Synthetic Control and Dynamic Panel Estimation: A Case Study of Iran

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SYNTHETIC CONTROL AND DYNAMIC PANEL ESTIMATION: A CASE STUDY OF IRAN

by

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The City University of New York
Abstract

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Adviser: Professor Wim Vijverberg

International sanctions imposed on Iran, targeting primarily Iran’s key energy sector and its ability to access the international financial system, have harmed Iran’s economic growth, specifically from 2011 to 2014. This thesis uses this case to study and compare the applicability of two different popular approaches used in comparative case studies exploring the effect of a policy intervention.

In the Chapter 1 we study the synthetic control method. Using this method, we estimate the effect of the intensification of sanctions on Iran’s GDP during the period 2011 to 2014. The year of 2011 was Iran’s first full year under these heavy sanctions, and in 2015, the Iran nuclear deal framework was established. Prior to this time, in spite of the ongoing U.S. sanctions, Iran’s GDP had a positive trend from 1990 to 2011. However, our estimates show that the GDP suffered a hit of more than 17 percent over the period under question. We find that these effects were particularly severe in 2012 – the same year of the enforcement by the European Union of an oil embargo and added financial boycotts against Iran.

In Chapter 2, we take a different approach to the same case, and incorporate a more structural and traditional framework. We use a Difference-in-Difference model as well as a dynamic panel data model to estimate the effect of sanctions. According to the dynamic panel data estimation, the cumulative effect of sanctions on the country’s GDP is $-11.40$, $-18.12$, and $-18.62$ percent for 2012, 2013, and 2014. In this chapter, we also compare the synthetic control method with the dynamic panel data regression framework. First, we show
that the synthetic control method provides an unbiased estimator if the underlying model of the outcome variable of interest is a dynamic panel data model. Second, we compare the prediction power of these two methods.

In Chapter 3 we design a Monte Carlo study to discuss the performance of the methods used in previous chapters over many replications. In this chapter, we examine the robustness of the method. We conclude that the dynamic panel data model seems to be performing well with the macro level aggregate data, and the assumptions are appropriate. However, for the synthetic control method we observe large standard error in the estimated values. If we translate that to a significance analysis, this means that even though we observe meaningful values reported as the effect of the intervention, they are not statistically significantly different from 0.
Acknowledgments

Firstly, I would like to express my sincere gratitude to my advisor Professor Wim Vijverberg for the continuous support of my Ph.D study and related research, for his patience, motivation, and immense knowledge. His guidance helped me in all the time of research and writing of this thesis. I still remember the first mathematical expression he wrote on the board five years ago. It was an “iota” vector. That was the start of my passion for Econometrics. I could not have imagined having a better advisor and mentor for my Ph.D study.

Besides my advisor, I would like to thank the rest of my thesis committee: Professor Partha Deb and Professor Sebastiano Manzan for their continues support and encouragement, but also for the comments which incented me to widen my research from various perspectives.

This thesis work is dedicated to my husband, Peyman, who has been a constant source of support and encouragement during the challenges of graduate school and life. Last but not the least, I would like to thank my family: my parents and my brother for supporting me spiritually throughout writing this thesis and my life in general. You are always there for me....
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Chapter 1

An Estimation of the Economic Cost of Recent Sanctions on Iran Using the Synthetic Control Method

1.1 Introduction

International sanctions imposed on Iran, targeting primarily Iran’s key energy sector and its ability to access the international financial system, have harmed Iran’s economic growth, specifically from 2011 to 2014. Using the synthetic control method, this paper estimates that sanctions during this period reduced Iran’s real GDP by more than 17 percent with the largest drop occurring in 2012.

Since the Islamic revolution of 1979 in Iran, sanctions have been the main feature of the US-Iran political relationship. Throughout the 1980s and 1990s, a wide range of sanctions and trade restrictions were imposed on the Islamic Republic targeting its regional power in the Middle East, but more recently, sanctions have been more focused on the country’s

\[1\] This chapter is partially published in the Economics Letters: https://doi.org/10.1016/j.econlet.2017.06.008
nuclear program. Before the late 2000s, the U.S. had kept a higher level of intervention in Iran’s nuclear program compared to the European countries and other U.N. members. The turning point came in 2010-2012, a period of a cooperation among the majority of these countries and the U.S., and the imposition of more sanctions, trade restrictions, and embargoes focused on the nuclear program (European Union Council Conclusion 2012, United Nations Security Council Resolution 1929, Comprehensive Iran Sanctions, Accountability, and Divestment Act of 2010).

Iran is one of the most significant countries in the oil industry worldwide. In 2014, with 157.53 billion barrels, the share of Iran’s crude oil reserve of the OPEC was 13.1 percent. OPEC in that year held 81 percent of the global share (OPEC Statistical Bulletin, 2016). This put Iran in third place in the OPEC ranking and fourth place on a global scale. Iran is also one of the most important countries in the gas production industry. In 2012, Iran’s marketed production of natural gas was 202.43 billion standard cubic meters, 26 percent of the total OPEC production and highest among all other OPEC countries.

Using the synthetic control method, we attempt to estimate the effect of the intensification of sanctions on Iran’s GDP during the period 2011 to 2014. 2011 was Iran’s first full year under these heavy sanctions, and in 2015, the Iran nuclear deal framework was established, and the Iran Deal was signed setting in motion the loosening of sanctions (JCPOA, July 2015). Prior to this time, in spite of the ongoing U.S. sanctions, Iran’s GDP had a positive trend from 1990 to 2011. However, our estimates show that the GDP suffered a hit of more than 17 percent over the period under question. We find that these effects were particularly severe in 2012 – the same year of the enforcement by the European Union of an oil embargo and added financial boycotts against Iran.
1.2 Method and Data

In small-sample social comparative studies, where interventions affect aggregate entities such as countries or states, it is often difficult to find suitable controls that are unaffected by the intervention, and also have similar characteristics to those of the affected unit (Abadie et al., 2010; Collier, 1993; Lijphart, 1971).

Instead of using a single control unit, the synthetic control method (Abadie et al., 2010, 2015; Abadie and Gardeazabal, 2003) uses a weighted average of a set of potential control units to provide a synthetic control unit that more closely resembles the affected unit in terms of predictors. Here we use the synthetic control method to construct a synthetic control unit for Iran representing expected GDP figures under a scenario in which there had been no sanctions after 2011. We refer to this control unit as “Synthetic Iran”.

The empirical analysis is based on annual country level panel data for the period 1980-2014. As international sanctions were imposed in 2011, this yields a pre-intervention period of more than 30 years. We divide our pre-sanction period to a training period from 1980 to 1994 and a validation period from 1995 to 2014 (see Abadie et al. (2015)). Our donor pool includes eight OPEC member countries: Algeria, Ecuador, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, and the United Arab Emirates. Also, in order to increase the size of the pool, we add donors from major non-OPEC oil producer countries (i.e. Canada and China) as well as other non-OPEC neighbors of Iran with close economic similarities (i.e. Oman, Bahrain, and Turkey). The variables used in our analysis are listed in the data appendix along with descriptions and data sources. The outcome variable of interest, \( Y_{jt} \), is the real GDP for country \( j \) at time \( t \). GDP is Purchasing Power Parity (PPP)-adjusted and measured in constant 2011 international dollars. Because our donor countries are heavily dependent

\(^2\)To construct the synthetic control unit, we left Venezuela and Iraq out of the donor pool due to economic fluctuations in these countries during the period of the analysis. However, we find the result is insensitive to this exclusion. We also left Angola out due to data limitations.
1.3 Synthetic Iran and the Effect on GDP

1.3.1 Construction of the Synthetic Iran

Figure 1.1 plots the real GDP of Iran versus the average of the donor pool from 1995 to 2014. This period includes our validation period, 1995 to 2011, as well as the post-sanction period, 2011 to 2014.

For the entire pre-sanction period there is a noticeable difference between Iran’s GDP and the average of the pool. As one of the wealthiest countries in the OPEC, and compared to other countries in our pool, Iran’s GDP is above average during nearly the entire pre-sanction period. After the sanctions, GDP drops and falls below the average of the pool. As the graph suggests, the average does not do a good job of resembling Iran’s GDP for the pre-sanction period. This would also be true of any of the individual donor countries.
However, as shown in the next section, it turns out that the synthetic control can very closely reproduce Iran’s value of GDP for a long period of time before the sanctions.

Table 1.1: GDP Analysis: Donor Pool Countries and Share of Each in the Construction of the Synthetic Iran

<table>
<thead>
<tr>
<th>County</th>
<th>Weight</th>
<th>Country</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algeria</td>
<td>0.138</td>
<td>Nigeria</td>
<td>0.002</td>
</tr>
<tr>
<td>Bahrain</td>
<td>0.000</td>
<td>Oman</td>
<td>0.001</td>
</tr>
<tr>
<td>Canada</td>
<td>0.268</td>
<td>Qatar</td>
<td>0.002</td>
</tr>
<tr>
<td>China</td>
<td>0.027</td>
<td>Saudi Arabia</td>
<td>0.112</td>
</tr>
<tr>
<td>Ecuador</td>
<td>0.000</td>
<td>Turkey</td>
<td>0.194</td>
</tr>
<tr>
<td>Kuwait</td>
<td>0.001</td>
<td>UAE</td>
<td>0.254</td>
</tr>
<tr>
<td>Libya</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1.1 provides the list of the donor countries and share of each in the construction of the Synthetic Iran. Iran’s counter-factual is best reproduced by a weighted average of Canada, United Arab Emirates, Turkey, Algeria, Saudi Arabia, and China. The share of other countries in the pool are either zero or very small. Canada has the highest weight followed by UAE.

Table 1.2 compares the pre-sanction fit of Synthetic Iran and a population weighted average of the countries in the donor pool.

\[ X_1 \] is a \((K \times 1)\) vector of preintervention characteristics (including different combination of the output variable for the affected unit, and similarly \(X_0\) is the same vector of \((K \times J)\) dimension for unaffected units, then these weights are picked to minimize the penalty term: \(\sqrt{(X_1 - X_0W)^T V (X_1 - X_0W)}\) where \(V\) is a positive semi-definite matrix of weights on the predictors. Usually the choice of \(V\) is to minimized the RMSPE (see Abadie et al. (2010)).
Table 1.2: GDP Predictor Means Before the Sanctions

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Iran</th>
<th>Synth</th>
<th>Pool</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total natural rent (% of GDP)</td>
<td>11.1</td>
<td>11.1</td>
<td>16.8</td>
</tr>
<tr>
<td>Agriculture (bn$)</td>
<td>16.6</td>
<td>16.8</td>
<td>24.8</td>
</tr>
<tr>
<td>GDP-2010 ($$)</td>
<td>1.3</td>
<td>1.3</td>
<td>1.5</td>
</tr>
<tr>
<td>Trade (% of GDP)</td>
<td>32.8</td>
<td>36.2</td>
<td>54.7</td>
</tr>
<tr>
<td>Population (million)</td>
<td>51.2</td>
<td>52.4</td>
<td>101.5</td>
</tr>
<tr>
<td>Industry (% of GDP)-not participating</td>
<td>33.9</td>
<td>19.6</td>
<td>21.8</td>
</tr>
<tr>
<td>Services ($) -not participating</td>
<td>94.2</td>
<td>49.9</td>
<td>47.2</td>
</tr>
</tbody>
</table>

Note: the last column is the population-weighted average of all the countries in the donor pool. All the variables are averaged over 1995-2011. We augmented this matching with a lagged value of GDP as a predictor. Weights on the last two predictors industry and services in the construction of the synthetic control is zero; this explains the discrepancy between the means.

We observe that the pool average does not demonstrate similarities to Iran in terms of pre-sanction predictors. However, the Synthetic Iran provides means much closer to the actual Iran. Overall, Table 1.2 suggests that Synthetic Iran provides a better comparison than the population weighted average of the pool.

1.3.2 The Effect of 2011 Sanctions

Figure 1.2 displays the paths of the real GDP of Iran and Synthetic Iran from 1995 to 2014. Synthetic Iran closely resembles Iran’s GDP over the pre-sanction period.

Our estimate of the effect of international sanctions imposed in 2011 is the difference between the GDP of actual Iran and the Synthetic Iran from 2011 to 2014 period. The discrepancy between the two after 2011 suggests a large negative effect of the sanctions on the country’s GDP.
Figure 1.2: Real GDP: Iran vs. Synthetic Iran.

Figure 1.3, the gap plot, also depicts annually the effect of the sanctions. The gap plot provides the exact value of the gap between the two paths shown in Figure 1.2. Both figures show that while the GDP of Synthetic Iran grows, the GDP of actual Iran drops notably after 2011 with the gap between the two growing in magnitude. Iran’s GDP in 2014 was 1289.9 billion dollars, which we estimate to be 271.3 billion dollars less than the value it would have been had there been no sanctions imposed in or after 2011. This is equal to a 17.3 percent drop in GDP over the course of three years of heavy sanctions. Relative to the Synthetic Iran benchmark, Iran’s GDP was reduced by 12.0 percent in the first year after the sanctions.

During the post-sanction period, the rial, Iran’s currency, weakened not just against the dollar but against all other major currencies. Also, inflation increased from 10.8 percent in 2010 to a peak of 34.7 percent in 2013 (Central Bank of Iran annual bulletin). Meanwhile, in order to resist the intensification of sanctions, Iran has shifted the structure of its economy to be more reliant on domestic capacities and less dependent on oil exports, which has helped to
diversify the country’s economy. The unemployment rate stayed constant around 10 percent during this period (“Annual Labor Force Survey Result” provided by the Statistical Center of Iran).

