error terms are fully correlated, I can easily construct the expenditure for Round 2 households in Round 1 using the \( \gamma \) coefficient, (\( y_{i1}^{2L} = \hat{\beta}_i x_{i2} + \gamma \hat{\epsilon}_i \)) and then compute the probabilities in Equations (7) and (8). The estimated results are presented in the first and last columns of Table 3.

According to Table 3, between 5.9% and 13.8% of the households below the 20th percentile of real expenditure at Round 1, suffered from chronic poverty in Round 2. There was a smaller group of households (0.6%–8.4%) that got out of poverty in this period (possibly benefiting from a bigger informal economy and speculative opportunities). Most importantly, between 4.1% and 11.9% of households moved into a lower living standard under the sanction. This result shows that sanctions had a significant effect on the poverty dynamics during these years, and up to 12% of the households were in transitory poverty due to the sanctions.

To sharpen the bounds of mobility further, I impose some parametric structure on the error terms. As discussed before, I assume that the two error terms \( \epsilon_i \) and \( \hat{\epsilon}_i \) have a binormal distribution with correlation coefficient \( \rho > 0 \). Poverty mobility will then depend on the value of \( \rho \). Dang et al. (2014), based on the actual panel data from seven countries with different income levels, estimated that \( \rho \) in the time horizon of 2–8 years is between 0.4 and 0.66, which is consistent with previous related studies.

**Figure 6** The distribution for logarithm of per capita expenditure: actual fit (solid) and estimated fit (dashed) [Color figure can be viewed at wileyonlinelibrary.com]
Due to the lack of panel data, it is not possible to have a point estimate for the income residual correlation coefficient ($\rho$) in Iran. Therefore, I use three different intervals to have the mobility bound under different levels of confidence. In one case, I set $\rho$ between 0.4 and 0.6 (Case 1), which is consistent with the values used for this parameter in most of the existing studies. In a more conservative scenario, I estimate the mobility bounds as the benchmark case for correlations between 0.2 and 0.8 (Case 2). Such a wide interval should include the true coefficient for my data. Finally, I obtain the parametric equivalence of my nonparametric estimation by setting $\rho = 1$ for the lower bound and $\rho = 0$ for the upper bound of poverty mobility (Case 3). The results are shown in Table 3. All the parametric estimations with bounded $\rho$ are inside the nonparametric intervals. According to the results in Case 2, the benchmark case, 5.8%–9.6% of the households in the sample suffered from chronic poverty, between 3% and 6.7% of them could move out of poverty, while 6.4%–10.2% of total households moved into poverty during the sanctions. In the poverty literature, this group is usually denoted as the vulnerable group that needs social support to stay above the poverty threshold. Since the government income dropped substantially during the years of the sanctions, most of them moved to a lower living standard. The remaining columns in Table 3 present a similar story with a wider (narrower) bound for the movement probabilities in Case 3 (Case 1).

To conclude this part, I discuss in short the validity of the bivariate normality assumption. In Figure 7, I depict, for each survey round, the distribution of the error terms ($\hat{\epsilon}_i$) against the normal distribution. To the naked eye, the two distributions look very similar to the normal distribution. Yet, formal tests reject the normality assumption. Since the normality assumption for the error terms is rejected, in another experiment, I simulate a binormal distribution for the error terms, given the moments of the actual errors. Then I perform the same parametric and non-parametric estimation for different values of $\rho$ to compare its results in this special case with the baseline specification. Unsurprisingly, the estimated results for upper and lower bounds are very close to those in Table 3 addressing possible concerns regarding the bivariate normality assumption. (These results are available in Appendix F).

### 3.4 Heterogeneity of poverty mobility

So far, I have discussed the aggregate effects of sanctions on Iran’s economy as well as on household’s living standards. The results show sanctions had a significant effect on the poverty

| Poverty mobility | Nonparametric | Lower bound | Upper bound |
|------------------|---------------|-------------|-------------|
|                  |               | Case 3      | Case 2      | Case 1      | Case 3      | Case 2      | Case 1      | Nonparametric |
| Poor, poor       | 13.8          | 12.1        | 9.6         | 8           | 4.9         | 5.8         | 6.8         | 5.9          |
| Poor, nonpoor    | 0.6           | 0.5         | 3           | 4.5         | 7.6         | 6.7         | 5.7         | 8.4          |
| Nonpoor, poor    | 4.1           | 3.9         | 6.4         | 8           | 11.1        | 10.2        | 9.2         | 11.9         |
| Nonpoor, nonpoor | 81.5          | 83.5        | 81          | 79.5        | 76.4        | 77.3        | 78.3        | 73.8         |
| Observations     | 30,029        | 30,029      | 30,029      | 30,029      | 30,029      | 30,029      | 30,029      | 30,029       |

