Do Immigrants Bring Crime? A Lesson from a Natural Experiment

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Abstract

Objective: Most of recent Syrian refugees are hosted in Turkey, which has more than 3.6 million people. In this study, we investigated the impact of refugees on the host country's crime rate in the context of the Syrian refugee flow into Turkey.

Method: Using statistics from Turkish Penal Institutions for the time period from 2010 to 2014, we applied the difference-in-difference estimation method. In addition, we implemented a synthetic control group for the analysis, additional to commonly used control regions in the previous literature. We also conducted various different robustness exercises to examine the relevance of the results.

Results: Our results suggest that the refugee influx into our sampled cities in Turkey does not have a statistically significant impact on the crime rate when compared with the control locations. All of the regression results in the robustness exercises were similar to our main result.

Conclusions: Our findings suggest that the Syrian refugees did not statistically increase the crime rates in Turkey. Given the ongoing debate about the relationship between immigrants and crime rates, there is not enough evidence for the common belief that immigrants who raise the crime rates in the host country.

Keywords: Refugees, Immigrants, Crime Rates, Natural Experiment

1. INTRODUCTION

According to the United Nations High Commissioner for Refugees (UNHCR), approximately 68.5 million people all over the world were forced to flee their home country by the end of 2017 because of persecution, conflict, or generalized violence, and 25.4 million of those are refugees (UNHCR, 2018). Although the conflicts in Burundi, the Central African Republic, the Democratic Republic of the Congo, Iraq, Myanmar, South Sudan, Ukraine, and Yemen have caused a displacement crisis, the major dislocation of people occurred because of the Syrian civil war that led approximately 6.3 million individuals to flee Syria by the end of 2017. The majority of Syrian refugees are hosted by Turkey (3,424,200), Lebanon (992,100), Jordan (653,000), Germany (496,700), Iraq (247,100), Egypt (126,700), Sweden (103,600), Austria (43,900), and the Netherlands (30,900) (UNHCR, 2018).

Refugees may pose enormous moral, political, and economic challenges for host countries; thus, they may not be welcome in some countries. An impressive example of a country that has welcomed refugees despite the challenges is Turkey, which hosted the largest number of global refugees, totaling approximately 3.5 million, by the end of 2017 (UNHCR, 2018). According to the Migrant Acceptance Index, which determines a country's attitude toward immigrants, Turkey ranks 117^{th} out of 140 countries (Fleming et al., 2018), which may suggest that Turkish people are prejudiced against immigrants. The underlying reason for this sentiment could be the threat of crime and terrorism brought by these immigrants from their countries, which could endanger public safety. This concern is true not only in Turkey but also in Europe and the US. For example, a recent nationwide survey reveals that Americans think that immigration is the second most important issue in the US (Newport, 2018). In addition, in Europe, former Italian president Berlusconi declared that "… migrants are a social bomb that risks exploding" (Jebreal, 2018), and Italy's far-right Northern League leader Matteo Salvini announced that "unchecked immigration brings chaos, anger" and "drug dealing, thefts, rapes and violence" (Horowitz, 2018). Furthermore, US President Donald Trump famously said

> The US has become a dumping ground for everybody else's problems. Thank you. It's true, and these are the best and the finest. When Mexico sends its people, they're not sending their best. They're not sending you. They're not

> sending you. They're sending people that have lots of problems, and they're bringing those problems with us. They're bringing drugs. They're bringing crime. They're rapists. And some, I assume, are good people. (Wolf, 2018)

Therefore, scientific investigation of the effect of immigrants on the crime rate of their host countries is essential to creating better policies.

Although we have stressed the importance of studying this effect, we must also note that the task is a difficult one because of several econometric challenges. For example, the problem of selection is one of the most important issues encountered when nonexperimental immigration data are used (Borjas, 1987, Borjas, Bronars and Trejo, 1992). One way to tackle this problem is by conducting a natural experiment in which immigrants do not self-select themselves into a host country. Previous studies have established that the Syrian refugee inflow to Turkey presents a great quasi-experimental estimation opportunity (Balkan and Tumen, 2016). Therefore, in this paper, we investigate the effect of Syrian refugees on crime rates in Turkey using a difference-in-difference (DiD) approach.