1.3.3 GDP Per Capita

We also apply the synthetic control method to look at the effect of sanctions on Iran’s per capita GDP. We use the same donor pool with the same set of predictors, but this time the outcome variable of interest is real GDP per capita, Purchasing Power Parity (PPP)-adjusted and measured in constant 2011 international dollars. Table 1.3 provides weights of the donors in the construction of the synthetic Iran which fits the figures of the per capita GDP. The implicit control unit is slightly different from the previous one and the weights on the donor countries contributing to the construction of the synthetic unit has changed. China is the country with the highest weight followed by Canada, Nigeria, and Libya.
Table 1.3: GDP Per Capita Analysis: Donor Pool Countries and Share of Each in the Construction of the Synthetic Iran

<table>
<thead>
<tr>
<th>Country</th>
<th>Weight</th>
<th>Country</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algeria</td>
<td>0.007</td>
<td>Nigeria</td>
<td>0.098</td>
</tr>
<tr>
<td>Bahrain</td>
<td>0.003</td>
<td>Oman</td>
<td>0.001</td>
</tr>
<tr>
<td>Canada</td>
<td>0.153</td>
<td>Qatar</td>
<td>0.010</td>
</tr>
<tr>
<td>China</td>
<td>0.671</td>
<td>Saudi Arabia</td>
<td>0.012</td>
</tr>
<tr>
<td>Ecuador</td>
<td>0.000</td>
<td>Turkey</td>
<td>0.001</td>
</tr>
<tr>
<td>Kuwait</td>
<td>0.020</td>
<td>UAE</td>
<td>0.000</td>
</tr>
<tr>
<td>Libya</td>
<td>0.023</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 1.4 displays the corresponding synthetic control unit as well as the actual per capita GDP. From 2011 to 2014, Iran’s population grew from 74.2 to 78.1 million inhabitants. On the other hand, real GDP per capita dropped from 17.9 to 16.5 thousand dollars over the same period. According to the synthetic control analysis, we estimate that in 2014, real GDP per capita would have been $3236.80 higher if no sanctions were imposed. In other words, real GDP per capita suffered a 16.4 percent drop over the course of three years after sanctions.
Table 1.4 provides the match of the mean of the predictors between the synthetic Iran and actual Iran. The population weighted average of the donor pool does not present similarities to actual Iran. But the mean of the synthetic Iran (i.e. the weighted mean of the countries selected to construct the synthetic control unit) is very close in the four dimensions that participate in the selection process.
Table 1.4: GDP Per Capita Analysis: Predictor Means Before the Sanctions

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Iran</th>
<th>Synth</th>
<th>Pool</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total natural rent (% of GDP)</td>
<td>11.5</td>
<td>11.5</td>
<td>17.8</td>
</tr>
<tr>
<td>Agriculture(\text{bn$})</td>
<td>16.2</td>
<td>16.0</td>
<td>24.1</td>
</tr>
<tr>
<td>GDP-2010(\text{t$})</td>
<td>1.7</td>
<td>1.7</td>
<td>3.9</td>
</tr>
<tr>
<td>Trade (% of GDP)</td>
<td>33.4</td>
<td>32.9</td>
<td>55.0</td>
</tr>
<tr>
<td>Population (\text{million})-not participating</td>
<td>50.3</td>
<td>74.2</td>
<td>100.1</td>
</tr>
<tr>
<td>Industry (% of GDP)</td>
<td>33.9</td>
<td>34.0</td>
<td>22.2</td>
</tr>
<tr>
<td>Services(\text{$})-not participating</td>
<td>94.6</td>
<td>19.7</td>
<td>45.2</td>
</tr>
</tbody>
</table>

Note: the last column is the population-weighted average of all the countries in the donor pool. All the variables are averaged over 1995-2011. We augmented this matching with value of GDP in 2011, 2010, and 2009, as well as 2003 and 2000 as predictors. Weights on two predictors services and population in the construction of the synthetic control is zero; this explains the discrepancy between the means.

### 1.3.4 GDP Growth

Iran’s annual GDP growth rates are positive for more than a decade before the sanctions. However, after the sanctions of 2011, GDP growth falls to -7.44 percent in 2012 and -0.19 percent in 2013, and it rose to 4.6 percent in 2014. We run the Synthetic Control analysis to estimate the figures of Iran’s growth of GDP for 2012, 2013, and 2014.

We use GDP growth as the outcome variable of interest this time. However, we change the predictors variables slightly. Instead of using population we use growth in the population, we use “agriculture” as percent of GDP instead of levels, we use “services” as percent of GDP. The other predictors are as before. We measure the growth rate of GDP as the annual change in the log GDP, and we use the annual growth of population which is more appropriate compared to level of the population.
Figure 1.5 provides the path plot of the GDP growth synthetic control analysis, and Figure 1.6 is the corresponding gap plot for it.

![Gaps: Treated - Synthetic](image)

Figure 1.5: Annual GDP Growth Gap Between Iran and Synthetic Iran.

![Growth in Real GDP: Iran vs. synthetic Iran](image)

Figure 1.6: Growth in Real GDP: Iran vs. synthetic Iran

The weights of the donors are provided in Table 1.5.
Table 1.5: GDP Growth Analysis: Donor Pool Countries and Share of Each in the Construction of the Synthetic Iran

<table>
<thead>
<tr>
<th>County</th>
<th>Weight</th>
<th>Country</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algeria</td>
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<td>Nigeria</td>
<td>0.039</td>
</tr>
<tr>
<td>Bahrain</td>
<td>0.001</td>
<td>Oman</td>
<td>0.001</td>
</tr>
<tr>
<td>Canada</td>
<td>0.002</td>
<td>Qatar</td>
<td>0.064</td>
</tr>
<tr>
<td>China</td>
<td>0.098</td>
<td>Saudi Arabia</td>
<td>0.002</td>
</tr>
<tr>
<td>Ecuador</td>
<td>0.090</td>
<td>Turkey</td>
<td>0.160</td>
</tr>
<tr>
<td>Kuwait</td>
<td>0.001</td>
<td>UAE</td>
<td>0.156</td>
</tr>
<tr>
<td>Libya</td>
<td>0.050</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1.6 provides the comparison of the mean of the predictors between Iran, synthetic Iran, and the population weighted average of the donors.

Table 1.6: GDP Growth Analysis: Predictor Means Before the Sanctions

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Iran</th>
<th>Synth</th>
<th>Pool</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population growth(_{m})</td>
<td>3.1</td>
<td>3.0</td>
<td>3.3</td>
</tr>
<tr>
<td>Total natural rent(_{% of GDP})</td>
<td>11.5</td>
<td>11.2</td>
<td>17.8</td>
</tr>
<tr>
<td>Trade(_{% of GDP})</td>
<td>33.4</td>
<td>33.7</td>
<td>55.0</td>
</tr>
<tr>
<td>Industry(_{% of GDP})</td>
<td>33.9</td>
<td>33.9</td>
<td>22.2</td>
</tr>
<tr>
<td>GDP growth-2010(_{%})</td>
<td>5.8</td>
<td>5.0</td>
<td>5.8</td>
</tr>
<tr>
<td>Agriculture(_{% of GDP})-not participating</td>
<td>13.4</td>
<td>11.0</td>
<td>9.0</td>
</tr>
<tr>
<td>Services(_{% of GDP})-not participating</td>
<td>52.8</td>
<td>38.6</td>
<td>21.9</td>
</tr>
</tbody>
</table>

Note: the last column is the population-weighted average of all the countries in the donor pool. All the variables are averaged over 1995-2011. We augmented this matching with value of GDP in 2011 and 2010 as predictors. Weights on 2 predictors in the construction of the synthetic control is zero, this explains the discrepancy between the means.
GDP growth of Iran in 2012 drops to -7.44 percent. However, synthetic Iran grew by 3.92 percent. Thus, according to the synthetic Iran the growth is -11.36 percent lower than what it would have been if there had been no sanctions. In 2013, the actual growth suffers a drop of -0.19, while according to the synthetic Iran, the growth would have been positive 3.8 percent if no sanctions had been imposed. Therefore we estimate the actual growth to be -3.99 lower than what it would be without the sanctions. In 2014 the growth would be 0.498 percent more than the actual value of 4.6 percent, meaning that 5.098 would have been the growth rate in the absence of sanctions.

We also look at the GDP per capita growth rate. Figures 1.7 and 1.8 below are the corresponding path plot and the gap plot for the synthetic control analysis. Iran’s population increases over the post-sanctions period. Iran’s GDP per capita growth rate in 2012, 2013, and 2014 are -8.61, -1.46, and 3.3 percent respectively. On the other hand, synthetic Iran’s per capita growth rate is 2.25, 2.41, and 4.08. This means the values of the per capita GDP for these years are -10.86, -3.87, and 0.78 percent lower than what they would have been if there had been no sanction.

![Gaps: Treated - Synthetic](image)

**Figure 1.7:** Annual GDP Growth Gap Between Iran and Synthetic Iran.
1.4 Placebo Studies

To evaluate the reliability of the result that we obtained in the previous section using the synthetic control method, we run two types of placebo studies (Abadie et al., 2015, Heckman and Hotz, 1989). First, we perform the “in-time placebo” study in which we repeat the synthetic control method but reassign the sanctions date to 2006, almost 5 years before the actual sanctions were actually imposed.\footnote{Among all the pre-sanctions years we can choose to run the placebo study, we pick the year 2006 to implicitly confirm that the former U.N. sanctions of 2006 did not cause any structural shock to the GDP.}

Figure 1.9 displays the result of our “in-time placebo” study. The synthetic control perfectly resembles the actual GDP for the entire period of 1995 to 2006, as well as 2006 to 2011. There is no divergence between the actual GDP of Iran and synthetic Iran, and there is no substantial effect estimated for the year 2006. This strengthens the case for the predictive power of the synthetic control, and for the estimated effect of the actual sanctions of 2011.

We also run another in-time placebo analysis in which we set the date of the sanctions to...
be 2002. Following the same reasoning mentioned above, we do not anticipate to have a substantial difference between figures of GDP of Iran and the synthetic Iran in this placebo study. As we can see in Figure 1.10, synthetic Iran and Iran behave almost the same. To be more precise and in order to have long enough period of time before the placebo sanctions of 2002, we extend the validation period for the placebo analysis to start at 1990 instead of 1995. The result is provided in Figure 1.11. One of the limitations of the synthetic control analysis is the lack of estimation for the standard errors. If there had been an estimation of the standard errors, we could have provided a test of how significant is any reported effect of the placebo studies. So by a simple comparison of numbers and trends, what we conclude here is that the synthetic control does not report a substantial effect for the placebo sanctions of 2002. But we will try to strengthen the result with the second placebo study mentioned below when we don’t have any underlining distribution of the estimated effect.

Figure 1.9: “In-time” Placebo Effect of 2006 Real GDP Iran vs. Synthetic Iran.
Next, in the “in-space placebo” study, we iteratively apply the synthetic control method that we used to estimate the effect of sanctions in Iran to every other control unit in the donor pool. In each iteration we reassign the intervention of 2011 to one of the countries in the donor pool and we remove Iran from the pool of the donors. Ultimately, we expect the
method to estimate insignificant effects for the other countries compared to Iran. In other 
words, when randomization is not an option and there is no distribution for the estimated 
effect to check the significance, we can rely on a distribution of the estimated placebo effects 
created by this study. We expect the estimated effect for Iran to be an outlier in the 
distribution of the placebo effects.

Figure 1.10 displays the result of our in-space placebo study. Each plot in the figure 
is a gap plot derived from a placebo synthetic control analysis in which the intervention is 
assigned to one of the countries in the pool iteratively.

In Figure 1.12 part B we include the gap plots for all the control units in the pool. As we 
can see, Iran is indeed an outlier in the distribution of the placebo effects. In Figure 1.12 part 
D we exclude those countries with an MSPE (total discrepancy between the country and its 
synthetic version for the pre-sanction period) of 3 times or higher than Iran. The remaining 
countries would be those with a better fit of the synthetic control. These countries would be 
more probable to report a higher placebo effect and are better candidates to include in the 
placebo distribution. In Figure 1.12 Part F we set the cutoff to be an MSPE of 2 times or 
higher than Iran. Not only is Iran an outlier in the most inclusive distribution of placebo 
effects according to Figure 1.12 part B, but also by leaving out the countries with a high 
MSPE in Figure 1.12 part D Part F we observe that Iran is still an outlier among the 
countries that would potentially report a higher placebo effect.

---

5 China is left out in all panels; no synthetic China could be constructed as the weighted average of the 
donor pool
6 Countries removed: Qatar, Bahrain, Turkey, Canada
7 Additional countries removed: Saudi Arabia, Nigeria, Libya
8 One valid concern regarding the role of Oil-based countries as donors is potential existence of spillover 
effects. Other countries in the donor pool should not be directly affected by the intervention. This placebo 
study also justifies the choice of the countries as we can observe none of them are significantly affected by 
Iran’s sanctions.
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(a) Including All the Controls.

(b) Leaving Out Controls with MSPE >3*MSPE of Iran.

(c) Leaving Out Controls with MSPE>2 *MSPE of Iran.

Figure 1.12: “In-space” Placebo Effect Distributions.
1.5 Conclusion

We apply the synthetic control method to study the effect of recent sanctions on Iran’s economic growth. As one of the wealthiest and most influential countries in the Middle East and among OPEC countries, Iran plays a critical role in any political interactions. We use a data-driven synthetic control unit constructed as a weighted average of the donor countries to estimate the negative effects of sanctions on economic growth of this country. We estimate that recent sanctions caused a 17.3 percent drop in GDP over the course of 3 years, with the highest effect, a 12.0 percent drop, taking place in 2012.
Chapter 2

A Comparison Between the Synthetic Control Method and the Dynamic Panel Data Model

2.1 Introduction

The synthetic control method has been used in comparative case studies in which the existence of a counter-factual unit with high level of similarities and comparability is crucial. On the other hand, many studies have been done and many methods have been offered in order to overcome the potential shortages of a traditional regression framework in such case studies. In this essay we compare the synthetic control method with a dynamic panel data regression framework. First, we show that the synthetic control method provides an unbiased estimator if the underlying model of the outcome variable of interest is a dynamic panel data model. Second, we compare the prediction power of these two methods. To apply the idea, we use the recent sanctions on Iran as the suitable case of a policy intervention and a comparative case study.
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In a randomized experiment as well as an observational case study, ideally, the treatment effect would be the difference of the values of the outcome variable between the treated unit and the same unit under no treatment (Rubin, 1974, 1977, 1978). But “the fundamental problem of causal inference” (Holland, 1986) here is the unknown and unobserved values of outcome for the treated units under no treatment. However, in randomized experiments, the random assignment assures that treated units and controls are balanced or matched in the covariates. Therefore a comparison between the treated and control units are very informative about the treatment effect. In contrast, in an observational study, the random assignment is not an option. Matching methods are one strand of the methods developed to provide the essential similarities between treated and control units (Rosenbaum, 2005).

In the absence of randomization, we need to assume “some form of exogeneity” (Imbens, 2002) of the treatment assignment. We need to assume the assignment to the treatment is exogenous to the covariates to enable us to compare the outcome between the treated units and controls, and meaningfully attribute the difference to the treatment. As Imbens (2002) shows, the literature has referred to this assumption under different names: unconfoundedness (Rosenbaum and Rubin, 1983), selection on observable (Barnow et al., 1980, Fitzgerald et al., 1998), or conditional independence (Lechner, 1999). Under this assumption, many studies have designed unbiased estimators for the treatment effect. Proposed methods can be summarized into few categories such as traditional regression of the outcome of interest on the covariates (Rubin, 1977), matching on covariates (Abadie et al., 2010, 2015, Card and Krueger, 1994), propensity score (Dehejia and Wahba, 1999, 2002, Heckman et al., 1997), and a combination of these approaches (Abadie and Imbens, 2002).

In large-sample studies, “matching” methods aim to equate (or “balance”) the distribution of covariates in the treated and control units. But in small-sample social comparative studies, where the interventions affect aggregate entities such as countries or states, it is often very difficult to find suitable controls that are unaffected by the intervention and also have
similar characteristics to those of the affected unit in the pre-intervention period \cite{Abadie2010, Collier1993, Lijphart1971}. Despite this fact, for example, in a well-known study, Card and Krueger \cite{Card1994} use the matching method to explore the effect of the 1992 change in minimum wages on the unemployment rate in New Jersey. They surveyed 410 fast-food restaurants in New Jersey and eastern Pennsylvania (which shows high similarities to New Jersey) before and after the rise. Comparisons of employment growth at stores in New Jersey and Pennsylvania provide simple estimates of the effect of the higher minimum wage.