*Note: Case 3 considers $\rho = 1$ and $\rho = 0$ for the lower and upper bounds (parametric tantamount for the nonparametric bounds). Case 2 is the conservative case and $\rho$ takes the value of 0.8 and 0.2, and Case 1 is less conservative with $\rho = 0.6$ and $\rho = 0.4$. \*
dynamics and around 10% of the total households moved into poverty during that period. This section investigates the dispersion of these effects: Which groups of households are suffering the most out of chronic poverty? Did households with different head education levels have the same probability of falling into poverty? Do those working in the public sector suffer more since the government is the main goal of the sanctions? Are female head households secure enough against these sanctions? How is the movement for households between different income groups (income quantiles)? Answering such questions helps us evaluate the effects of the sanctions and possible policy responses to alleviate the negative effects on the disadvantaged groups.

To compare different households’ groups, I divide them by different characteristics of the household’s head (age, sex, education, sector of activity, location, and house ownership) and then estimated the four probabilities for each subgroup. The corresponding conservative bounds for the mobility of poor households are shown in Figure 8.

As panel (a) of Figure 8 shows, there is vast heterogeneity in chronic poverty between different groups of households. The lower bound of poverty immobility varies from 0% to 15%. Households living in rural areas or living in religious minority provinces, households with illiterate household head and working in the private sector experienced the highest degree of chronic poverty. Given that the lower bound of moving out of poverty for these groups in panel (b) of Figure 8 is not very different from those in other groups, we expect that the poverty rate in these groups significantly increases. Also, the youngest group of households in our sample has the highest rate of chronic poverty, and heterogeneity based on gender and wealth is not significant.

Finally, I trace the nonpoor households in round one to compare their mobility into poverty between different groups of households. Figure 9 summarizes the estimation results for mobility bounds. According to the estimation results, female head households have a slightly higher but close to male head households’ mobility rate into poverty. Between different sectors of activity, households active in the public sector are suffering much less than those in the private sector, with no permanent jobs or those dependent on other sources of income. Between different educational groups, households with illiterate head, probably because of lack of financial literacy to secure their expenditure, have the highest mobility rate into poverty, while highly educated households are on the opposite side.
With respect to age groups, younger generations have a higher rate of moving into poverty. Also, there is a significant difference between the corresponding probabilities for religious groups, which supports the claim that those states gained the least during the redistribution of resources in the sanction period. To summarize, rural households, those without a permanent and stable job or working in the private sector, households with less access to the public resources (like religious minorities), low educated and younger heads households have the highest rate of mobility from nonpoor to poor population. Ironically, households that relate the most to the government are almost unaffected in this period of severe economic recession, which again raises the concern on whether the sanctions are achieving their goals.

4 | DO SANCTIONS INCREASE POVERTY?

So far, results showed a high rate of chronic poverty and movement into poverty with a drastic heterogeneity between different groups of the population. To attribute this significant effect to the economic sanctions, one needs to compare the household’s poverty dynamics to a proper counterfactual. Due to the magnitude of the shock and dependency of the economy on the oil sector, there are no perfect counterfactual households that are not exposed to the sanctions, since either directly or indirectly, all sectors and activities are affected. But comparing the accumulated growth rate of the different economic sectors during the sanctions with their presanction growth shows that besides the oil sector, industry, and service sectors are also

FIGURE 8  Heterogeneous mobility of poor households. (a) Poor–poor immobility and (b) poor–nonpoor mobility. 1. Households are classified based on their heads’ sex, age (less than 30, 30–44, 45–59, 60 and higher in the base year), education (illiterate, primary, secondary, and high (university) education), sector of activity (public, private, free jobs (including employers and self employed), unemployed or no permanent job, without job but with income), urban/rural, house ownership, religion minority/majority, and living in the capital. 2. There is no data available for the religion of each household. There are six provinces in Iran that with informal data households with a minority religion are the majority in those states which we classify them as minority states 3. Black (solid) lines show the midpoint of conservative bound for the whole sample [Color figure can be viewed at wileyonlinelibrary.com]
significantly affected by the shock, while the agriculture sector is much less affected. I use this notable difference in exposure to the shock to discuss how important the sanction was in boosting poverty dynamics. Figure 10 compares the poverty dynamics for the households working in agriculture, forestry, fishing, and mining sectors compared to the households working in industry and service sectors. The difference between these two groups is noteworthy: chronic poverty (poor to poor immobility) is 1.2% for the former while 7.5% for the latter. Moreover, movement into poverty is 3.6% for households working in the agricultural sector, while it is 10.6% for other households. A similar result holds if we compare the four provinces where the oil industry is mainly located with the rest of the provinces. Figure G1 in Appendix shows that chronic poverty (movement into poverty) is 6.6 (11.3)% in the provinces with the oil industry and 6.2 (9.6)% in the other provinces. The difference in this case is smaller since all oil income goes directly to the government, and through government spending, all provinces are significantly affected.