According to statistics from Turkish penal institutions, the number of inmates in prisons has increased between 2009 and 2015 in Turkey. Our estimates are based on a sampling of those cities that have the highest Syrian refugee populations in Turkey. The pre-treatment period we used is from 2010 to 2011, while the post-treatment period is from 2012 to 2014 for our main analysis.

Even though we have crime data at the city level, in order to be compatible with previous studies, we chose the same treatment and control groups (e.g., Ceritoglu et al., 2015), focusing on regions that include several cities (up to four cities). It is called as NUTS2 by Eurostat. Moreover, we also had the advantage of having a dataset at the city level, which corresponds to the NUTS3 subdivision level and focused on the Turkish cities that had the highest immigration in proportion to the city's population as the treatment perform a robustness check. According to our estimates, the refugee influx into the treatment area in Turkey has no statistically significant effect on the crime rate compared with the influx to the control area. We also performed various robustness exercises to check the relevance of the results. First, we investigated the refugee−crime relationship in the five cities that had the highest immigrant to population ratio. Then, based on the refugee density, we established new post-immigration periods of 2012, 2013, 2014 and 2015. Finally, we considered two alternative control areas instead of our original control area to ensure the accuracy of the control group. The control groups are entire provinces that exclude the treatment area and entire provinces that exclude both the treatment and original control areas. Almost, all of the regression results in the robustness exercises support our baseline findings.

This paper is divided into six main sections. The second section briefly discusses the history of the Syrian refugee inflow into Turkey and provides a review of the existing empirical literature on the relationship between immigration/refugees and crime. The third section introduces the data, estimating methods, and the model. The fourth section presents the applied results of the model estimated using the DiD method. The fifth section documents our robustness exercises for the same regression analyses using the DiD method and the Synthetic Control Method. Finally, the sixth section contains the conclusion and final remarks.

2. THE HISTORY OF SYRIAN REFUGEES IN TURKEY

Following the outbreak of civil war in Syria in March 2011, numerous refugees fled from northern Syria to the southeastern areas of Turkey. Initially, only 252 refugees were reported on April 29, 2011, but by March 2015 the number of refugees had reached 1,858,000 (Erdogan, 2014). As of October 26, 2015, 10−12% of these Syrian refugees lived in camps, while 88−90% lived outside the camps (Erdogan and Unver, 2015). A total of 25 camps, each described as a "center for peace," are found in the following 10 provinces (with the number of refugees in camps indicated in parentheses): Sanliurfa (104,890), Gaziantep (52,277), Kilis (33,651), Hatay (14,803), Kahramanmaras, (17,853), Mardin (15,740), Adana (10,598), Adiyaman (9,599), Osmaniye (9,160), and Malatya (7,813). The cities with the highest Syrian refugee population are Sanliurfa (356,390), Hatay (341,174), Istanbul (305,067), Gaziantep (277,905), Adana (121,851), Kilis (114,567), Mersin (114,148), Mardin (88,139), Izmir (73,314), and Kahramanmaras (72,653). Most of the local managers claim that the official Figures do not reflect the actual numbers, which could be much higher.

The Figure-1 below illustrates the number of registered Syrian refugees in Turkey from 2012 to 2018 as of August 2018. The data sources are the UNHCR and the Government of Turkey.

[Figure- 1]

The impact of Syrian refugees has been a prominent theme in many studies, such as in studies of labor markets (Akgunduz, van der Berg and Hassink, 2015, Ceritoglu et al., 2015, Del Carpio and Wagner, 2015, Tumen, 2016), consumer prices (Balkan and Tumen, 2016), and perceptions of Turkish university students of their Syrian classmates (Ergin, 2016). More recently, a working paper by Balkan et al. (2018) investigated the effect of Syrian refugees on housing rents and perceived crime in areas hosting these refugees in Turkey.