Instead of using a single control unit, the synthetic control method \cite{Abadie2010, 2015, Abadie2003} uses a weighted average of potential control units to provide a synthetic control unit that behaves more closely to the affected unit in terms of related predictors of outcome of interest. For example, Abadie and Gardeazabal \cite{2003} develop a synthetic unit control as a weighted average of two other Spanish regions to find the effect of an outbreak of terrorism in Basque Country in the late 1960s, on the economic growth of this region. Abadie et al. \cite{2010} study the effect of California’s tobacco control program (Proposition 99) on cigarette consumption using the synthetic control method. In another study, Abadie et al. \cite{2015} implement the synthetic control method to study the effect of German reunification in 1990 on west Germany’s GDP.

As mentioned earlier we can also rely on a regression framework to predict the effect of an intervention on an outcome. A dynamic panel data model would be a suitable model to study the effect of policy interventions on the macro economic variables such as economic growth in aggregate entities such as countries. In this essay, we compare the synthetic control method with a dynamic panel data model. For the empirical analysis, we use recent sanctions on Iran as a suitable case of a policy intervention.

First, in Section 2.2 we confirm that the synthetic control method can provide an unbiased estimator if the outcome variable of interest follows a dynamic panel data model. This
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strengthens the comparison. In Section 2.3, we estimate the dynamic panel data model to find the effect of recent sanction on Iran’s GDP, and we compare the prediction power between the two methods. The details of the synthetic control estimation can be found in the first chapter. Section 2.4 concludes.

2.2 Unbiasedness of the Synthetic Control Estimator

We use this section to clarify that under specific assumptions the synthetic control estimator will be an unbiased estimator in a two way error component dynamic panel data model. For unit \( i = 1, \ldots, J + 1 \) and \( t = 1, \ldots, T_0, \ldots, T \), where \( T_0 \) is the last period before the intervention, we have:

\[
y_{it}^N = \rho y_{it-1}^N + Z_{it} \theta' + X_i \gamma + \mu_i + \delta_t + \epsilon_{it} \quad (2.1)
\]

\[
Z_{it} = A_1 Z_{it-1} + A_2 y_{it-1}^N + \mu_{zi} + \delta_{zt} + \nu_{it} \quad (2.2)
\]

where \( y_{it}^N \) is the outcome that would be observed for country \( i \) at time \( t \) in the absence of the intervention, for unit \( i = 1, \ldots, J + 1 \) and \( t = 1, \ldots, T_0, \ldots, T \). Let \( y_{it}^I \) is the outcome that would be observed for unit \( i \) at time \( t \) if unit \( i \) is exposed to the intervention in periods \( T_0 + 1 \) to \( T \). \( \delta_t \) is time fixed effects which we assume to be constant across units. \( X'_i \) is a \((1 \times M)\) row vector of time-invariant explanatory variables and \( \gamma \) is a \((M \times 1)\), and \( \theta \) is a \((K \times 1)\) vector of parameters. \( \mu_i \) is the unit \( i \) fixed effect. \( Z'_{it} \) is a \((1 \times K)\) row vector of time-varying covariates that moves over time by a process given in equation \((2.2)\). \( \epsilon_{it} \) and \( \nu_{it} \) are the idiosyncratic shocks at unit level with mean zero. So, for \( t = 1, \ldots, T_0 \) and all \( i = 1, \ldots, J + 1 \), we have that \( y_{it}^N = y_{it}^I \)

\footnote{We consider our model to be a specific case of Abadie et al. (2010)’s factor model. In the paper, they show that the synthetic control estimator is an unbiased estimator for the intervention effect in a factor model such as:

\[
y_{it}^N = \delta_i + \theta_i Z_i + \lambda_i \mu_i + \epsilon_{it} \quad (2.3)
\]
Following Abadie et al. (2010), let $\alpha_{it} = y^I_{it} - y^N_{it}$ be the effect of the intervention for unit $i$ at time $t$, and let $D_{it}$ be an indicator that equals 1 if unit $i$ is exposed to the intervention at time $t$, and equals 0 otherwise. Therefore, the observed outcome for unit $i$ at time $t$ is $Y_{it} = y^N_{it} + \alpha_{it} D_{it}$. We assume unit $i = 1$ is exposed to the intervention for $t = T_0 + 1, ..., T$, therefore we want to estimate $\alpha_{1t} = y^I_{1t} - y^N_{1t}$ for $t = T_0 + 1, ..., T$. Note that $y^I_{1t}$ is observed, so we just need to estimate $y^N_{1t}$.

We start at one period post intervention, and we show that the synthetic control estimator which uses the weighted average of the donors when the outcome variable of interest is unobservable, is an unbiased estimator if the outcome variable follows the DPD data generating process mentioned in 2.1. We will provide the same derivation for second post intervention period, and we conclude under the same assumption, the synthetic control provides an unbiased estimator if the outcome variable follows a DPD generating process.

Period $T_0 + 1$:

When we substitute (2.2) into (2.1), we obtain:

$$y^N_{it} = \rho y^N_{it-1} + Z_{it-1}' A_1' \theta + y^N_{it-1} A_2' \theta + \mu_1' \theta + \delta_1' \theta + \nu_1' \gamma + \mu_1 + \delta_1 + \epsilon_{it} \quad (2.4)$$

Now we use $(J \times 1)$ vector of weights $W = (w_2, w_3, w_4, ..., w_{J+1})'$ such that $w_j \geq 0$ for $j = 2, ..., J + 1$ and $w_2 + w_3 + w_4 + ... + w_{J+1} = 1$. Therefore, we have:

$$\sum_{j=2}^{J+1} w_j y^N_{jt} = [\rho + A_2' \theta] \sum_{j=2}^{J+1} w_j y^N_{j(t-1)} + \sum_{j=2}^{J+1} w_j Z_{jt-1}' A_1' \theta + \sum_{j=2}^{J+1} w_j \mu_{zj}' \theta + \delta_1' \theta + \sum_{j=2}^{J+1} w_j \nu_{j}' \gamma + \sum_{j=2}^{J+1} w_j \mu_1 + \delta_1 + \sum_{j=2}^{J+1} w_j \epsilon_{jt} \quad (2.5)$$

where $\delta_1$ is an unknown common factor with constant factor loadings across units, $Z_{it}$ is a $(r \times 1)$ vector of observed covariates (not affected by the intervention), $\theta_i$ is a $(1 \times r)$ vector of unknown parameters, $\lambda_i$ is a $(1 \times F)$ vector of unobserved common factors, $\mu_i$ is an $(F \times 1)$ vector of unknown factor loadings, and the error terms $\epsilon_{it}$ are unobserved transitory shocks with zero mean.
So in the first post intervention period we have:

\[
y_{1T_0+1}^N - \sum_{j=2}^{J+1} w_j y_{1T_0+1}^N = A(y_{iT_0}^N - \sum_{j=2}^{J+1} w_j y_{jT_0}) + (Z_{1T_0} - \sum_{j=2}^{J+1} w_j Z_{jT_0})' A' \theta + (X_1 - \sum_{j=2}^{J+1} w_j X_j)' \gamma
\]

\[
+ (\mu_{z1} - \sum_{j=2}^{J+1} w_j \mu_{zj})' \theta + (\mu_1 - \sum_{j=2}^{J+1} w_j \mu_j)
\]

\[
+ \sum_{j=2}^{J+1} w_j (\nu_{it} - \nu_{jt})' \theta + \sum_{j=2}^{J+1} w_j (\epsilon_{it} - \epsilon_{jt})
\]

\[(2.6)\]

where \( A = \rho + A'_2 \theta \) is a scalar. Note that \( \delta'_{i} \theta \)s will be dropped out of the equation because sum of the weights is 1. Following [Abadie et al. 2010], let \( Y_i^{pre} \) be a \((T_0 \times 1)\) vector of pre-intervention values of \( y \) for unit \( i \). Therefore for the first unit \((i = 1)\) we have

\[
\begin{bmatrix}
y_{11} \\
y_{12} \\
\vdots \\
y_{1T_0}
\end{bmatrix}, \text{ and } Y_{1(-1)}^{pre} =
\begin{bmatrix}
y_{10} \\
y_{11} \\
\vdots \\
y_{1T_0-1}
\end{bmatrix}, \text{ and } Z_{1}^{pre} =
\begin{bmatrix}
Z_{11}' \\
Z_{12}' \\
\vdots \\
Z_{1T_0}'
\end{bmatrix}, \text{ and } Z_{1(-1)}^{pre} =
\begin{bmatrix}
Z_{10}' \\
Z_{11}' \\
\vdots \\
Z_{1T_0-1}'
\end{bmatrix}
\]

\[(2.7)\]

Note that by construction \((Z_{1(-1)}^{pre} - \sum_{j=2}^{J+1} w_j Z_{j(-1)}^{pre})'\) is a \((T_0 \times K)\) matrix. \( \iota_{T_0} \) is a vector of ones of length \( T_0 \). Since \((X_1 - \sum_{j=2}^{J+1} w_j X_j)'\gamma\) is a scalar, \( \iota_{T_0}(X_1 - \sum_{j=2}^{J+1} w_j X_j)'\gamma\) is a
(\mathbf{T}_0 \times 1) \text{ vector with elements equal to } (X_1 - \sum_{j=2}^{J+1} w_j X_j) \gamma.

We multiply both sides of (2.7) by \((\ell'_T \ell_{T_0})^{-1} \ell'_T\), and we add and subtract the resulting expression from (2.6). So we can write:

\[
y_{N1}^{T_0+1} - \sum_{j=2}^{J+1} w_j y_{jT_0+1}^N = [(\ell'_T \ell_{T_0})^{-1} \ell'_T (Y_{1}^{pre} - \sum_{j=2}^{J+1} w_j Y_j^{pre})] \\
+ A[(y_{1T_0} - \sum_{j=2}^{J+1} w_j y_j T_0) - (\ell'_T \ell_{T_0})^{-1} \ell'_T (Y_{1}^{pre} - \sum_{j=2}^{J+1} w_j Y_j^{pre})] \\
+ [(Z_{1T_0} - \sum_{j=2}^{J+1} w_j Z_j T_0) A_1 \theta - (\ell'_T \ell_{T_0})^{-1} \ell'_T (Z_{1}^{pre} - \sum_{j=2}^{J+1} w_j Z_j^{pre}) A_1 \theta] \\
+ [(X_1 - \sum_{j=2}^{J+1} w_j X_j) \gamma - (\ell'_T \ell_{T_0})^{-1} \ell'_T \ell_{T_0} (X_1 - \sum_{j=2}^{J+1} w_j X_j) \gamma] \\
+ [(\mu_{z1} - \sum_{j=2}^{J+1} w_j \mu_{zj}) \theta - (\ell'_T \ell_{T_0})^{-1} \ell'_T \ell_{T_0} (\mu_{z1} - \sum_{j=2}^{J+1} w_j \mu_{zj})] \theta \\
+ [(\mu_1 - \sum_{j=2}^{J+1} w_j \mu_j) - (\ell'_T \ell_{T_0})^{-1} \ell'_T \ell_{T_0} (\mu_1 - \sum_{j=2}^{J+1} w_j \mu_j)] \\
+ \left[ \sum_{j=2}^{J+1} w_j (\nu_{jT_0+1} - \nu_{jT_0+1}) - (\ell'_T \ell_{T_0})^{-1} \ell'_T (\nu_{1}^{pre} - \sum_{j=2}^{J+1} w_j \nu_j^{pre}) \right] \theta \\
+ \left[ \sum_{j=2}^{J+1} w_j (\epsilon_{1T_0+1} - \epsilon_{jT_0+1}) - (\ell'_T \ell_{T_0})^{-1} \ell'_T (\epsilon_{1}^{pre} - \sum_{j=2}^{J+1} w_j \epsilon_j^{pre}) \right]
\]

(2.8)

Note that in this equation we cancel out \((\mu_1 - \sum_{j=2}^{J+1} w_j \mu_j), (\mu_{z1} - \sum_{j=2}^{J+1} w_j \mu_{zj}), \) and also
(X_1 - \sum_{j=2}^{J+1} w_j X_j) \gamma. Noting that \((t'_{T_0})^{-1} = \frac{1}{T_0}\), we may rewrite (2.8) as:

\[
y_{1T_0+1} - \sum_{j=2}^{J+1} w_j y_{jT_0+1} = \frac{1}{T_0} \sum_{t=1}^{T_0} (y_{1t}^{pre} - \sum_{j=2}^{J+1} w_j y_{jT_0+1}^{pre}) + A((y_{1T_0} - \sum_{j=2}^{J+1} w_j y_{jT_0}) - \frac{1}{T_0} \sum_{t=1}^{T_0} (y_{1t}^{pre} - \sum_{j=2}^{J+1} w_j y_{jT_0+1}^{pre})) + \left((Z_{1T_0} - \sum_{j=2}^{J+1} w_j Z_{jT_0})' A'_1 \theta - \frac{1}{T_0} \sum_{t=1}^{T_0} ((Z_{1t}^{pre} - \sum_{j=2}^{J+1} w_j Z_{jT_0+1}^{pre})' A'_1 \theta)\right)
\]

\[
\sum_{j=2}^{J+1} w_j (\nu_{1T_0+1} - \nu_{jT_0+1}) - \frac{1}{T_0} \sum_{t=1}^{T_0} (\nu_{1t}^{pre} - \sum_{j=2}^{J+1} w_j \nu_{jT_0}^{pre}) + \sum_{j=2}^{J+1} w_j (\epsilon_{1T_0+1} - \epsilon_{jT_0+1}) - \frac{1}{T_0} \sum_{t=1}^{T_0} (\epsilon_{1t}^{pre} - \sum_{j=2}^{J+1} w_j \epsilon_{jT_0}^{pre})
\]

(2.9)

Now suppose we find the synthetic control method weights \(W^* = (w_2^*, ..., w_{J+1}^*)\) such that for each \(t \in (1, ..., T_0)\) we get \(\sum_{j=2}^{J+1} w_j^* y_{jt} = y_{1t}\) and \(\sum_{j=2}^{J+1} w_j^* Z_{jt} = Z_{1t}\). Then \(\frac{1}{T_0} \sum_{t=1}^{T_0} (y_{1t}^{pre} - \sum_{j=2}^{J+1} w_j^* y_{jt}^{pre})\) which is the average of total deviation between observed values of outcome for the first unit \(i = 1\) and the synthetic control unit, during the pre-intervention period, is equal to zero, and so is \(\frac{1}{T_0} \sum_{t=1}^{T_0} (y_{1t}^{pre} - \sum_{j=2}^{J+1} w_j^* y_{jt}^{pre})\), and so is \(\frac{1}{T_0} \sum_{t=1}^{T_0} (Z_{1t}^{pre} - \sum_{j=2}^{J+1} w_j^* Z_{jt}^{pre})\). For the last period before the intervention \(T_0\) we also have \(y_{1T_0} - \sum_{j=2}^{J+1} w_j^* y_{jT_0} = 0\) and also \(Z_{1T_0} - \sum_{j=2}^{J+1} w_j^* Z_{jT_0} = 0\). The rest of the terms are idiosyncratic error terms with mean zero. Therefore, eventually we can show for \(t = T_0 + 1\):

\[
E[y_{1T_0+1}^{N} - \sum_{j=2}^{J+1} w_j y_{jT_0+1}^{N}] = 0
\]