Moreover, to better understand how considerable is the heterogeneity of poverty dynamics, I did the same exercise for the last 3 years before the sanctions and computed the poverty mobility for different population groups between 1387 (2008–2009) and 1390 (2011–2012). Figure 11 plots the upper bound of poverty dynamics for the different groups of households and compares it to the one in normal time before the sanctions. The probability of entering into poverty during the sanction period is higher than the corresponding one before the sanctions for all household groups. Figure G2 in the appendix shows similar results for chronic poverty.
Focusing on within-group heterogeneity patterns reveals that female head households have slightly higher mobility into poverty than male head households, unlike the presanction period. Living conditions for highly educated households, for households located in the capital, and working in the public sector are very close to the presanction period. In contrast, rural households, low educated, religious minorities, and old households are strictly worse off compared to their presanction poverty dynamics. This shows that vulnerable household groups that have limited access to the economic resources and rents or have less financial literacy to secure their expenditure against economic recessions are suffering more in terms of living standards. Finally, compared to the period before the sanctions, there is a huge difference in the poverty dynamics between households working in the public sector compared to those in the private sector or households with an unemployed head, which again shows that sanctions mostly affect private-sector workers than households occupied in state-related activities. Part of these differences can be explained by the high inflation imposed on the economy as a result of an increase in the government's nominal expenditure.13

This heterogeneous effect of the sanctions on expenditures may be partially attributed to substituting market consumption with home-produced goods by some households. Unfortunately, there is no data directly referring to home production in the survey. Therefore, I investigate two different proxies, which are highly correlated with the amount of home production. First, the total costs on energy and fuels in the survey that include all costs for electricity, natural and liquid gas, oil, gasoline and all kinds of solid fuels. We expect these costs to increase at the household level due to home production. Second, housing costs, including all costs regarding cleaning, gardening, and maintenance of facilities that a household pays per year and should decrease due to home production.

As Figure 12 shows, the increase in the housing expenditures, which is a small part of the total expenditure, looks very similar for different groups of households, suggesting that home production did not change significantly for any household group. Regarding the energy and fuel costs, rural and religious minority households spent significantly more compared to their counterparts after the sanctions, suggesting that for those groups there were possibly a substitution of market for home production. Therefore, although we can expect a different change.
in home production for the aforementioned groups, there is no reason to expect the same between different households based on their sector of activity, age, or education.

Finally, I classify households based on their per capita expenditure before the sanctions and analyze how the mobility dynamics compare in those different quantiles in the pre- and post-sanction period. The upper bound estimates of this exercise are depicted in Figure 13. When looking at the 0–20 percentile of the expenditure distribution, it is clear that poverty immobility has increased significantly during the sanction years (panel (b)) relative to the presanction period (panel (a)). From 33% in the 2008–2011 period, immobility for the lowest percentile...
group has increased to about 50% during the sanction period. Moreover, middle-income households (in the 40–60 and 60–80 percentiles) have a drastically higher rate of downward mobility compared to the presanction years. Households in these groups have experienced 39% and 48% of mobility to a lower expenditure percentile, respectively, which is about 12% higher than the 2008–2011 period. Table F1 in Appendix I reports the details for mobility between different income groups before and after the sanctions.

5 | CONCLUSION

Sanctions are a popular political instrument that is used to force countries to comply with international agreements and laws. In recent years, several sanctions have been imposed on different countries. This paper focused on the economic sanctions imposed on Iran by the EU and the US between 2012 and 2015.

First, I try to quantify the overall effect of those sanctions and its persistency on the Iranian economy. Using the synthetic control method, I show that the sanction caused 12.5% fall in real GDP in the first year and around 19.1% 4 years after the application of the sanctions. This effect was persistent. Real GDP remained 5% lower than its counterfactual 2 years after the removal of the sanctions in 2015.

Second, I analyze the heterogeneous poverty dynamics in Iran due to the sanctions. Following Dang et al. (2014), I perform parametric and non-parametric estimations of the bounds for poverty mobility. About 10% of the households in Round 1 moved into poverty during the sanction years and just a maximum of 6% could move out of poverty. Contributing to the existing literature, I quantify the poverty mobility among different households based on their head’s characteristics. Rural, young, and low-educated households, households working in the private sector, religious minorities, young households, and households belonging to the low and middle-income group have the highest rate of moving into poverty in the sanction period, while households working in the public sector and high educated households are suffering the least.
In summary, the sanctions, along with poor domestic policies, resulted in a significant and huge negative impact on the Iranian economy. However, among all households, some vulnerable groups had suffered more and sanctions drastically decreased their welfare, while public sector employees did not seem to suffer. This shows that the economic consequences of the sanctions are not consistent with their initial claimed goal of punishing the government. On the other hand, this implies that policymakers in Iran should support more the vulnerable groups and direct more transfers or other social support toward them.