3. LITERATURE REVIEW

Although a growing body of literature has investigated the labor market effects of immigration (e.g., Altonji and Card, 1991, Aydemir and Borjas, 2011, Borjas, 2005, 2003, 2006, 1987, Card, 2005, Friedberg and Hunt, 1995), few studies have delved into the effect of immigration on crime. More specifically, studies have reviewed either the role of legal status on a migrant's criminal activity (e.g., Freedman, Owens and Bohn, 2018, Mastrobuoni and Pinotti, 2015, Pinotti, 2017) or the relation between migration influx and criminal activity, of which the latter topic is our interest in the present study. The considerable literature on this topic has been published for the US but with contradictory findings. A growing body of literature that exploits a variety of data and methods found that immigrants commit crime at lower rates than natives. Previous studies on this issue have demonstrated that in US cities where immigrants are concentrated, crime rates between 1980 and 1990 were relatively higher than those in other cities. Even though I after controlling for the demographic characteristics of cities, immigrants, and natives, recent immigrants were shown to have a lower propensity to commit crimes than natives or to have no influence on crime rates at all (Butcher, 1998). Another empirical demonstration of this effect is that Hispanic immigrants were less likely to be complicit in crime than US citizens (Hagan and Palloni, 1999). In contrast to earlier findings, no evidence of a relationship was detected by a study (Lee, Martinez and Rosenfeld, 2001) that specifically investigated whether there was a relationship between the homicide rate of Latinos and African Americans and immigration. The results of that study indicate that recent immigration does not increase the rate of homicide trends in the US. Although many studies have found either a negative or no relationship between immigration and crime, several studies have found a positive link between these variables. For instance, a study based on prison censuses has demonstrated that the involvement of foreign-born people in minor crimes is more prevalent than that of natives, whereas the rate of major crime involvement for the two groups is quite similar (Moehling and Piehl, 2009). A longitudinal study of crime and immigration has reported a positive, statistically significant relationship between immigrants and the property crime rate; however, no significant link was reported between immigrants and violent crime rates in US counties for the period from 1980 to 2000 (Spenkuch, 2013). In addition, the previous literature suggests that the contradictory findings may be explained by the type of crime. One article asserts that there is no link between violent and property crimes and Mexican immigration (Chalfin, 2013). However, a subsequent study found that aggravated assault is one crime that increases as a result of Mexican immigrants, while other crimes, such as rape and molestation, larceny, and motor vehicle theft, have an associated decrease (Chalfin, 2015).

More recently, researchers have shown an increased interest in European data. A longitudinal study assessed the significance of the relationship between crime and immigration across Italian provinces during the period from 1990 to 2003 (Bianchi, Buonanno and Pinotti, 2012). The researchers explored the link between the total number of migrants and total crime by utilizing the fixed-effect (FE) estimation method, which yielded a positive coefficient. In contrast with the FE estimation, the results obtained from the instrumental variable estimation show that there is no significant effect of immigrants on total crime, especially on property crimes. Another study used cross-sectional data that were collected in four waves between 2002 and 2008 for 16 Western European countries (Nunziata, 2015). This study used both FE and instrumental variable methods and concluded that an increase in immigration does not have an impact on crime victimization. Another important study explored the connection between immigration and crime rates in West Germany between 1996 and 2002 (Piopiunik and Ruhose, 2017). The researchers focused on the impact on crime of the descendants of German immigrants who had migrated from Russia and other East European countries after the collapse of the Soviet Union. They found that the areas with higher preexisting crime levels and overpopulation after immigration experienced higher crime rates.