(2.10)

**Period \(T_0 + 2\):**

Let us restate the dynamic panel data model in equation (2.11) and (2.12):

\[
y_{it}^{N} = \rho y_{it-1}^{N} + Z_{it}' \theta + X_{it}' \gamma + \mu_i + \delta_t + \epsilon_{it}
\]

(2.11)
\[ Z_{it} = A_1 Z_{it-1} + A_2 y_{it-1}^N + \mu_{zi} + \delta_{zt} + \nu_{it} \quad (2.12) \]

and let us go one period back:

\[ y_{it-1}^N = \rho y_{it-2}^N + Z_{it-1}' \theta + X_i' \gamma + \mu_i + \delta_{t-1} + \epsilon_{it-1} \quad (2.13) \]

\[ Z_{it-1} = A_1 Z_{it-2} + A_2 y_{it-2}^N + \mu_{zi} + \delta_{zt-1} + \nu_{it-1} \quad (2.14) \]

So by plugging in \( Z_{it} \) from (2.12) we can write (2.11) as:

\[ y_{it}^N = \rho y_{it-1}^N + [A_1 Z_{it-1} + A_2 y_{it-1}^N + \mu_{zi} + \delta_{zt} + \nu_{it}]' \theta + X_i' \gamma + \mu_i + \delta_t + \epsilon_{it} \quad (2.15) \]

Now by inserting (2.13) for \( y_{it-1} \) and (2.14) for \( Z_{it-1} \) and rearranging the terms we have:

\[ y_{it}^N = G y_{it-2}^N + Z_{it-2}' H + \mu_{zi} I + \delta_{zt-1}' B + \nu_{it-1}' B + X_i' J + K \mu_i + K \delta_{t-1} + K \epsilon_{it-1} \]

\[ + \delta_{zt}' \theta + \nu_{it}' \theta + \delta_t + \epsilon_{it} \quad (2.16) \]

where \( A = [(\rho + A_2 \theta) \rho] \) and \( G = A + A_2 B \) are scalars. \( H = A_1' B \) is a \((K \times 1)\) vector, \( \mu_{zi} \) is a \((1 \times K)\) row vector, \( I = B + \theta \) is a \((K \times 1)\) vector, and \( B = [(\rho + A_2 \theta)(\theta) + A_1' \theta] \) is a \((K \times 1)\) vector. \( J = C + \gamma \) where \( \gamma \) is a \((K_2 \times 1)\) vector of coefficients on the \( X_i \) and \( C = \gamma[\rho + A_2/\theta] \) is a \((K_2 \times 1)\) vector as well, and \( K = [\rho + A_2 \theta] \) is a scalars and \( \theta \) is a \((K \times 1)\) vector.

\[
\sum_{j=2}^{J+1} w_j y_{jt}^N = G \sum_{j=2}^{J+1} w_j y_{jt-2}^N + \sum_{j=2}^{J+1} w_j Z_{jt-2}' H + \sum_{j=2}^{J+1} w_j X_j' J + \\
\sum_{j=2}^{J+1} w_j \mu_{z_j} I + K \sum_{j=2}^{J+1} w_j \mu_j + \delta_{zt-1}' B + \delta_{zt}' \theta + K \delta_{t-1} + \delta_t + \\
\sum_{j=2}^{J+1} w_j \nu_{jt-1}' B + \sum_{j=2}^{J+1} w_j \nu_{jt}' \theta + K \sum_{j=2}^{J+1} w_j \epsilon_{jt-1} + \sum_{j=2}^{J+1} w_j \epsilon_{jt} \quad (2.17) \]

Now we can write:
\( y_{1t}^N - \sum_{j=2}^{J+1} w_j y_{jt}^N = G(y_{1t-2}^N - \sum_{j=2}^{J+1} w_j y_{jt-2}^N) + (Z_{1t-2} - \sum_{j=2}^{J+1} w_j Z_{jt-2})'H + (X_1 - \sum_{j=2}^{J+1} w_j X_j)'J \\
+ (\mu_{z1} - \sum_{j=2}^{J+1} w_j \mu_{zj})'I + K(\mu_1 - \sum_{j=2}^{J+1} w_j \mu_j) \\
+ \sum_{j=2}^{J+1} w_j(\nu_{1t-1} - \nu_{jt-1})'B + \sum_{j=2}^{J+1} w_j(\nu_{1t} - \nu_{jt})'\theta \\
+ K(\sum_{j=2}^{J+1} w_j(\epsilon_{1t-1} - \epsilon_{jt-1})) + \sum_{j=2}^{J+1} w_j(\epsilon_{1t} - \epsilon_{jt}) \\
(2.18) \)

So if we stack the pre-intervention matrices we have:

\( Y_1^{pre} - \sum_{j=2}^{J+1} w_j Y_j^{pre} = G[Y_1^{pre} - \sum_{j=2}^{J+1} w_j Y_j^{pre}] + [(Z_1^{pre} - \sum_{j=2}^{J+1} w_j Z_j^{pre})]'H \\
+ \iota_T X_1 - \sum_{j=2}^{J+1} w_j X_j)'J + \iota_T[\mu_{z1} - \sum_{j=2}^{J+1} w_j \mu_{zj}]'I + \iota_T K(\mu_1 - \sum_{j=2}^{J+1} w_j \mu_j) \\
+ [(\nu_1^{pre} - \sum_{j=2}^{J+1} w_j \nu_j^{pre})]'B + [(\nu_1^{pre} - \sum_{j=2}^{J+1} w_j \nu_j^{pre})]'\theta \\
+ K(\epsilon_1^{pre} - \sum_{j=2}^{J+1} w_j \epsilon_j^{pre}) + (\epsilon_1^{pre} - \sum_{j=2}^{J+1} w_j \epsilon_j^{pre}) \\
(2.19) \)

We multiply both sides of (2.19) by \((\iota_T' \iota_T)^{-1} \iota_T'\), and we add and subtract the resulting
expression from \((2.18)\). So we can write:

\[
y_1^{T_0+2} = \sum_{j=2}^{J+1} w_j y_j^{T_0+2} = \left[ (t_{T_0}^{'} t_{T_0}^{-1}) (Y_1^{pre} - \sum_{j=2}^{J+1} w_j Y_j^{pre}) \right]
\]

\[
+ \left[ (y_1 T_0 - \sum_{j=2}^{J+1} w_j y_j T_0) - (t_{T_0}^{'} t_{T_0}^{-1}) (y_1^{pre} - \sum_{j=2}^{J+1} w_j y_j^{pre}) \right] G
\]

\[
+ \left[ (Z_1 T_0 - \sum_{j=2}^{J+1} w_j Z_j T_0) - (t_{T_0}^{'} t_{T_0}^{-1}) (Z_1^{pre} - \sum_{j=2}^{J+1} w_j Z_j^{pre}) \right] H
\]

\[
+ \left[ (X_1 - \sum_{j=2}^{J+1} w_j X_j) - (t_{T_0}^{'} t_{T_0}^{-1}) (X_1 - \sum_{j=2}^{J+1} w_j X_j) \right] J
\]

\[
+ \left[ (\mu_1 - \sum_{j=2}^{J+1} w_j \mu_j) - (t_{T_0}^{'} t_{T_0}^{-1}) (\mu_1 - \sum_{j=2}^{J+1} w_j \mu_j) \right] K
\]

\[
+ \left[ \sum_{j=2}^{J+1} w_j (\nu_{1T_0+1} - \nu_{jT_0+1}) - (t_{T_0}^{'} t_{T_0}^{-1}) (\nu_1^{pre} - \sum_{j=2}^{J+1} w_j \nu_j^{pre}) \right] B
\]

\[
+ \left[ \sum_{j=2}^{J+1} w_j (\nu_{1T_0+2} - \nu_{jT_0+2}) - (t_{T_0}^{'} t_{T_0}^{-1}) (\nu_1^{pre} - \sum_{j=2}^{J+1} w_j \nu_j^{pre}) \right] \theta
\]

\[
+ \left[ \sum_{j=2}^{J+1} w_j (\epsilon_{1T_0+1} - \epsilon_{jT_0+1}) - (t_{T_0}^{'} t_{T_0}^{-1}) (\epsilon_1^{pre} - \sum_{j=2}^{J+1} w_j \epsilon_j^{pre}) \right] K
\]

\[
+ \left[ \sum_{j=2}^{J+1} w_j (\epsilon_{1T_0+2} - \epsilon_{jT_0+2}) - (t_{T_0}^{'} t_{T_0}^{-1}) (\epsilon_1^{pre} - \sum_{j=2}^{J+1} w_j \epsilon_j^{pre}) \right]
\]

(2.20)

Finally we can write:
\[
\begin{align*}
N_{Y_{T_0+2}} - \sum_{j=2}^{2N} w_j y_{jT_0+2} &= \frac{1}{T_0} \sum_{t=1}^{T_0} (y_{1t} - \sum_{j=2}^{2N} w_j y_{jT_0+2}) \\
&+ [(y_{1T_0} - \sum_{j=2}^{2N} w_j y_{jT_0})/G - \frac{1}{T_0} \sum_{t=1}^{T_0} (y_{1t} - \sum_{j=2}^{2N} w_j y_{jT_0})/G] \\
&+ [(Z_{1T_0} - \sum_{j=2}^{2N} w_j Z_{jT_0})/H - \frac{1}{T_0} \sum_{t=1}^{T_0} (Z_{1t} - \sum_{j=2}^{2N} w_j Z_{jT_0})/H] \\
&+ \sum_{j=2}^{2N} w_j (\nu_{1t+1} - \nu_{jT_0+1})/B - \frac{1}{T_0} \sum_{t=1}^{T_0} (\nu_{1t} - \sum_{j=2}^{2N} w_j \nu_{jT_0})/B \\
&+ \sum_{j=2}^{2N} w_j (\epsilon_{1T_0+1} - \epsilon_{jT_0+1})/K - \frac{1}{T_0} \sum_{t=1}^{T_0} (\epsilon_{1t} - \sum_{j=2}^{2N} w_j \epsilon_{jT_0})/K \\
&+ \sum_{j=2}^{2N} w_j (\epsilon_{1T_0+2} - \epsilon_{jT_0+2}) - \frac{1}{T_0} \sum_{t=1}^{T_0} (\epsilon_{1t} - \sum_{j=2}^{2N} w_j \epsilon_{jT_0})/K \\
&= (2.21)
\end{align*}
\]

Now again consider the synthetic control method weights \( W^* = (w_2^*, ..., w_j^*+1) \) such that for each \( t \in (1, ..., T_0) \) we get \( \sum_{j=2}^{J+1} w_j^* y_{jt} = y_{1t} \) and \( \sum_{j=2}^{J+1} w_j^* Z_{jt} = Z_{1t} \). Then \( \frac{1}{T_0} \sum_{t=1}^{T_0} (y_{1t} - \sum_{j=2}^{J+1} w_j^* y_{jT_0} - \sum_{j=2}^{J+1} w_j^* Z_{jT_0}) \) which is the average of total deviation between observed values of outcome for the first unit \( i = 1 \) and the synthetic control unit, during the pre-intervention period, is equal to zero, and so is \( \frac{1}{T_0} \sum_{t=1}^{T_0} (y_{1t} - \sum_{j=2}^{J+1} w_j^* y_{jT_0}) \), and so is \( \frac{1}{T_0} \sum_{t=1}^{T_0} (Z_{1t} - \sum_{j=2}^{J+1} w_j^* Z_{jT_0}) \). For the last period before the intervention \( T_0 \) we also have \( y_{1T_0} - \sum_{j=2}^{J+1} w_j^* y_{jT_0} = 0 \) and also \( Z_{1T_0} - \sum_{j=2}^{J+1} w_j^* Z_{jT_0} = 0 \). The rest of the terms are idiosyncratic error terms with mean zero. Therefore, eventually we can show for \( t = T_0 + 2 \):

\[
E[y_{1T_0+2} - \sum_{j=2}^{J+1} w_j y_{jT_0+2}] = 0 \tag{2.22}
\]

This can be done with all the post intervention periods. Therefore, this shows that the
bias of the synthetic control estimator, given the assumptions mentioned above, is zero in a DPD data generating process such as equation (2.1).

2.3 Empirical Analysis, Estimation of the Dynamic Panel Data Model

Abadie et al. (2015) compare the synthetic control method with a regression framework. They show that a regression counter-factual unit for post-intervention period is a \((t-T_0)\times 1\) vector of \(\hat{\beta}'X_1\), where \(\hat{\beta}\) is the matrix of regression coefficients of \(Y_0\) on \(X_0\). \(Y_0\) is the matrix of the values of the outcome variable for control units, \(X_1\) is \((K \times 1)\) vector containing the values of predictors of the treated unit that we aim to match as closely as possible and \(X_0\) is the \((K \times J)\) matrix containing the values of the same variables for the donor units. Therefore the regression estimated counter-factual of the affected unit is \(Y_0W_{reg}\) where \(W_{reg} = X_0'(X_0'X_0')^{-1}X_1\). (See Abadie et al. (2015))

In fact they show that similar to the synthetic control method, the regression estimator is a weighting estimator with weights that sum to one, and the counter-factual unit in a regression is also a linear combination of the control units, and the weights on the controls sum to one. But unlike the synthetic control method, in the regression, weights are not restricted to the \([0, 1]\) interval. This allows for “extrapolation outside the support of the data” (King and Zeng, 2006).

The point they make above highlights an advantage of the synthetic control method over the regression. Here we look more closely at the counter-factual units created from both methods, the synthetic control unit, and the counter-factual unit driven from a regression. We compare the fit of the synthetic control unit with the prediction power of the estimated counter-factual from the regression for the pre-intervention period.

To do the empirical analysis, we consider recent sanctions against Iran as a suitable case
of policy intervention in an aggregate entity. The outcome variable of interest is GDP, and as mentioned earlier, we consider a dynamic panel data in which the value of GDP in each period depends on the lagged values. We think this is a reasonable model to consider for economic indicators such as GDP.

For the synthetic control empirical result we rely on the result provided in the first chapter. The study uses the synthetic control method to estimate the effect of intensification of sanctions in 2011 on Iran’s GDP and it estimates that Iran’s real GDP suffered a hit of more than 17 percent in the period between 2011 and 2014.