ACKNOWLEDGMENTS
I am grateful to Evi Pappa for her guidance, suggestions, and valuable comments. I would also like to thank Jan Stuhler, Luigi Minale, Alan Crawford, Matilde Machado, seminar participants at the Ph.D. Students UC3M Workshop, and UC3M Applied Reading Group for helpful comments and discussions. I am thankful to Benjamin Born and Gernot Müller for their comments and for sharing their codes on synthetic control method with me.

DATA AVAILABILITY STATEMENT
Data are publicly available in www.cbi.ir and www.amar.org.

ENDNOTES
1For a recent application of this method, see Born et al. (2019).
2The complete list of donor countries is in Appendix A. Most of them are oil exporters or are developing countries similar to Iran in some aspects.
3In Appendix B, I perform the same exercise excluding Saudi Arabia, and construct the Synthetic Iran with the rest of countries and compare it with actual Iran. The results show a similar effect of sanctions on the Iranian economy.
4Apart from openness which is somehow higher in Synthetic Iran.
5The data are available here: https://www.amar.org.ir.
6See Khor and Pencavel (2006) for China, Kopczuk et al. (2010) for the US, Jenkins (2011) for the UK, Dang et al. (2014) for Indonesia, Bosnia-Herzegovina, Peru, Lao PDR, Nepal, and Vietnam.
7Proofs are readily available at Dang et al. (2014).
8See Ferreira et al. (2013), for Latin American countries, Martinez et al. (2013), for the Philippines, Garbero (2014), for surveys in Vietnam, Dang et al. (2014), for Vietnam and Indonesia, Cancho et al. (2015), for some European and also Central Asian countries, Cruces et al. (2015), for Latin American countries, Dang and Lanjouw (2018) for India, Bourguignon and Moreno (2018), for Mexico, and Dang and Dabalen (2019), for Sub-Saharan African countries.
9Figure J1 in Appendix J shows that the main results are robust to different thresholds for the poverty line.
10To compare the income residual correlation coefficient in Iran with the existing literature, in a more aggregated exercise, I use the cohort-based analysis under two different scenarios. In one case, I divide the population in Rounds 1 and 2 to 160 different cohorts based on birth groups, educational levels, sectors of activity, and location (urban/rural), and take the average of residuals for the main regression. The two cohort-based residuals in the two rounds have a correlation of 0.41. In another scenario, I construct 80 cohorts based on age, sectors of activity, location, and level of literacy and find a correlation of 0.49 between the residuals of the two rounds.
11Figure J1 in Appendix J shows that this pattern of heterogeneity is robust to different values for the poverty line.
The cumulative growth rate for the agriculture, industry, and service sector during 2008 to 2011 were 16.4%, 16.7%, and 13.3%, respectively, while the corresponding rates during the 3 years of sanction (2011 to 2014) were 14.4%−3.8%, and 2.8%, showing a drastic downturn effect on industry and service sectors compared to agricultural activities.

Figure H1 in Appendix H shows how government expenditure evolves during this period.

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**How to cite this article:** Ghomi, M. (2021). Who is afraid of sanctions? The macroeconomic and distributional effects of the sanctions against Iran. *Economics & Politics*, 1–34. https://doi.org/10.1111/ecpo.12203
APPENDIX A: LIST OF COUNTRIES FOR SYNTHETIC CONTROL METHOD

| Countries in the donor pool |
|----------------------------|
| Algeria                    |
| Colombia                   |
| Ireland                    |
| Norway                     |
| Tunisia                    |
| Argentina                  |
| Czech Rep.                 |
| Italy                      |
| Oman                       |
| Turkey                     |
| Australia                  |
| Denmark                    |
| Jordan                     |
| Peru                       |
| Turkmenistan               |
| Austria                    |
| Ecuador                    |
| Kazakhstan                 |
| Poland                     |
| Emirates (UAE)             |
| Azerbaijan                 |
| Egypt                      |
| Korea Rep.                 |
| Portugal                   |
| United Kingdom             |
| Brazil                     |
| El Salvador                |
| Kyrgyz Rep.                |
| Russia                     |
| Uruguay                    |
| Bulgaria                   |
| Georgia                    |
| Lebanon                    |
| Saudi Arabia               |
| Canada                     |
| Greece                     |
| Malaysia                   |
| Sudan                      |
| Chile                      |
| India                      |
| Mexico                     |
| Tajikistan                 |
| China                      |
| Indonesia                  |
| Nigeria                    |
| Thailand                   |