Much of the existing research has focused on the link between crime and immigration; however, far too little attention has been paid to the criminal behavior of refugees. Bell et al. (2013) examined local violent and property crime patterns in England and Wales in the period from 2002 to 2009. They considered two immigrant flows, namely, an asylum wave and an A8 wave.[3] In their paper, they highlight that the natives and immigrants from EU accession countries (the A8 wave) have better labor market opportunities than those in the asylum wave, thereby suggesting that crime rates would be much higher in the second group. The results of this study show that although there was no significant increase in violent crime for either wave, the asylum and A8 waves have a statistically significant positive and negative effect on property crime, respectively. These results are consistent with those from a spatial econometric analysis in a previous study of immigrant flow to London (Jaitman and Machin, 2013). By contrast, a study that evaluated the short-run effects of the refugee influx into 16 German states in 2014 and 2015 indicated an increase in nonviolent crime rates, especially drug offenses and fare-dodging, due to lack of economic opportunities (Gehrsitz and Ungerer, 2017). In another important study, refugees exposed to civil conflict or mass killings at the age of 1−12 years old are documented to be 40% more prone to commit violent crimes than the average cohort in Switzerland during the period from 2009 to 2012 (Couttenier et al., 2016). Recent preliminary work on the relation between refugee settlements and local crime rates in the US indicates that refugees may not have had a significant effect on local crime rates during the period from 2006 to 2014 (Amuedo-Dorantes, Bansak and Pozo, 2018). Even when the researchers restricted the sample to refugees who came from the seven countries on which a travel ban was imposed on

[3]An asylum wave refers to the influx of people from Iraq, Afghanistan, Somalia, and the former Yugoslavia in the late 1990s and early 2000s. An A8 wave refers to the inflow of workers from the European Union (EU) accession countries, including Poland, Hungary, the Czech Republic, Slovakia, Slovenia, Estonia, Latvia, and Lithuania, after the EU expansion in 2004.

January 27, 2017, by executive order, they did not find any statistically significant evidence of a relationship between refugee inflows and an increase in crime rates.

A recent systematic literature review for the US that focuses on studies published between 1994 and 2014 attributes the different findings across studies that examined the relationship between crime and immigration to variability in the measurement of immigration and crime, study units of analysis, temporal design, and destination context (Ousey and Kubrin, 2018). The reviewers suggest that a common view among studies is null or has no significant association and note that 62% of the studies reviewed indicate no statistical significance at a 5% confidence level. Furthermore, the majority of the statistically significant regression coefficients are negative, and the number of studies with significant negative effects is 2.5 times higher than those with positive effects.

To the best of our knowledge, two related studies that mention the effect of Syrian refugees on crime in Turkey have been conducted. A recent working paper reports that crimes do not significantly increase in neighborhoods that take in refugees (Balkan et al., 2018). However, our study is implicitly different because the researchers' analysis in that study was based on the perceptions of the natives rather than the official crime rates. Moreover, the previous study assessed the respondents' perceptions of whether crimes in the neighborhood changed relative to the previous year, which perceptions are unlikely to represent actual crime in the region, especially if we consider the aforementioned prejudice against immigrants. In addition, the previous study used the highest classification level of Turkey's geographic subdivisions based on Eurostat's Nomenclature of Territorial Units for Statistics (NUTS), namely, NUTS1, which corresponds to 12 geographic regions in Turkey. However, our dataset contained information at the city level, which corresponds to the NUTS3 subdivision level. Finally, the previous study did not separate the impact of refugees by different types of crimes, which is essential because the previous literature suggests that the relationship between immigrants and crime varies by type of crime. For instance, another related study deduced that the influx of refugees from Syria resulted in an increased number of illicit drug seizures between 2008 and 2013 in Hatay, a Turkish city (Arslan et al., 2015).