2.3.1 Sample and Data

Same as the first chapter, the empirical analysis is based on annual country level panel data for the period 1980-2014. As international sanctions were imposed in 2011, this yields a pre-intervention period of more than 30 years. Our control pool (called donor pool in the synthetic control method) includes eight OPEC member countries: Algeria, Ecuador, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, and the United Arab Emirates. Also, in order to increase the size of the pool, we add countries from major non-OPEC oil producer countries (i.e. Canada and China) as well as the rest of non-OPEC Iran’s neighbors with close economic similarities (i.e. Oman, Bahrain, and Turkey). The variables used in our analysis are listed in the data appendix along with descriptions and data sources. The outcome variable of interest, $Y_{jt}$ is the log of real GDP for country $j$ at time $t$. We also use GDP growth as the outcome variable of interest in some of the estimations. GDP is Purchasing Power Parity (PPP)-adjusted and measured in constant 2011 international dollars. Because our control countries are heavily dependent on rents from natural resources, for the pre-sanction predictors, we rely on a standard set of economic growth indicators for

---

2We left Venezuela and Iraq out of the pool due to economic fluctuations in these countries during the period of the analysis. We also left Angola out due to data limitations.
2.3.2 Difference-in-Difference

Ever since Ashenfelter and Card (1985) use the longitudinal structure of earnings of trainees and a comparison group to estimate the effectiveness of training for participants in the 1976 CETA programs, the use of the "Diff-in-Diff" technique has become very widespread. In another study, Card and Krueger (1994) evaluate the impact of the 1992 change in minimum wages on the unemployment rate in New Jersey. Using the difference in difference method, they provide simple estimates of the effect of the higher minimum wage by comparing the employment growth in New Jersey and Pennsylvania (where the minimum wage was constant). Unlike the synthetic control method that creates a weighted average of the donor control units, the diff-in-diff methods find controls with a high level of similarity with the treated unit, and hence comparison of the outcome variable of interest for the treated units with the value of the controls would provide a simple estimate of the effect of the treatment/policy intervention.

In generic term we may write the Diff-in-Diff model as below:

\[ y_{it} = \beta_0 + \beta_1(treated_i) + \beta_2(time_t) + \delta(treated_i \times time_t) + Z_{it}'\theta + \epsilon_{it} \]  \hspace{1cm} (2.23)

where \( treated_i \) is a dummy which is equal to 1 for the treated units and 0 for controls. The coefficient \( \beta_1 \) will pickup the default difference of \( y_{it} \) between treated unit and control. Variable \( time_t \) is a dummy equal to 1 for the treatment period (we include three difference dummies for three years of treatment in our case). The coefficient \( \beta_2 \) picks up the effect of time difference on \( y_{it} \). The coefficient of the interaction is interpreted as the effect of treatment. \( Z_{it} \) is the set of predictors which may be included in the regression. In our setup
we have three interaction terms. To be clear, we consider:

\[ GDP_{it} = \beta_0 + \beta_1(D1) + \beta_2(T2012) + \beta_3(T2013) + \beta_4(T2014) + \delta_1(D1 \times T2012) + \delta_2(D1 \times T2013) + \delta_3(D1 \times T2014) + Z_{it}'\theta + \epsilon_{it} \]  

(2.24)

Bertrand et al. (2004) show that with many years of data, we need to adjust the standard errors for auto-correlation. One simple remedy suggested by the authors is to cluster on the unit of observation panel identifier. We follow this suggestion by using a panel data regression instead of pooled OLS.
**Table 2.1: Difference in Difference Estimation Result**

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Robust standard errors in parentheses. The dependent variable is log GDP and GDP growth.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 
Table 2.1 summarizes the results of the diff-in-diff analysis. In the first three regressions the dependent variable is log GDP, and for the rest it is GDP annual growth. First regression is a simple diff-in-diff model with a dummy for Iran, 3 time dummies representing 3 consecutive years of sanction, and three interaction of time dummies and Iran dummy. The result of the sanctions is estimated to be a drop of 18.5 percent in 2012, 23.1 percent in 2013, and 20.1 percent for 2014. The estimated coefficient report a dramatic drop in GDP for all three years, however the third coefficient is not significant and the first and second values are significant at the 10 percent level. In the second column we add the predictors in the regression and in the third column, we consider time fixed effects for the entire period. The result does not follow the logical direction for the second and third regression. This might be due to the small sample. The identification of the diff-in-diff here comes from only three data points. We only have one treated unit in our case (Iran) and we only have 3 years of the treatment. This might not be in support of a diff-in-diff study. However when we choose annual growth of GDP to be outcome variable of interest the result of the diff-in-diff estimation becomes more in line with previous observed result. The more important point here is that in the diff-in-diff analysis, we ignore the dynamic term in the log GDP data generating process. Later in this chapter, we will see the weight of the dynamic term in the data generating process is strong and significant. We provide unit root and co-integration test later in this chapter and we address this matter in depth. However, as we can observe with the growth which follows a stationary process, the result of the diff-in-diff estimation is in line with previous result.

As mentioned above, in the fourth regression, we use a simple diff-in-diff analysis with the time dummies for sanctions period, the dummy for Iran, and the interactions. The effect of the first year of sanctions is reported to be a drop of 10.9 percent in the growth, it is further reduced by a drop of 3.074 percent in 2013, and it is followed by a positive growth of 2.428 in 2014. All the three coefficients in this regression are significant at 1 percent level.
In the fourth regression we add the predictors to the regression. The estimated effect of sanctions for is similar to the previous regression. In the first year Iran’s GDP growth drops by 10.19 percent, followed by a drop of 2.569 percent, and a positive growth of 2.802 percent for 2014. The estimated positive coefficient of 2014 is significant at the 10 percent level. The last column includes time dummies for the entire period of analysis. The effect of the first year of sanctions is reported to be a significant drop of 11.39 percent in the growth, further reduces by a drop of 3.693 percent in 2013, and a positive growth of 1.705 in 2014. The last coefficient is not significant.

As mentioned earlier, due to the fact that there is not as many treated unit in the data as the controls (in fact there is only one treated unit), and there is not as many years after treatment as pre-treatment, we believe the identification of the estimated diff-in-diff effect might be weak.

### 2.3.3 Fixed Effect and First Difference Model

Equivalent to equation 2.1 in the dynamic panel data model for country \( i \in 1, \ldots, J + 1 \) and for \( t \in 1, \ldots, T_0, \ldots, T \) we have in generic terms:

\[
y^N_{it} = \rho y^N_{it-1} + Z_{it}'\theta + X_j'\gamma + \delta_t + \mu_i + \epsilon_{it} \tag{2.25}
\]

and in our specific application:

\[
GDP_{it} = \rho GDP_{it-1} + X_{it}'\beta + \delta_t + \mu_i + \nu_{it} \tag{2.26}
\]

where GDP in this set up depends on the lagged value of itself, parameter \( \rho \) captures the effect of the lagged GDP, \( X_{it} \) is the set of predictors, same as those used in synthetic control method. Now to cancel out the countries fixed effects \( \mu_i \) we subtract the average of each
country.

\[ \widetilde{GDP}_{it} = \rho \widetilde{GDP}_{it-1} + \widetilde{X}_{it}' \beta + \widetilde{\delta}_t + \widetilde{\nu}_{it}. \] (2.27)

where \( \widetilde{GDP}_{it} = GDP_{it} - \overline{GDP}_i \) and the \( \overline{GDP}_i \) is the average of GDP for country \( i \) over the validation period (\( \overline{GDP}_i = GDP_{it} - \frac{1}{T}(GDP_{i1} + GDP_{i2} + \ldots + GDP_{iT}) \)). Due to the correlation between \( \widetilde{\nu}_{it} \) and \( \widetilde{GDP}_{it-1} \) (Nickell (1981), Bond (2002)), we use one period lagged values of the explanatory variables (\( X_{it-1} \)) as instruments.

Another approach to eliminate the fixed effects is suggested by Anderson and Hsiao (1981) in the form of the first difference approach:

\[ \ddot{GDP}_{it} = \rho \ddot{GDP}_{it-1} + \ddot{X}_{it}' \beta + \ddot{\delta}_t + \ddot{\nu}_{it}. \] (2.28)

where \( \ddot{GDP}_{it} = GDP_{it} - GDP_{it-1} \) and so on. In this setup, the first difference cancels out the fixed effects, however the transformed lagged dependent variable is still correlated with the error term. Anderson and Hsiao suggest using level instruments \( GDP_{it-2} \) or the lagged difference \( GDP_{it-2} - GDP_{it-3} \) as the instruments for the differences lagged endogeneous regressor \( GDP_{it} - GDP_{it-1} \). However, Arellano et al. (1989) suggest using levels due to lower variance and no points of singularities where a condition of \( \rho = 0 \) invalidates the instruments.

The estimators mentioned above are consistent with our assumptions, however in order to increase efficient in the next section we move to a more inclusive set of instruments and a more comprehensive dynamic panel data analysis.
2.3.4 GMM and System GMM Estimation

The Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998) dynamic panel estimators are very popular. They are general estimators designed for situations with: 1) small T, large N panels, meaning few time periods and many individuals; 2) a linear functional relationship; 3) a single left-hand-side variable that is dynamic, depending on its own past realizations; 4) independent variables that are not strictly exogenous, meaning correlated with past and possibly current realizations of the error; 5) fixed individual effects; and 6) heteroskedasticity and autocorrelation within individuals but not across them (e.g., see Roodman (2006)).

Arellano-Bond estimation starts by transforming all regressors, usually by differencing, and uses the Generalized Method of Moments (Hansen, 1982), and so is called Difference GMM. The Arellano-Bover/Blundell-Bond estimator augments Arellano-Bond by making an additional assumption, that first differences of instrument variables are uncorrelated with the fixed effects. This allows the introduction of more instruments, and can dramatically improve efficiency. It builds a system of two equations -the original equation as well as the transformed one- and is known as the System GMM estimator.

To open the methods mentioned above, let us go back to the general dynamic panel data model we consider:

\[
GDP_{it} = \beta_0 + \rho GDP_{it-1} + X_{it}'\beta + \delta_t + \mu_i + \nu_{it}
\]  

With the Arellano-Bond estimation, to improve efficiency, we can take the Anderson-Hsiao approach further, using longer lags of the dependent variable as additional instruments. So Arellano-Bond estimation starts with the first-difference transform (just like the Anderson Hsiao estimation discussed earlier) followed by a GMM estimator. If we assume a matrix $M_\Delta$ with the orthogonal of -1’s and sub-diagonal of 1’s just to the right, and the matrix $I_N$ the
identity matrix of order $N$ then the transformation is to multiply the model by $(M_\Delta \otimes I_N)$. This takes us to equation (2.28).

$$M_\Delta = \begin{bmatrix} -1 & 1 & 0 & 0 & \ldots \\ 0 & -1 & 1 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 \\ \vdots & \vdots & \vdots \\ 0 & \ldots & 0 & -1 & 1 \end{bmatrix}$$

The fixed effects are gone, but as mentioned earlier, the lagged dependent variable is still potentially endogenous as well as any predetermined variables in the regressors set that are not strictly exogenous become potentially endogenous. But longer lags of the regressors remain orthogonal to the error, and available as instruments.

Another possible transformation can be the “orthogonal deviations transform” Proposed by Arellano and Bover (1995), in which rather than subtracting the previous observation, we subtract the average of all available future observations. Like first-differencing, taking orthogonal deviations removes fixed effects. In a balanced panel the transformation can be done by multiplication of the model by transformation is to multiply the model by $(M_\perp \otimes I_N)$, where the matrix $I_N$ is the identity matrix of order $N$ and $M_\perp$ is as below. Because lagged observations of a variable do not enter the formula for the transformation, they remain orthogonal to the transformed errors, and available as instruments. On balanced panels, GMM estimators based on the two transforms return numerically identical coefficient estimates, holding the instrument set fixed (Arellano and Bover, 1995)³.

³Our result is robust to the choice of the transformation (FD or FOD, in order to avoid too many reported regressions we will not provide the result of this transformation in the tables.
A potential weakness in the Arellano-Bond DPD estimator was revealed in later work by Arellano and Bover (1995) and Blundell and Bond (1998). As Blundell and Bond (1998) demonstrate in simulations, if $y_{it}$ is close to a random walk, then Difference GMM performs poorly because past levels convey little information about future changes, so that un-transformed lags (levels) are weak instruments for transformed variables.

Note that we can also write the model above as:

$$\Delta GDP_{it} = (\rho - 1)GDP_{it-1} + X_{it}'\beta + \delta_t + \mu_i + \nu_{it} \quad (2.30)$$

So the model can equally be thought of as being for the level or increase of $y$. Therefore:

$$\Delta GDP_{it-1} = (\rho - 1)GDP_{it-2} + X_{it-1}'\beta + \delta_{t-1} + \mu_i + \nu_{it-1} \quad (2.31)$$

This will introduce more options for instruments as long as $\rho$ does not equal to 1. So where Arellano-Bond instruments endogenous first differences or orthogonal deviations with lagged levels, Blundell-Bond instruments levels with differences. For variables that follow a random walk process in fact, past changes may indeed be more predictive of current levels than past levels are of current changes, so that the new instruments are more relevant (Blundell and Bond, 1998, Roodman, 2006). Blundell-Bond estimation builds a stacked data set with twice the observations to use new moment conditions while retaining the Arellano Bond moments.
The matrix $M^+$ is as follow:

\[
M^+ = \begin{bmatrix}
M_* \\
I
\end{bmatrix}
\]

where $M_*$ can be $M_\Delta$ or $M_\perp$.

We used the methods mentioned above to estimate our model mentioned in equation (2.29). The results of the estimations of models mentioned above are summarized in Table 2.2.