APPENDIX B: AGGREGATE EFFECT EXCLUDING SAUDI ARABIA
Since Saudi Arabia is the main contributor of synthetic Iran and therefore may drive the main results, I construct the synthetic Iran by excluding Saudi Arabia. As shown in the following figures and tables, the results are very similar to the previous case and show a considerable, significant, and long-lasting effect.

| TABLE B1 Composition of the synthetic Iran excluding Saudi Arabia: country weights |
|-----------------------------------------------|
| Country          | Weight | Country     | Weight |
| Algeria          | 0.50   | Argentina   | 0.06   |
| Oman             | 0.13   | Russia      | 0.05   |
| Lebanon          | 0.12   | Indonesia   | 0.03   |
| Nigeria          | 0.07   | China       | 0.02   |

Note: Other countries have either weight zero or less than $10^{-4}$. 
APPENDIX C: PLACEBO TESTS FOR THE SYNTHETIC CONTROL METHOD

To evaluate whether the estimated gap between the two time series in Figure 4 comes from the sanctions or whether it is just because of the method’s inability to match the growth path after the sanctions, I report some placebo tests in this section.

C.1 | Time placebo test

First, I perform the “time placebo” test by applying the same method but changing the treatment date to the different years between 2006 until the last year before the sanctions, which is 2011 (following Abadie et al., 2010). According to Figure C1, the counterfactual economy paths are very close to our baseline series and they all exhibit a considerable divergence from the Iranian GDP path at the “true” sanction date.
C.2 | Country placebo test
In Figure C2, each green (light) line represents the path of a counterfactual obtained by excluding one of the countries with positive weight in Table 1. All counterfactual time series obtained are following the actual GDP path of Iran very closely, and all show a huge and significant effect at the sanctions date.

C.3 | Different treatment countries
Here I construct a counterfactual country for the two main drivers of the main results (Saudi Arabia in the first exercise and Algeria in the second one) to check if they are also severely affected by the treatment. In Figure C3, we observe the difference between actual and synthetic economy for these two countries besides Iran. Saudi Arabia performs a bit better than its counterfactual path right after the sanction, but the effect is not very significant. Similarly, Algeria follows more or less the same as its counterfactual and is not significantly affected by the sanctions on Iran.

**FIGURE C2** Country placebo test: excluding countries with positive weight one by one [Color figure can be viewed at wileyonlinelibrary.com]

**FIGURE C3** Difference between actual and synthetic economy for Iran, Saudi Arabia, and Algeria [Color figure can be viewed at wileyonlinelibrary.com]
## APPENDIX D: OLS ESTIMATION RESULTS

Dependent variable: Log of per capita expenditure (2011–2012)