4. METHODOLOGY

4.1. Data

The previous literature uses the incarceration rate as a proxy for involvement in criminal activity (Bell, Fasani and Machin, 2013, Borjas, Grogger and Hanson, 2010, Butcher and Piehl, 1998, 2000, 2007, Chalfin, 2013, Moehling and Piehl, 2009). Therefore, the crime datasets used in this study were based on Turkish penal institution statistics for the period 2009 to 2015[4]. The crime data on 25 criminal activities are annually published by the Turkish Statistical Institute (TurkStat) and formulated as cross-sectional data at a given point in the year for all Turkish cities. In the dataset, the city indicated is where the crime occurred, not the penitentiary's location. As the data covered only the civilian population, crimes against the military criminal law are excluded because these are not related to Syrian refugees. Moreover, opposition to the Bankruptcy and Enforcement Law was not included because those are not related to immigrants and the incarceration rates were heavily affected by legal changes during the sample period. Similar to the previous literature, crime types are classified into two groups: nonincome-generating which includes 13 crime types and income-generating crimes which include 9 crime types (e.g., Freedman, Owens and Bohn, 2018)[5]. The nonincome- generating crimes consisted of homicide, assault, sexual crimes, kidnapping, defamation, bad treatment, prevention of performance, traffic crimes, forestry crimes, crimes related to firearms and knives, criminal threats, damage to property, and contrary to the measures for family protection. The income-generating crimes consisted of theft, smuggling, opposition to cheque laws, swindling, the use and purchase of drugs, the production, and sale of drugs, forgery, embezzlement, and bribery. In this study, we assessed six different crime categories as follows: nonincome-generating crimes, income-generating crimes, theft, assault, homicide, and total crime. Total crime was generated by aggregating all available crime types, except for crimes against military criminal law and under bankruptcy laws. The dependent variable is the logarithm of the proportion of these crime types per thousand residents (e.g., Freedman, Owens and

[4] We did not use data after 2014, because in Turkey from 2015 incarceration rates were rise steeply because of the investigations about the religious sect who is responsible for the military coup attempt on 15th July 2016.

[5] The number of theft and robbery crime types are summed up due to small figures and named as theft.

Bohn, 2018). Only homicide crime rates are taken in one out of a million residents of census tracts.

Selection problems are one of the most important issues encountered when non-experimental immigration data are used (Borjas, 1987, Borjas, Bronars and Trejo, 1992). One way to address this problem is to identify circumstances where immigrants do not self-select into a certain country. The displacement of Syrian refugees to Turkey presents an appropriate context for deploying a quasi-experimental estimation strategy (Balkan and Tumen, 2016). Therefore, we use the DiD methodological approach to estimate the effect of Syrian refugees on crime rates in Turkey.

In 2002, the TurkStat has implemented the Nomenclature of Territorial Units for Statistics (NUTS) within the framework of the EU accession period. There are three classifications for Turkey; NUTS1 (12 Regions), NUTS2 (26 Subregions), NUTS3 (81 Provinces). The previous literature that focuses on the influx of Syrian refugees to Turkey utilizes NUTS2 classification (e.g., Balkan and Tumen, 2016, Tumen, 2016). Our dataset contained crime data based on province, but in order to be compatible with previous studies, we used the same treatment and control groups as they did (Ceritoglu et al., 2015). Treatment area included 14 cities[6] from the southeastern part of Turkey where the proportion of refugees to the population is above 2% (AFAD, 2013) and the control area included 15 cities[7] with similar cultural properties, socio-demographic aspects, and economic development level to the treatment area. In these cities, the ratio of refugees to the population is close to zero. Moreover, we used the advantage of having a dataset at the province level. For additional robustness check, we focus on the Turkish cities that received the highest immigration in proportion to the city's population as the treatment area. In that analysis, we define areas that received large influxes of refugees and small influxes of refugees as the treatment and control areas, respectively. In addition, Figure-3 shows a map of Turkey on which we have highlighted the ratio of immigrants to natives for treatment and control areas in 2015.

[6] At the NUTS2-level regional division, the treatment group includes TR62 (Adana, Mersin), TR63 (Hatay, Kahramanmaras, Osmaniye), TRC1 (Gaziantep, Adiyaman, Kilis), TRC2 (Sanliurfa, Diyarbakir), and TRC3 (Mardin, Batman, Sirnak, Siirt).

[7] The control group includes TRA1 (Erzurum, Erzincan, Bayburt), TRA2 (Agri, Kars, Igdir, Ardahan), TRB1 (Malatya, Elazig, Bingol, Tunceli), and TRB2 (Van, Mus, Bitlis, Hakkari).

We focused on the period between 2010 and 2014 for our main analysis. Since Syrian refugees started to arrive in Turkey at the beginning of 2012, a year interval is constituted around this cutoff date: the pre-immigration period is defined as 2010−2011, and the post-immigration period as 2012−2014. Moreover, we conduct the same analysis for robustness check using two different year intervals; 2010-2013 and 2009-2015 (we define them as short-term and long-term, respectively).