\footnote{The notation for matrix $M$ is borrowed from Roodman (2006).}
Table 2.2: Dynamic Panel Data Model Estimation Result

<table>
<thead>
<tr>
<th></th>
<th>(FE)</th>
<th>(FD)</th>
<th>(AB)</th>
<th>(AB)</th>
<th>(BB)</th>
<th>(BB)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>lgdp</td>
<td>lgdp</td>
<td>lgdp</td>
<td>lgdp</td>
<td>lgdp</td>
<td>lgdp</td>
</tr>
<tr>
<td>Iran 2012</td>
<td>-0.121***</td>
<td>-0.097***</td>
<td>-0.117***</td>
<td>-0.111***</td>
<td>-0.123***</td>
<td>-0.114***</td>
</tr>
<tr>
<td></td>
<td>(0.0153)</td>
<td>(0.0138)</td>
<td>(0.0213)</td>
<td>(0.0159)</td>
<td>(0.0107)</td>
<td>(0.0117)</td>
</tr>
<tr>
<td>Iran 2013</td>
<td>-0.0659***</td>
<td>-0.0418</td>
<td>-0.0585***</td>
<td>-0.0616***</td>
<td>-0.0659***</td>
<td>-0.0666***</td>
</tr>
<tr>
<td></td>
<td>(0.0149)</td>
<td>(0.0419)</td>
<td>(0.0196)</td>
<td>(0.0147)</td>
<td>(0.00625)</td>
<td>(0.0112)</td>
</tr>
<tr>
<td>Iran 2014</td>
<td>0.00150</td>
<td>0.022</td>
<td>0.00808</td>
<td>-0.00451</td>
<td>-0.000283</td>
<td>-0.00414</td>
</tr>
<tr>
<td></td>
<td>(0.0152)</td>
<td>(0.058)</td>
<td>(0.0187)</td>
<td>(0.0161)</td>
<td>(0.00612)</td>
<td>(0.0112)</td>
</tr>
<tr>
<td>L.lgdp</td>
<td>0.901***</td>
<td>0.927***</td>
<td>0.966***</td>
<td>0.979***</td>
<td>0.992***</td>
<td>1.005***</td>
</tr>
<tr>
<td></td>
<td>(0.0573)</td>
<td>(0.317)</td>
<td>(0.0203)</td>
<td>(0.0199)</td>
<td>(0.0141)</td>
<td>(0.00867)</td>
</tr>
<tr>
<td>Log pop</td>
<td>0.0414</td>
<td>0.079</td>
<td>0.0466**</td>
<td>0.0680*</td>
<td>0.0108</td>
<td>-0.000139</td>
</tr>
<tr>
<td></td>
<td>(0.0284)</td>
<td>(0.138)</td>
<td>(0.0208)</td>
<td>(0.0378)</td>
<td>(0.0164)</td>
<td>(0.00306)</td>
</tr>
<tr>
<td>Rents</td>
<td>-0.128</td>
<td>-0.056</td>
<td>-0.0216</td>
<td>0.0951</td>
<td>-0.0224</td>
<td>-0.00575</td>
</tr>
<tr>
<td></td>
<td>(0.0947)</td>
<td>(0.094)</td>
<td>(0.0274)</td>
<td>(0.0647)</td>
<td>(0.0183)</td>
<td>(0.0261)</td>
</tr>
<tr>
<td>Trade</td>
<td>-0.00564</td>
<td>(-0.069)</td>
<td>-0.0529*</td>
<td>-0.0452</td>
<td>0.00822</td>
<td>0.0138</td>
</tr>
<tr>
<td></td>
<td>(0.0445)</td>
<td>(0.079)</td>
<td>(0.0322)</td>
<td>(0.0565)</td>
<td>(0.0247)</td>
<td>(0.0147)</td>
</tr>
<tr>
<td>Agriculture</td>
<td>-0.173</td>
<td>0.034</td>
<td>0.0300</td>
<td>-0.109</td>
<td>0.0169</td>
<td>0.0621</td>
</tr>
<tr>
<td></td>
<td>(0.203)</td>
<td>(0.233)</td>
<td>(0.127)</td>
<td>(0.140)</td>
<td>(0.0937)</td>
<td>(0.0625)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>279</td>
<td>265</td>
<td>272</td>
<td>272</td>
<td>286</td>
<td>286</td>
</tr>
<tr>
<td>Time Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>AR AR(2) (Pr &gt; a)</td>
<td>.</td>
<td>.</td>
<td>0.364</td>
<td>0.252</td>
<td>0.310</td>
<td>0.228</td>
</tr>
<tr>
<td>Overid. (Pr &gt; a)</td>
<td>.</td>
<td>.</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses. The dependent variable is log GDP.

Variables in the FD model are first-differenced.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 
CHAPTER 2.

The first three regressors are dummies representing Iran undergoing sanctions as of 2012, 2013, and 2014. For the predictors we again rely on a set of growth predictors that are standard in analysis of countries heavily dependent on natural resources rent. Specifically, we include log of population, and rents, trade, and agriculture value added as percentage of GDP. For the Fixed Effect and First Difference model we rely on the standard set of instrument for these models. For the Arellano-Bond and Blundell-Bond model we treat the lagged of log GDP as endogenous and other predictors as predetermined.

The effect of first year of sanctions on the country’s GDP is a negative effect from 9.7 percent to 12.28 percent. According to the fixed effect model:

\[
\begin{align*}
\Delta lGDP_{2012} &= -0.121 \\
\Delta lGDP_{2013} &= -0.0659 + 0.901 \times \Delta lGDP_{2012} = -0.175 \\
\Delta lGDP_{2014} &= 0.00150 + 0.901 \times \Delta lGDP_{2013} = -0.156.
\end{align*}
\]

Following the same calculation for the first difference model:

\[
\begin{align*}
\Delta lGDP_{2012} &= -0.097 \\
\Delta lGDP_{2013} &= -0.0418 + 0.927 \times \Delta lGDP_{2012} = -0.1317 \\
\Delta lGDP_{2014} &= 0.022 + 0.927 \times \Delta lGDP_{2013} = -0.1001.
\end{align*}
\]

For the Arellano Bond with time fixed effects:

\[
\begin{align*}
\Delta lGDP_{2012} &= -0.117 \\
\Delta lGDP_{2013} &= -0.0585 + 0.966 \times \Delta lGDP_{2012} = -0.1715 \\
\Delta lGDP_{2014} &= 0.00808 + 0.966 \times \Delta lGDP_{2013} = -0.1576.
\end{align*}
\]
For the Arellano Bond with no time fixed effects:

\[
\begin{align*}
\Delta \log GDP_{2012} &= -0.111 \\
\Delta \log GDP_{2013} &= -0.0616 + 0.979 \times \Delta \log GDP_{2012} = -0.1703 \\
\Delta \log GDP_{2014} &= -0.00451 + 0.979 \times \Delta \log GDP_{2013} = -0.1712.
\end{align*}
\]

For the Blundell Bond with time fixed effects:

\[
\begin{align*}
\Delta \log GDP_{2012} &= -0.123 \\
\Delta \log GDP_{2013} &= -0.0659 + 0.992 \times \Delta \log GDP_{2012} = -0.1879 \\
\Delta \log GDP_{2014} &= -0.000283 + 0.992 \times \Delta \log GDP_{2013} = -0.1867.
\end{align*}
\]

And finally for the Blundell Bond with no time fixed effects:

\[
\begin{align*}
\Delta \log GDP_{2012} &= -0.114 \\
\Delta \log GDP_{2013} &= -0.0666 + 1.005 \times \Delta \log GDP_{2012} = -0.1812 \\
\Delta \log GDP_{2014} &= -0.00414 + 1.005 \times \Delta \log GDP_{2013} = -0.1862.
\end{align*}
\]

The Arellano Bond test of AR(2) of \( \nu_{it} \) is reported in Table 2.2. If the idiosyncratic part of the error term \( \nu_{it} \) is serially correlated of order 1, then \( y_{it-2} \) will be endogenous to \( \nu_{it-1} \) and therefore would not serve as a good instrument. Because in Arellano Bond estimation we take first difference first, then of course the AR(1) process in the \( \Delta \nu_{it} \) is normal, so we look at the AR(2) test result of the differences error term (and the \( \epsilon_{it} \) includes fixed effects therefore is serially correlated). The result does not support the AR(2) process in the differenced error term both for AB and BB estimation.

The fitted values of the models estimated above are presented in Figures 2.1 to 2.4. So far we know that if outcome variable of interest follows a random walk-like process, BB
would perform better. That might be one reason for the better fit of the model, and higher prediction power that we can observe in Figure 2.4.
The estimation results in Table 2.2 raise a cautionary flag: the estimate of $\rho$, which is the slope of the lagged dependent variable, is close to 1 in every regression. This suggests that the dependent variable (log GDP) may well have a unit root. In the next subsection, we examine the issue of unit roots and co-integration in relation to these data.
2.3.5 Unit Root and Co-integration Tests

A. Unit root tests

We consider a panel-data model with a first-order auto-regressive component for our series:

\[ y_{it} = \rho_i y_{it-1}' + Z_{it}' \gamma_i + \epsilon_{it} \] (2.32)

where \( i \) indexes the units; \( t = 1, ..., T \) indexes the time; \( y_{it} \) is the variable being tested for unit root; \( \gamma_i \) is a vector of coefficients on \( Z_{it} \); the deterministic terms that control for panel-specific effects and linear time trends. Dependent on the test and specifications, \( Z_{it}' \gamma_i \) will provide the unit fixed effects, unit specific linear time trends. \( \epsilon_{it} \) is the error term. The test of the unit-root is to test the null hypothesis \( H_0 : \rho_i = 1 \) for all units \( i \) against the alternative \( H_a : \rho_i < 1 \). In some tests, the alternative may hold for one unit, for some it holds for a fraction of all units or all.

One of the key differences between different unit root tests is how they treat the auto-regressive parameter \( \rho_i \). Out of the 6 unit root tests available, the Levin-Lin-Chu test (Levin et al., 2002), Harris-Tsavalis test (Harris and Tzavalis, 1999), and Breitung test (Breitung, 2001, Breitung and Das, 2005) assume that all the units share the same auto-regressive parameter meaning \( \rho_i = \rho \) for all \( i \). However, if as an example, the variable being tested is economic growth rate, and we are testing whether economic growth rates of countries converges to a long run value, this restrictive assumption implies that the rate of convergence would be the same for all the countries (Maddala and Wu, 1999).

Another key difference is whether these tests assume \( N \) or \( T \) is fixed, and if not at what rate they tend to infinity. Hlouskova and Wagner (2006) provide an overview of these assumption and compare the performance of these test using Monte Carlo simulation. Another difference across these test is whether they perform with balanced or unbalanced data. The
first three tests mentioned above only perform with the balanced data. The Im-Pesaran-Shin test (Im et al. 2003) assumes $T$ and $N$ are fixed or $N$ can be infinite, assumes auto-regressive parameter is unit specific, and it performs well with unbalanced data. The Fisher type test (Choi 2001) assumes $T$ is not finite and $N$ can be both finite and infinite. The test assumes unit specific auto-regressive parameter and it performs well with unbalanced data. The last test, Hadri LM test (Hadri 2000) also assumes infinite $T$ and $N$ and it requires balanced data. The most appropriate test for our case of study seems to be the Im-Pesaran-Shin test. However, we also provide the result of Fisher type test in Table 2.3 below. The Hardi LM test is not feasible due to the missing values (the test requires strongly balanced data). We also will not consider the first three tests due to the reasons mentioned above. The series included in the tests are: log GDP, log population, trade, natural rents, and agriculture. As we can see in this table, log GDP and trade are two series that follow a unit root process.
Table 2.3: Unit Root Tests Results

<table>
<thead>
<tr>
<th>Tests</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Im-Pesaran-Shin Test:</td>
<td></td>
</tr>
<tr>
<td>Log GDP</td>
<td>1.0000</td>
</tr>
<tr>
<td>Log population</td>
<td>0.0009</td>
</tr>
<tr>
<td>Total natural rent(% of GDP)</td>
<td>0.0000</td>
</tr>
<tr>
<td>Trade(% of GDP)</td>
<td>0.2407</td>
</tr>
<tr>
<td>Agriculture(% of GDP)</td>
<td>0.0000</td>
</tr>
<tr>
<td>The Fisher Type Test:</td>
<td></td>
</tr>
<tr>
<td>Log GDP</td>
<td>1.0000</td>
</tr>
<tr>
<td>Log population</td>
<td>0.0000</td>
</tr>
<tr>
<td>Total natural rent(% of GDP)</td>
<td>0.0319</td>
</tr>
<tr>
<td>Trade(% of GDP)</td>
<td>0.2359</td>
</tr>
<tr>
<td>Agriculture(% of GDP)</td>
<td>0.0003</td>
</tr>
</tbody>
</table>

Note: For the Im-Pesaran-Shin Test: \( H_0 \): All panels contain unit roots and \( H^a \): Some panels are stationary. For the Fisher type test we have \( H_0 \): All panels contain unit roots and \( H^a \): At least one panel is stationary.

**B. Co-integration tests**

A non-stationary process wanders over time because it has time-varying first two moments (mean, variance, or both). Our variables are integrated of order one, meaning that we have stationary first-differences processes \( I(1) \), and we want to check if the linear combination of our several \( I(1) \) series is stationary and the series are co-integrated (Engle and Granger, 1987). If we find from our test that our series are co-integrated, it means in long run, they move together although they can each wander arbitrarily.

The panel data model considered for all the co-integration tests is as follow and for this
section we stick to the same notation:

\[ y_{it} = X_{it}'\beta_i + Z_{it}'\gamma_i + e_{it} \] (2.33)

For each unit \( i \) the predictors \( X_{it} \) is considered to be an \( I(1) \) process. \( \beta_i \) denotes the co-integrating vector, which may vary across units. \( \gamma_i \) is a vector of coefficients on \( Z_{it} \), the deterministic terms that control for panel-specific effects and linear time trends. Dependent on the test and specifications, \( Z_{it}' \) can be \( (1, t) \) where \( Z_{it}'\gamma_i \) will provide the unit fixed effects, unit specific linear time trends. \( e_{it} \) is the error term.

The common null hypothesis in the tests is that the dependent variable and predictors are not co-integrated. The tests check the co-integration by testing if \( e_{it} \) is non-stationary. If the null of non-stationary error term is rejected, it means \( Y_{it} \) and \( X_{it} \) are co-integrated.

We will provide the result of three co-integration tests: The Kao test, the Pedroni test, and the Westerlund test. The different DF statistics that are reported by the first two tests use different regression frameworks to incorporate the serial correlation in \( e_{it} \). The VA test reported by the latter two, do not require any accommodations for serial correlation. All different Dicky Fuller t test statistics that are reported with these tests are constructed by fitting a version of the model (2.33) using ordinary least squares, obtaining the predicted residuals, and then fitting the DF regression model:

\[ \hat{e}_{it} = \rho \hat{e}_{i,t-1} + \nu_{it} \] (2.34)

where \( \rho \) is the AR parameter and \( \nu_{it} \) is a stationary error term. The DF \( t \) and un-adjusted DF \( t \) check if \( \rho = 1 \). On the other hand, the Modified DF \( t \) and un-adjusted Modified DF \( t \) check if \( \rho - 1 = 0 \), and non-stationarity under the null hypothesis causes these two to be different.

For the PP \( t \) statistic reported by Pedroni test, first we fit the model (2.33) using ordinary
least square, and then we fit the DF regression model below which is slightly different than above:

\[ \hat{e}_{it} = \rho_i \hat{e}_{i,t-1} + \nu_{it} \]  

(2.35)

In this model, we have unit specific $\rho$, and a PP $t$ tests if $\rho_i = 1$, and a modified pp $t$ tests if $\rho_i - 1 = 0$.

The Augmented DF $t$ uses additional lags of the error terms to incorporate serial correlation. We still check if $\rho = 1$ but the ADF regression model is :

\[ \hat{e}_{it} = \rho_i \hat{e}_{i,t-1} + \sum_{j=1}^{p} \rho_{ij} \Delta \hat{e}_{i,t-1} + \nu_{it}^* \]  

(2.36)

where $\Delta \hat{e}_{i,t-1}$ is the $j^{th}$ lag of the first difference of $\hat{e}_{it}$ and $j = 1,...,p$ where $p$ is the number of lag differences.