| Variables | Coefficient | SE | Coefficient | SE | Coefficient | SE | Coefficient | SE | Coefficient | SE |
|-----------|-------------|----|-------------|----|-------------|----|-------------|----|-------------|----|
| Female    | 0.160***    | 0.017 | 0.140***    | 0.017 | −0.011      | 0.020 | −0.034      | 0.022 | −0.007      | 0.017 | −0.030      | 0.019 |
| Birth year| 0.205***    | 0.068 | −0.772***   | 0.100 | 0.950***    | 0.055 | 0.725***    | 0.095 | 0.703***    | 0.053 | 0.539***    | 0.087 |
| (birth year)$^2$ | −0.000*** | 0.000 | 0.000***    | 0.000 | −0.000***   | 0.000 | −0.000***   | 0.000 | −0.000***   | 0.000 | −0.000***   | 0.000 |
| Urban     | 0.254***    | 0.019 | 0.234***    | 0.019 | 0.241***    | 0.019 | 0.215***    | 0.019 | 0.215***    | 0.019 | 0.198***    | 0.019 |
| Primary education/illiterate | 0.214*** | 0.013 | 0.210***    | 0.013 | 0.223***    | 0.013 | 0.207***    | 0.013 | 0.170***    | 0.012 | 0.157***    | 0.012 |
| Secondary education/illiterate | 0.473*** | 0.017 | 0.474***    | 0.017 | 0.446***    | 0.017 | 0.432***    | 0.017 | 0.353***    | 0.015 | 0.342***    | 0.016 |
| High education/illiterate | 0.701*** | 0.025 | 0.706***    | 0.026 | 0.657***    | 0.024 | 0.643***    | 0.024 | 0.538***    | 0.020 | 0.529***    | 0.021 |
| Private sector/public | −0.231*** | 0.018 | −0.242***   | 0.020 | −0.229***   | 0.018 | −0.238***   | 0.019 | −0.202***   | 0.016 | −0.210***   | 0.018 |
| Free jobs/public | −0.096*** | 0.015 | −0.116***   | 0.016 | −0.139***   | 0.014 | −0.142***   | 0.016 | −0.142***   | 0.013 | −0.142***   | 0.015 |
| No per. job/public | −0.236*** | 0.024 | −0.286***   | 0.029 | −0.227***   | 0.022 | −0.265***   | 0.025 | −0.215***   | 0.022 | −0.243***   | 0.025 |
| Income without job/public | −0.121*** | 0.022 | −0.135***   | 0.021 | −0.262***   | 0.020 | −0.252***   | 0.019 | −0.249***   | 0.017 | −0.238***   | 0.016 |
| Household size | −0.257*** | 0.009 | −0.288***   | 0.009 | −0.293***   | 0.010 | −0.319***   | 0.011 | (household size)$^2$ | 0.013*** | 0.015*** | 0.015*** | 0.017*** | 0.017*** | 0.001 | 0.017*** | 0.001 | 0.017*** | 0.001 |
| Married | 0.018 | (0.013) | 0.023 | (0.017) | −0.005 | (0.012) | 0.002 | (0.015) | Owning a house | 0.042*** | (0.013) | 0.039*** | (0.013) |
| Log of the house area | 0.316*** | (0.016) | 0.304*** | (0.015) | Constant | −119.265** | (45.336) | 538.371*** | (67.214) | −616.861*** | (36.945) | −464.391*** | (63.886) | −455.287*** | (35.239) | −344.063*** | (58.297) |
| State fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | 25 ≤ age ≤ 65 | No | Yes | No | Yes | No | Yes | (Continues) |
### Dependent variable: Log of per capita expenditure (2011–2012)

#### Variables

| Observations   | 37,333 | 30,048 | 37,333 | 30,048 | 37,333 | 30,048 |
|----------------|--------|--------|--------|--------|--------|--------|
| $R^2$          | 0.31   | 0.33   | 0.40   | 0.43   | 0.46   | 0.48   |

***p < .01, **p < .05, *p < .1.

### Dependent variable: Log of per capita expenditure (2014–2015)

#### Variables

| Female | 0.118*** | 0.126*** | −0.084*** | −0.083*** | −0.070*** | −0.073*** |
|--------|----------|----------|-----------|-----------|-----------|-----------|
| (0.016)| (0.018)  | (0.015)  | (0.022)   | (0.014)   | (0.019)   |          |

Birth year  

| Birth year | 0.267*** | −0.473*** | 0.891*** | 0.843*** | 0.667*** | 0.667*** |
|------------|----------|-----------|----------|----------|----------|----------|
| (0.077)    | (0.110)  | (0.063)   | (0.087)  | (0.055)  | (0.077)  |          |

(birth year)$^2$  

| (birth year)$^2$ | −0.000*** | 0.000*** | −0.000*** | −0.000*** | −0.000*** | −0.000*** |
|-------------------|-----------|----------|-----------|-----------|-----------|-----------|
| (0.000)           | (0.000)   | (0.000)  | (0.000)   | (0.000)   | (0.000)   |          |

Urban  

| Urban | 0.247*** | 0.225*** | 0.235*** | 0.211*** | 0.210*** | 0.192*** |
|-------|----------|----------|----------|----------|----------|----------|
| (0.015)| (0.016)  | (0.015)  | (0.016)  | (0.016)  | (0.016)  | (0.016)  |

Primary education/illiterate  

| Primary education/illiterate | 0.205*** | 0.213*** | 0.227*** | 0.224*** | 0.179*** | 0.177*** |
|-----------------------------|----------|----------|----------|----------|----------|----------|
| (0.012)                     | (0.014)  | (0.013)  | (0.014)  | (0.012)  | (0.013)  |          |

Secondary education/illiterate  

| Secondary education/illiterate | 0.397*** | 0.415*** | 0.392*** | 0.397*** | 0.310*** | 0.316*** |
|--------------------------------|----------|----------|----------|----------|----------|----------|
| (0.017)                        | (0.020)  | (0.017)  | (0.019)  | (0.016)  | (0.016)  | (0.016)  |

High education/illiterate  

| High education/illiterate | 0.636*** | 0.648*** | 0.605*** | 0.608*** | 0.496*** | 0.501*** |
|--------------------------|----------|----------|----------|----------|----------|----------|
| (0.024)                  | (0.026)  | (0.025)  | (0.025)  | (0.022)  | (0.023)  |          |