To be more clear, the Kao test assumes $\beta_i = \beta$ meaning that there is a co-integration vector that is the same across all the units, and there is a unit fixed effect and no linear time trend ($Z_{it} = (1,0)$). As mentioned above, the null hypothesis of the Kao test is that there is no co-integration among the series. So, the co-integration relationship is :

\[ y_{it} = X_{it}' \beta + \gamma_i + \epsilon_{it} \]  

(2.37)

The tests derived by Pedroni on the other hand, allow for unit-specific co-integrating vectors $\beta_i$. Also the DF regression model incorporates heterogeneous unit-specific AR coefficients ($\rho_i$), although the tests allows to restrict the AR coefficient to be the same across units. Considering a linear time trend is also possible with this test. Same as the Kao test, the null hypothesis is no co-integration between dependent variable and covariates.

In the Westerlund tests similar to Pedroni’s tests, the AR parameter is considered to be
unit-specific ($\rho_i$). In contrast to the Kao and Pedroni tests that check the null hypothesis against an alternative of “all series are co-integrated”, this test checks the null against the alternative that some of the series are co-integrated. However, the test allows for the alternative of “all series are co-integrated” under the restriction $\rho_i = \rho$. So the Westerlund derived two Variance Ratio statistics one for unit-specific AR parameter and one for same AR parameter across all units.
Table 2.4: Co-integration Tests Results

<table>
<thead>
<tr>
<th>Tests</th>
<th>Statistics</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kao Tests</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Modified Dickey-Fuller t</td>
<td>2.8071</td>
<td>0.0025</td>
</tr>
<tr>
<td>Dickey-Fuller t</td>
<td>3.0129</td>
<td>0.0013</td>
</tr>
<tr>
<td>Augmented Dickey-Fuller t</td>
<td>3.2682</td>
<td>0.0005</td>
</tr>
<tr>
<td>Unadjusted modified Dickey-Fuller t</td>
<td>2.5224</td>
<td>0.0058</td>
</tr>
<tr>
<td>Unadjusted Dickey-Fuller t</td>
<td>2.4996</td>
<td>0.0062</td>
</tr>
<tr>
<td>Pedroni Tests (Same AR Parameter):</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Modified variance ratio</td>
<td>-3.8702</td>
<td>0.0001</td>
</tr>
<tr>
<td>Modified Phillips-Perron t</td>
<td>1.6607</td>
<td>0.0484</td>
</tr>
<tr>
<td>Phillips-Perron t</td>
<td>2.0511</td>
<td>0.0201</td>
</tr>
<tr>
<td>Augmented Dickey-Fuller t</td>
<td>1.8093</td>
<td>0.0352</td>
</tr>
<tr>
<td>Westerlund Tests (Against All Panels):</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance ratio</td>
<td>-2.5285</td>
<td>0.0057</td>
</tr>
<tr>
<td>Westerlund Tests (Against Some Panels):</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance ratio</td>
<td>-2.5644</td>
<td>0.0052</td>
</tr>
</tbody>
</table>

Table 2.4 above provides the result of the co-integration tests. The series included in the tests are: log GDP and trade, the two non-stationary series in our analysis. As we can see in the table, all test statistics reject the null hypothesis of no co-integration in favor of the alternative hypothesis of the existence of a co-integrating relation among the series.

In principle, regression based on non-stationary panel variables may prove spurious as in the case of time-series. However Kao (1999) showed that estimates of the structural parameter binding two independent non-stationary variables converges to zero in the case of panel data, whereas in the case of time series it is a random variable. This means that
although non-stationary panel data may lead to biased standard errors, the point estimations of the value of parameters are consistent. We also have co-integrated series in our data so the previous results in Table 2.2 will hold. However, we will provide the same panel data analysis for the growth of GDP as well; in this analysis we also consider growth of trade as a predictor instead of levels.
Table 2.5: Dynamic Panel Data Model Estimation Result

<table>
<thead>
<tr>
<th></th>
<th>(FE) Growth</th>
<th>(FD) Growth</th>
<th>(AB) Growth</th>
<th>(AB) Growth</th>
<th>(BB) Growth</th>
<th>(BB) Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iran 2012</td>
<td>-12.13***</td>
<td>-6.615***</td>
<td>-12.41***</td>
<td>-10.89***</td>
<td>-11.16***</td>
<td>-9.98***</td>
</tr>
<tr>
<td></td>
<td>(2.211)</td>
<td>(1.94)</td>
<td>(0.986)</td>
<td>(0.217)</td>
<td>(0.994)</td>
<td>(0.364)</td>
</tr>
<tr>
<td>Iran 2013</td>
<td>-2.93</td>
<td>0.60</td>
<td>-3.94***</td>
<td>-2.18***</td>
<td>-0.561</td>
<td>0.905</td>
</tr>
<tr>
<td></td>
<td>(4.891)</td>
<td>(3.757)</td>
<td>(1.35)</td>
<td>(0.633)</td>
<td>(1.375)</td>
<td>(1.085)</td>
</tr>
<tr>
<td>Iran 2014</td>
<td>0.27</td>
<td>4.72**</td>
<td>-0.348</td>
<td>1.027***</td>
<td>2.054***</td>
<td>2.87***</td>
</tr>
<tr>
<td></td>
<td>(2.339)</td>
<td>(2.289)</td>
<td>(1.188)</td>
<td>(0.282)</td>
<td>(0.579)</td>
<td>(0.294)</td>
</tr>
<tr>
<td>L.Growth</td>
<td>0.198</td>
<td>-0.065</td>
<td>0.12***</td>
<td>0.156***</td>
<td>0.295***</td>
<td>0.383***</td>
</tr>
<tr>
<td></td>
<td>(0.304)</td>
<td>(0.216)</td>
<td>(0.036)</td>
<td>(0.0334)</td>
<td>(0.104)</td>
<td>(0.098)</td>
</tr>
<tr>
<td>Pop Growth</td>
<td>0.375*</td>
<td>0.629</td>
<td>0.417</td>
<td>0.216</td>
<td>0.269</td>
<td>0.354*</td>
</tr>
<tr>
<td></td>
<td>(0.205)</td>
<td>(0.552)</td>
<td>(0.315)</td>
<td>(0.036)</td>
<td>(0.241)</td>
<td>(0.197)</td>
</tr>
<tr>
<td>Rents</td>
<td>2.571</td>
<td>15.929**</td>
<td>4.89**</td>
<td>12.1***</td>
<td>-4.197**</td>
<td>1.888</td>
</tr>
<tr>
<td></td>
<td>(4.554)</td>
<td>(7.886)</td>
<td>(1.96)</td>
<td>(2.37)</td>
<td>(2.035)</td>
<td>(2.033)</td>
</tr>
<tr>
<td>Trade Growth</td>
<td>-7.64</td>
<td>-14.39**</td>
<td>-8.92</td>
<td>-2.94</td>
<td>-7.636**</td>
<td>-0.086*</td>
</tr>
<tr>
<td></td>
<td>(9.261)</td>
<td>(6.618)</td>
<td>(5.60)</td>
<td>(7.748)</td>
<td>(5.809)</td>
<td>(7.405)</td>
</tr>
<tr>
<td>Agriculture</td>
<td>20.39**</td>
<td>-5.317</td>
<td>21.10**</td>
<td>-1.71</td>
<td>7.705*</td>
<td>8.876*</td>
</tr>
<tr>
<td>N</td>
<td>280</td>
<td>271</td>
<td>279</td>
<td>279</td>
<td>293</td>
<td>293</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses. The dependent variable is GDP Annual Growth.

Variables in the FD model are first-differenced.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 
Same as Table 2.2, the first column provides the result of a Fixed Effect model, the second column provides the result of the first difference model, and column 3 to 6 report the result of the Arellano Bond and Blundell Bond models with and without time fixed effects. The result of the table is in line with previous result we obtained earlier in this chapter. As we can see the coefficient of the lagged term is not close to one. The effect of sanction on Iran’s growth is reported to be from -6.6 to -12.41 percent for the first year. For 2013, the coefficients are negative for most of the regressions. for 2014, all of the models report a positive coefficient. The actual growth of is Iran is reported to suffer a -7.4 percent drop in 2012, followed by a -0.2 percent drop in 2013, and a change of a positive 4.6 percent for 2014. According to all the regressions in the table except the first difference model, the negative effect of sanctions is reported to be higher at least for the first year. The result of the AR test does not show a dependency of the idiosyncratic error term to the lagged values of the growth which are being used as instruments, and the result of the over-identification test shows the in dependency of the instruments to the included predictors.

2.4 Conclusion

In comparative case studies we need similarities in the covariates between the treated unit and the controls. The synthetic control method creates a control unit which resembles the values of outcome variable as well as predictors almost perfectly. However, the product of the method is a point estimate with no estimation of the underlying distribution. We compare the result of the synthetic control method obtained in the first chapter with a traditional regression framework. We compare the method with a Diff-in-Diff regression framework, as well as a dynamic panel data analysis. We also show that the synthetic control method provides an unbiased estimator if the outcome variable follows a dynamic panel data model.
Chapter 3

A Monte Carlo Analysis of
Robustness of Synthetic Control
Method and Dynamic Panel
Estimation

We design a Monte Carlo study to compare the methods we used in previous chapters more in depth. We involve fewer donor countries in the Monte Carlo Analysis due to the missing values of the predictors for a substantial period of time. We have Iran as the treated unit, and the donor pool consists of Algeria, Ecuador, Saudi Arabia, China, Turkey, and Nigeria. Similar to the first chapter, the empirical analysis is based on annual country level panel data, but for the period 1990-2014.

The set up of the Monte Carlo study is as follows. We assume the dynamic panel data model below

$$y_{it} = \rho y_{i,t-1} + X_{it}'\beta + D_{it}'\kappa + \mu_i + \nu_{it} \quad (3.1)$$
in which $y_{it}$ is the outcome variable (log GDP, as well as Growth) for country $i$ at time $t$. $x_{it}$ is the set of predictors, $D_{it}$ is the set of three dummies which equal to one for Iran for 2012, 2013, and 2014. $\mu_i$s are countries fixed effects. We estimate the model above for the new donor pool. An estimation of the equation (3.1) provides $\hat{\rho} = 1.0054$, $\hat{\beta}_{agriculture} = 0.062$, $\hat{\beta}_{trade} = 0.0136$, $\hat{\beta}_{rents} = -0.00531$, $\hat{\beta}_{population} = -0.000139$, $\hat{\kappa}_{2012} = -0.114$, $\hat{\kappa}_{2013} = -0.0662$, $\hat{\kappa}_{2014} = -0.0037$, and $\hat{\sigma}_\nu = 0.0529$. We calculate

$$\hat{\mu}_i = y_i - \hat{\rho}y_{i,-1} - X'_{it}\hat{\beta} + D'_{it}\hat{\kappa}$$

(3.2)

and we use $X_{it}$ the set of predictors we have in the actual data set for $i = 1, ..., 7$ and $t = 1, ..., T$. We have $\hat{\mu}_i = 0.0155$, $\hat{\sigma}_\mu = 0.0136$ as the mean and standard deviation of the seven values of the $\hat{\mu}_i$ calculated from equation (3.2). For the Monte Carlo replications, we draw $\mu_i$ from $N(\hat{\mu}_i, \hat{\sigma}_\mu^2)$ where the mean and standard error are calculated from equation (3.2). Moreover, for each replication we draw $\nu_{it}$ from $N(0, \hat{\sigma}_\nu^2)$ where the standard error is estimated from equation (3.1).

We generate the outcome variable using all the information put together. For $y_{i0}$ we use actual values of the outcome variable for the first period of the analysis. Then, for $i = 1, ..., 7$ and $t = 1, ..., T$, we generate a Monte Carlo value for the outcome variable for each replication using $\hat{\rho}$, $\hat{\beta}$, $\hat{\kappa}$, $\hat{\sigma}_\nu$, $\mu_i$, and $\nu_{it}$ using equation (3.3) below:

$$y_{it,MC} = \hat{\rho}y_{i,t-1,MC} + X'_{it}\hat{\beta} + D'_{it}\hat{\kappa} + \mu_i + \nu_{it}$$

(3.3)

Now using the Monte Carlo values for the outcome variable we estimate different models and compare the methods we discussed in previous chapter. We estimate a dynamic panel data model using Blundell Bond method (as it was the best approach in chapter 2). We also use the Monte Carlo values and run a synthetic control analysis.
We also do the same analysis with Growth instead of GDP. We use the Blundell Bond estimation result for growth as well. The list of the parameters included for growth is as follow: \( \hat{\rho} = 0.38, \hat{\beta}_{\text{agriculture}} = 8.88, \hat{\beta}_{\text{trade growth}} = -0.086, \hat{\beta}_{\text{rents}} = 1.89, \hat{\beta}_{\text{population growth}} = 0.354, \hat{\kappa}_{2012} = -9.98, \hat{\kappa}_{2013} = 0.090, \hat{\kappa}_{2014} = 2.912, \hat{\mu} = -3.23, \hat{\sigma}_\mu = 2.03, \) and \( \hat{\sigma}_\nu = 5.52. \)

As discussed earlier, the caveat of the synthetic control method is that it only gives us one point estimate of the effect of the intervention. The method does not provide any assumption for the underlying distribution of the estimator; there is no estimation of the standard error, and the method lacks any significance analysis. We want to use the benefit of the replication with the Monte Carlo study to explore more.

In the previous chapter, we provided an “unbiasedness” analysis showing that if the outcome variable of interest follows a dynamic panel data model the synthetic control estimator is an unbiased estimator. With the Monte Carlo analysis, the goal in this chapter is to see how well the method would perform if we replicate the intervention. The goal is to estimate a standard error of the estimation, and also check the robustness of the methods.

On the other hand, we picked a dynamic panel model to represent a traditional regression framework. This model seems to be appropriate in comparison with the synthetic control method, because usually the synthetic control method is used to study an aggregate level effect of a policy intervention on macro variables. So with the Monte Carlo study, we also examine the performance of the panel data model. One of the most important assumptions of this model is the orthogonality of the units fixed effects and the idiosyncratic error term. If this assumption or any of the assumptions of the dynamic panel model does not hold, we would observe a distance between what we set to be the “true” coefficients and the ones we will get from the Monte Carlo replications. The result of the Monte Carlo analysis is provided in Table 3.1.
Table 3.1: Monte Carlo Analysis, 100 Replications

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>SE</th>
<th>Total Effect</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>a. DPD With Log GDP:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iran 2012</td>
<td>-0.117**</td>
<td>0.054</td>
<td>-0.117</td>
<td>0.054</td>
</tr>
<tr>
<td>Iran 2013</td>
<td>-0.071*</td>
<td>0.056</td>
<td>-0.191</td>
<td>0.075</td>
</tr>
<tr>
<td>Iran 2014</td>
<td>0.002</td>
<td>0.054</td>
<td>-0.187</td>
<td>0.097</td>
</tr>
<tr>
<td><strong>b. SCM With Log GDP:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iran 2012</td>
<td>-0.109</td>
<td>0.231</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iran 2013</td>
<td>-0.196</td>
<td>0.229</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iran 2014</td>
<td>-0.203</td>
<td>0.238</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>c. DPD With GDP Growth:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iran 2013</td>
<td>1.764</td>
<td>6.007</td>
<td>-5.203</td>
<td>7.068</td>
</tr>
<tr>
<td>Iran 2014</td>
<td>1.677</td>
<td>4.925</td>
<td>-0.999</td>
<td>6.428</td>
</tr>
<tr>
<td><strong>d. SCM With GDP Growth:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iran 2012</td>
<td>-13.004</td>
<td>8.205</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iran 2013</td>
<td>-4.516</td>
<td>8.639</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iran 2014</td>
<td>0.473</td>
<td>6.393</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>RMSPE SE</strong></td>
<td></td>
<td></td>
<td>0.095</td>
<td>0.047</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01.