Private sector/public  

| Private sector/public | −0.241*** | −0.255*** | −0.247*** | −0.254*** | −0.226*** | −0.232*** |
|-----------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| (0.019)               | (0.020)   | (0.019)   | (0.019)   | (0.018)   | (0.018)   |          |

Free jobs/public  

| Free jobs/public | −0.102*** | −0.122*** | −0.149*** | −0.153*** | −0.152*** | −0.154*** |
|------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| (0.016)          | (0.017)   | (0.015)   | (0.016)   | (0.016)   | (0.016)   | (0.016)   |

No per. job/public  

| No per. job/public | −0.295*** | −0.344*** | −0.306*** | −0.344*** | −0.304*** | −0.327*** |
|--------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| (0.027)            | (0.030)   | (0.030)   | (0.033)   | (0.027)   | (0.030)   |          |

Income without job/public  

| Income without job/public | −0.163*** | −0.178*** | −0.305*** | −0.291*** | −0.296*** | −0.282*** |
|----------------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| (0.022)                   | (0.021)   | (0.018)   | (0.018)   | (0.016)   | (0.016)   | (0.016)   |

Household size  

| Household size | −0.265*** | −0.282*** | −0.298*** | −0.309*** |          |          |
|----------------|-----------|-----------|-----------|-----------|-----------|-----------|
| (0.010)       | (0.010)   | (0.011)   | (0.011)   | (0.011)   | (0.011)   |          |

(household size)$^2$  

| (household size)$^2$ | 0.014*** | 0.015*** | 0.016*** | 0.016*** |          |          |
|----------------------|----------|----------|----------|----------|-----------|-----------|
| (0.001)              | (0.001)  | (0.001)  | (0.001)  | (0.001)  | (0.001)   |          |

Married  

| Married | 0.016 | 0.011 | −0.012 | −0.008 |          |          |
|---------|-------|-------|--------|--------|-----------|-----------|
| (0.017) | (0.019)|       | (0.015)| (0.017)|          |          |

Owning a house  

| Owning a house | 0.018 | 0.013 | (0.012) | (0.013) |          |          |
|----------------|-------|-------|---------|---------|-----------|-----------|
| Variables                      | 0.341***  | 0.328***  |
|-------------------------------|-----------|-----------|
| Log of the house area         | (0.014)   | (0.014)   |
| Constant                      | $-161.310^{***}$ | $338.372^{***}$ |
|                               | (51.523)  | (73.882)  |
| State fixed effect            | Yes       | Yes       |
| $25 \leq age \leq 65$         | No        | Yes       |
| Observations                  | 37,030    | 30,029    |

Note: Robust standard error of estimations are in parentheses.

***p < .01, **p < .05, *p < .1.
APPENDIX E: COMPARING THE DISTRIBUTION OF THE TIME-ININVARIANT CHARACTERISTICS IN THE TWO SURVEY ROUNDS

FIGURE E1  Comparing the distributions of the time-invariant characteristics in the two different survey rounds [Color figure can be viewed at wileyonlinelibrary.com]
### Appendix F: Poverty Mobility from Synthetic Panel with Partially Simulated Errors

#### Table E1

**t** test for the equality of means of the characteristic distributions

| Characteristics     | 2011–2012 |          |          | 2014–2015 |          |          | Difference | p value |
|---------------------|-----------|----------|----------|-----------|----------|----------|------------|---------|
|                     | Mean      | SE       | Mean     | SE        |          | Mean     | SE         |          |
| Gender              | 0.875     | 0.001    | 0.871    | 0.001    | 0.004    |          | 0.067      |         |
| Locality            | 0.487     | 0.002    | 0.494    | 0.002    | −0.007   |          | 0.054      |         |
| Marital status      | 0.860     | 0.001    | 0.859    | 0.001    | 0.001    |          | 0.49       |         |
| Education           | 0.99      | 0.004    | 1.06     | 0.004    | −0.07    |          | 0.00       |         |
| Activities          | 2.812     | 0.006    | 2.829    | 0.006    | −0.016   |          | 0.07       |         |
| House ownership     | 0.780     | 0.002    | 0.778    | 0.001    | 0.002    |          | 0.39       |         |
| Religious minority  | 0.194     | 0.002    | 0.191    | 0.002    | 0.003    |          | 0.27       |         |

**Note:**
1. Gender: households’ heads' sex (female = 0 and male = 1), Locality: living area (rural = 0 and urban = 1), Marital status: households’ heads’ status (married = 1 and single = 0), Education: (illiterate = 0, primary = 1, secondary = 2, and high [university] education = 3), Activity: sector of activity (public = 1, private = 2, free jobs [including employers and self employed] = 3, unemployed or no permanent job = 4, without a job but with income = 5), House ownership: (owns a house = 1 and otherwise = 0). 2. There is no data available for the religion of each household. There are six provinces in Iran that, with informal data, households with a minority religion are the majority in those states which are classified as minority states = 1. 3. p value corresponds to testing the null hypothesis of the equality of mean in the two distributions.