SMC stands for the Synthetic Control Method and DPD stands for the Dynamic Panel Data model.
The result of the 100 replications for the dynamic panel data models is as follow:

\[
\begin{align*}
\Delta LGDP_{2012} &= \frac{1}{100} \sum_{r=1}^{100} \hat{\kappa}_{2012r} = -0.117 \\
\Delta LGDP_{2013} &= \frac{1}{100} \sum_{r=1}^{100} [\hat{\kappa}_{2013r} + \hat{\rho}_r \times \hat{\kappa}_{2012r}] = -0.196 \\
\Delta LGDP_{2014} &= \frac{1}{100} \sum_{r=1}^{100} [\hat{\kappa}_{2014r} + \hat{\rho}_r \times \hat{\kappa}_{2013r}] = -0.188.
\end{align*}
\]

Following the same calculation for growth we have:

\[
\begin{align*}
\Delta Growth_{2012} &= -13.67 \\
\Delta Growth_{2013} &= -5.203 \\
\Delta Growth_{2014} &= -0.999.
\end{align*}
\]

For the synthetic control method:

\[
\begin{align*}
\Delta LGDP_{2012} &= -0.109 \\
\Delta LGDP_{2013} &= -0.196 \\
\Delta LGDP_{2014} &= -0.203.
\end{align*}
\]

\[
\begin{align*}
\Delta Growth_{2012} &= -13.04 \\
\Delta Growth_{2013} &= -4.516 \\
\Delta Growth_{2014} &= 0.473.
\end{align*}
\]

As mentioned in previous chapters, by solving an optimization problem to minimize RMSPE, synthetic control suffers from lack of providing a distribution for the estimates and any standard error estimation. As we expected, the point estimates of the Synthetic Control method over many replications are in line with the true estimates. However there is a large
variation in the point estimates over replications and we obtain large standard errors. In other word, in contrast to the dynamic panel data method, the coefficients provided by the Synthetic Control method are insignificant.

A second conclusion suggested by the result in Table 3.1 is the following. The standard errors of the synthetic control estimates are more in line with those of the dynamic panel data estimation when the dependent variable is GDP growth than when the dependent variable is log GDP. Tentatively, we conclude that synthetic control estimates are much less robust when the variable under study contains a unit root. We leave it for a future study to explore this in greater detail.

### 3.1 Sensitivity Analysis

#### 3.1.1 Before and After the Intervention, RMSPE Analysis

The result provided in the previous section mainly refers to the post intervention period. We can also study the synthetic control method for pre-intervention period by analyzing the RMSPE as well as the dynamic of the donor pool. The RMSPE for Iran over 100 replications is 0.095. We explain below how we study this number.

In chapter 1 we provided a “In space” placebo study in which we assigned the sanctions to one of the donor countries iteratively and compare the gap plot of Iran with the ones driven from this exercise. RMSPE represents how well fitted the synthetic control method is able to produce a control unit. The goal of this exercise was to provide a placebo distribution for the estimator, and to confirm that the estimated effect of intervention for Iran is an outlier in the placebo distribution for countries with or without well-fitted synthetic control unit. Here, with having the benefit of replication, we repeat this placebo assignment. We iteratively assign the treatment to one of the donor countries, and we run the synthetic
control method with 100 replications. We preserve RMSPE for each of the 7 countries. Figure 3.1 to 3.7 below provide a density function for the RMSPE for the countries in the pool; Figure 3.3 refers to Iran. For Ecuador and China, the range of the error is larger than all other five countries; for these countries finding a synthetic control as a weighted average of other donors is difficult. The reason is that China has the largest economy in terms of gross domestic product among all the donors, and Ecuador has the smallest. Synthetic control is constructed as the weighted average of the donors with weights between zero and one. Therefore, the construction of the synthetic control unit from the donors is not plausible.

![Figure 3.1: Density Function of the RMSPE for Algeria, 100 Replications.](image1)

![Figure 3.2: Density Function of the RMSPE for Ecuador, 100 Replications.](image2)
Figure 3.3: Density Function of the RMSPE for Iran, 100 Replications.

Figure 3.4: Density Function of the RMSPE for Nigeria, 100 Replications.

Figure 3.5: Density Function of the RMSPE for Saudi Arabia, 100 Replications.
Over 100 replications, the density function of the Iran’s RMSPE seems to be similar to those of the other four countries: Algeria, Nigeria, Saudi Arabia, and Turkey. For Ecuador and China, the synthetic control is not performing well and we observe larger values of RMSPE over 100 replications.

We remove the two countries with less fitted synthetic control unit (Ecuador and China). We provide the density function of the RMSPE of all the donors combined (excluding Iran) in Figure 3.8 below. Note that Iran’s value of the predicted error is 0.09. This value is not an outlier in the distribution which 5 donor countries over 100 repeated trials. This means that the synthetic control method is working well for all the remaining donors, and is providing a well fitted synthetic control for the pre-intervention period. Therefore, the analysis of
the post-intervention effects which we will provide in the next section is reasonable. In the next section, we compare the placebo intervention effects for the donor countries, and this comparison only would be logical if we have well fitted synthetic control units for pre-intervention period.

![RMSPE Density Function, All Countries Excluding Iran](image)

Figure 3.8: Density Function of the RMSPE - All Donors Combined, 100 Replications.

### 3.1.2 Before and After the Intervention, Density Functions of the Placebo Effects

We already observed large variation in the annual effects that are reported in Table 3.1 by the synthetic control method. However, we expand the placebo studies and we look at the reported placebo effects of sanction for all the donor countries. Figure 3.9 provides the density function of the estimated placebo effects of the donor countries for year 2012. Each donor is treated for 100 replications. Figure 3.10 provides the same information for year 2013, and Figure 3.11 provides the information for year 2014.
Iran’s cumulative effect of sanction on log GDP, predicted by the synthetic control analysis over 100 replications is estimated to be -0.109 for 2012, followed by an estimate of
-0.196 for 2013 and -0.203 for 2014 according to Table [3.1]. The critical values of the density function for $\alpha = 0.05$ for 2012, 2013, and 2014 are -0.339, -0.414, and -0.445. Therefore, in comparison to the distribution of the placebo effect in Figure [3.9] [3.10] and [3.11], Iran’s effect is not statistically significant. We should note that as we move to the last year of the analysis, 2014, the cumulative effect of sanction on Iran becomes more widely spread out around the center of the distribution of the placebo effects as seen in Figure [3.11]. Also, all the distribution of the placebo effects for 2012, 2013, and 2014 are centered around zero; this shows the method correctly does not report any effect on average for the donor countries.

### 3.1.3 Sensitivity Analysis, Assignment of the Intervention

In this exercise, we iteratively start by changing the assignment of Iran’s sanctions to one of the donor countries. So, in the Monte Carlo we assign the intervention to one of the donor countries in the data generating process, and we estimate a placebo sanction for that donor country. In another trial, we do not assign any treatment to the country in the data generating process, but we treat the unit to be intervened upon and we look at the reported effect of the sanctions. Table [3.2] summarizes the result of this exercise. Each number is driven from 100 Monte Carlo replications. For Algeria, one time we assign Iran’s sanctions in the data generating process, we estimate the effect of the assigned sanctions on this country, and one time we do not assign any treatment and we will look at the reported effect if any. For 2012 and for Algeria when assigned the sanction, the dynamic panel data reports significant coefficients similar to those of Iran, and when there is no assigned sanctions, the method reports almost 0 as the effect of sanctions. The synthetic control method on the other hand, reports smaller effect for 2012 when there is no assigned sanctions in the data generating process, and reports larger numbers when the country is assigned to the sanctions. Note that the RMSPE which refers to pre-sanction disparity between the synthetic unit and actual unit is the same number for both cases for all the countries.
The result of this exercise for all the countries in the donor pool is similar to Algeria. The dynamic panel data reports significant and very similar numbers for Ecuador, Nigeria, Saudi Arabia, China, and Turkey as the effect of the sanctions, when actually we assign the sanctions to them in the data generating process, while the method reports almost 0 for all countries as the effect of the sanctions when no sanctions had been assigned to the country in the data generating process. However, there is a large variation in the result reported by the synthetic control method.

Table 3.2: Sensitivity Analysis, Varying the Intervention Unit

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<td>2013</td>
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<td>0.168</td>
<td>0.187</td>
<td>0.205</td>
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</tr>
</tbody>
</table>

Each value are averaged for 100 trials.
The second number below each coefficient is the standard error over 100 replications.
The first three columns report the result of the dynamic panel data regression.
The second three columns report the synthetic control method result.
CHAPTER 3.

3.1.4 Sensitivity Analysis, Donor Pool Size

We reduced the donor pool size from 13 units to 7 (including Iran) to have a precise Monte Carlo analysis and reduce the issue with missing values. This reduction had an insubstantial effect on the estimated values. Here, we want to study the sensitivity of our methods to the sample size (donor pool size in case of the synthetic control). The first row of Table 3.3 provides another round of 100 replications with all the donor countries same as previous trial reported in Table 3.1. We also report the average of the weights on each donor in this table (W1 to W7). As we can see the sum of the weights are equal to one. In the first row the RMSPE is 0.095.

In order to evaluate the sensitivity of the methods to the sample size and the dynamic of the donor pool, we remove one of the donors one by one and we rerun the Monte Carlo study. The result is reported in the second to seventh row of Table 3.3. As we can see, the result of the dynamic panel data is almost exactly the same as the one with all the donors included. The synthetic control methods reports similar result but with a larger variation. Also, the prediction error of the synthetic control increases by reducing one donor.

We extend this exercise more by removing 2 donors from the donor pool. Following rows of Table 3.3 reports the result of this exercise with all possible combinations of the donor. As we can see the dynamic panel data, with fewer number of observations still reports the same coefficients and is insensitive to the removal of 2 donors.

We reduce the sample size and finally we only keep 2 units in the donor pool. The result of the methods with only 2 donors is reported in the last row. This gives the dynamic panel data model 24 years of data for only 3 units (including Iran) for each iteration. But still the model is showing insensitivity to the small sample size. However, the average of the RMSPE of the synthetic control method over the 100 replications is very large.
Table 3.3: Sensitivity Analysis, Donor Pool Size

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<th></th>
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### Table 3.1: Summary Statistics for the Donor Countries

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### Notes
- Numbers are averaged for 100 replications. W1 to W7 are the weights on the donor countries; note that country 3 is the treated unit (“Iran”).
- If no weight is reported that unit is left out of the analysis.
3.2 Conclusion

In this chapter we discuss the performance of the methods we used in previous chapters over many replications. We use a Monte Carlo generated values of GDP and we run a synthetic control method, and estimate a dynamic panel data model over repeated trials. We showed in chapter 2, the synthetic control estimator can be an unbiased estimator if the underlying model of the outcome variable of interest is a dynamic panel data. In this chapter, we examine the robustness of the method. We conclude that the dynamic panel data model seems to be performing well with the macro level aggregate data, and the assumptions are appropriate. However, for the synthetic control method we observe large standard error in the estimated values. If we translate that to a significance analysis, this means that even though we observe meaningful values reported as the effect of the intervention, they are not statistically significant.
Appendix

The data source employed for the analysis are as follow:


Table A.1 to A.15 provide descriptive statistics:
Table A.1: Descriptive Statistics

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<tr>
<th>Variable</th>
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<th>Max</th>
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### Table A.2: Descriptive Statistics, Algeria

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<td>0.33</td>
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<td>Growth</td>
<td>3.11</td>
<td>4.89</td>
<td>-2.37</td>
<td>9.63</td>
</tr>
<tr>
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<td>33.56</td>
<td>3.17</td>
<td>30.58</td>
<td>38.54</td>
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Table A.6: Descriptive Statistics, Nigeria

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<th>Max</th>
</tr>
</thead>
<tbody>
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<td>GDP</td>
<td>431.84</td>
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<td>1000.87</td>
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<tr>
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<td>8.39e+07</td>
<td>1.77e+08</td>
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<td>10.04</td>
<td>63.52</td>
</tr>
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<td>54.38</td>
<td>15.12</td>
<td>23.72</td>
<td>81.81</td>
</tr>
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<td>Industry</td>
<td>37.78</td>
<td>8.14</td>
<td>24.95</td>
<td>52.99</td>
</tr>
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<td>20.24</td>
<td>48.57</td>
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<td>7.29</td>
<td>-10.75</td>
<td>33.74</td>
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<td>54.82</td>
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Table A.7: Descriptive Statistics, Saudi Arabia

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<th>Max</th>
</tr>
</thead>
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<td>1532.56</td>
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<td>9912917</td>
<td>3.09e+07</td>
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<td>11.81</td>
<td>17.40</td>
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<tr>
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<td>75.60</td>
<td>11.20</td>
<td>56.47</td>
<td>96.10</td>
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<td>37.82</td>
<td>71.49</td>
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<td>.99</td>
<td>6.34</td>
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<td>7.99</td>
<td>-20.73</td>
<td>17.01</td>
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<td>57.25</td>
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Table A.8: Descriptive Statistics, UAE

<table>
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<td>579.97</td>
</tr>
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<td>3217865</td>
<td>9086139</td>
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</tr>
<tr>
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<td>30.42</td>
<td>89.86</td>
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<td>0.64</td>
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<td>3.92</td>
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<td>9.84</td>
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Table A.9: Descriptive Statistics, Qatar

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<td>286.97</td>
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<td>613720</td>
<td>2172065</td>
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<td>5.05</td>
<td>17.37</td>
<td>32.49</td>
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<td>69.76</td>
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<td>3.72</td>
<td>26.17</td>
</tr>
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## Table A.10: Descriptive Statistics, Libya

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<td>45.86</td>
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<td>66.08</td>
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## Table A.11: Descriptive Statistics, China

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<tr>
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<td>1.31</td>
<td>19.003</td>
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<td>Trade</td>
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<td>3.91</td>
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</tr>
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<tbody>
<tr>
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Table A.13: Descriptive Statistics, Turkey

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</thead>
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<td>7.75e+07</td>
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<tr>
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<td>.35</td>
<td>0.12</td>
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</tr>
<tr>
<td>Trade</td>
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<td>11.03</td>
<td>17.09</td>
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<td>2.98</td>
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</tr>
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</tr>
<tr>
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<td>63.91</td>
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Table A.14: Descriptive Statistics, Oman

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</thead>
<tbody>
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<td>38.67</td>
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<td>100.31</td>
<td>128.22</td>
</tr>
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<tr>
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Table A.15: Descriptive Statistics, Canada

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</thead>
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<td>1488.33</td>
</tr>
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<td>66.92</td>
</tr>
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