### Appendix F: Poverty Mobility from Synthetic Panel with Partially Simulated Errors

#### Table F1

Poverty dynamics in Iran from synthetic panel data between periods 2010-11 to 2014-15

| Poverty Mobility | Nonparametric | Lower Bound |          |          |          | Upper Bound |          |          |          |
|------------------|---------------|-------------|----------|----------|----------|-------------|----------|----------|----------|
|                   |               | Case 3      | Case 2   | Case 1   |          | Case 3      | Case 2   | Case 1   | Nonparametric |
| Poor, Poor        | 14.6          | 11.9        | 9.6      | 8.1      | 5.1      | 6           | 7         | 6.6      |           |
| Poor, Nonpoor     | 0.7           | 0.5         | 2.8      | 4.3      | 7.3      | 6.4         | 5.4       | 7.9      |           |
| Nonpoor, Poor     | 4.7           | 4.5         | 6.7      | 8.2      | 11.2     | 10.3        | 9.4       | 12.4     |           |
| Nonpoor, Nonpoor  | 80            | 83.2        | 80.9     | 79.4     | 76.4     | 77.3        | 78.3      | 73.1     |           |
| Observations      | 30,029        | 30,029      | 30,029   | 30,029   | 30,029   | 30,029      | 30,029    | 30,029   | 30,029   |

**Note:**
Case 3 considers \( \rho = 1 \) and \( \rho = 0 \) for the lower and upper bounds (parametric tantamount for the non-parametric bounds). Case 2 is the conservative case and \( \rho \) takes the value of 0.8 and 0.2, and case 1 is less conservative with \( \rho = 0.6 \) and \( \rho = 0.4 \).
APPENDIX G: COMPARISON BASED ON EXPOSURE TO OIL INDUSTRY

FIGURE G1  Poverty mobility during the sanction period for provinces having main oil industries (Khuzestan, Bushehr, Hormozgan, Fars) versus other provinces [Color figure can be viewed at wileyonlinelibrary.com]

FIGURE G2  Comparing upper bound estimation for poor to poor immobility during the sanction period with its counterfactual [Color figure can be viewed at wileyonlinelibrary.com]
APPENDIX H: DRASTIC INCREASE IN GOVERNMENT NOMINAL EXPENDITURE AND BUDGET DEFICIT

(a) Government expenditure and (b) budget deficit. Source: Central bank of Iran, www.cbi.ir

[Color figure can be viewed at wileyonlinelibrary.com]

APPENDIX I: MOBILITY BETWEEN INCOME GROUPS

TABLE I1  Transition matrix: mobility between income groups

| Quantiles mobility | Quantiles in 2014 |
|--------------------|------------------|
|                    | 0–20   | 20–40  | 40–60  | 60–80  | 80–100 | Total |
| Quantiles: 2011    |        |        |        |        |        |       |
| 0–20               | 48.3   | 25     | 15.8   | 8.3    | 2.5    | 100   |
| 20–40              | 27.1   | 26.5   | 22.6   | 16.8   | 7.1    | 100   |
| 40–60              | 16.6   | 22.3   | 24.4   | 23.3   | 13.5   | 100   |
| 60–80              | 8.6    | 16.5   | 23     | 28.4   | 23.5   | 100   |
| 80–100             | 2.8    | 8      | 15.6   | 28     | 45.7   | 100   |

Note: Percentages are calculated based on the upper bound of mobility between income groups. Each number in the table \(a_{ij}\) refers to the percentage of households in quantile \(i\) in 2011 that moved to the quantile \(j\) in 2014.
APPENDIX J: ROBUSTNESS TO DIFFERENT POVERTY LINES

Figure J1  Lower bound of mobility for different threshold for poverty lines (2011-2012 to 2014-2015).
1. Households are classified based on their heads’ sex, age (less than 30, 30-44, 45-59, 60, and higher in the base year), education (illiterate, primary, secondary, and high (university) education), sector of activity (public, private, free jobs (including employers and self employed), unemployed or no permanent job, without job but with income), urban/rural, house ownership, religion minority/majority, and living in the capital. 2. There is no data available for the religion of each household. There are six provinces in Iran that with informal data households with a minority religion are the majority in those states which we classify them as minority states.

[Color figure can be viewed at wileyonlinelibrary.com]