In this study, the control variables used in the analyses are based on the previous literature (e.g., Amuedo-Dorantes, Bansak and Pozo, 2018, Spenkuch, 2013). Total employment, real GDP per capita, education variables are obtained from the TurkStat at province-level. Total employment is employment rate at province level. Real GDP per capita is calculated as deflating per capita by using consumer price index (CPI). With regard to the education level of individuals, we created two groups: those with high school degree or lower and those who have higher degree than high school diploma per thousand residents. To proxy for the likelihood of getting caught by law enforcement, we control for the proportion of lawyers registered with the Bar Association per thousand residents (Republic of Turkey Ministry of Justice, 2019). Housing costs are considered as a prominent determinant of refugee placements, so we include house price index that varies yearly for NUTS2-level regional division (Central Bank of the Turkish Republic, 2019). Religiosity is another important factor in the explanation of crime, thus, the proportion of participants in Quran courses are controlled analysis (e.g., Brettfeld and Wetzels, 2006). The data is attained from the Presidency of Religious Affairs. Moreover, year and city dummies are included, models.

Table-1 presents the summary statistics for both the treatment group and control group. It suggests that the means of theft, homicide, income-generating crimes and total crimes are higher in the treatment group than in the control group. In addition, the number of inmates who committed income-generating crimes is higher than those who committed non-income generating crimes in the treatment group and vice versa in the control group. Moreover, theft is the highest crime committed in the treatment and control groups among three crime types, namely theft, assault, and homicide. In addition, on average treatment cities have slightly higher GDP per capita and house prices. However, total employment, in the control group both formal education and religious education numbers are higher.

Table-2 shows the number of crimes during the periods before and after 2012. On the other hand, Figure-2 shows the total crime rates per thousand residents for both treatment cities and control cities from 2009 to 2015. As shown, the crime rates after 2012 increased in both the treatment and control groups. Moreover, it is seen that for both treatment group and control group, there is an increasing trend for crime rates between post-immigration and pre-immigration periods.

4.2. Model

Our quasi-experimental estimation strategy aims at estimating the effect of refugees on the crime rates in the host countries by comparing the number of crimes during pre-immigration and post-immigration periods in the treatment versus control cities. To achieve this purpose, we created two dummy variables: (i) $T = 1$, if the city is in the treatment area; otherwise, $T = 0$; and (ii) $P = 1$ for the post-immigration period (2012, 2013 and 2014) and P = 0 for the pre-immigration period (2010 and 2011). This framework led to the following DiD formula:

$$\ln(y_{i,j,t}) = \beta_1 + \beta_2(T_i.P_i) + \beta_3 X_{i,j,t} + f_j + f_t + \varepsilon_{i,j,t},$$

where i, j, and t are the index provinces, areas, and years, respectively. The dependent variable is the logarithm of the proportion of total crime per thousand residents, X is a vector of province-level socioeconomic variables, and ε is an error term. The elements f_i and f_j are the region-level and year-level FEs, respectively. The main coefficient of interest is β_2, which renders the average change in the crime rates in the treatment area as a result of the refugee influx.[8]

5. RESULTS

This section presents baseline estimates considering between the year 2010 and 2014. Table-3 shows the refugee influx impact on crime rates in the treatment area in comparison with the control area for between the years 2010 and 2014. The analysis is

[8]See Tumen (2016), Balkan and Tumen (2016), and Ceritoglu, Gurcihan Yunculer, Torun, and Tumen (2017) for details of a similar empirical setup.

performed using the DiD method. Our dependent variable is the logarithm of the proportion of total crime per thousand residents. In addition, all columns include the following control variables: employment rate, the rate of per capita GDP, the number of lawyers and counselors registered with the Bar Association per thousand residents, house price, the rate of college or higher degree graduates, year and city dummies are included.

[Table-3]

Throughout the paper, we applied two different estimation approaches for DiD, according to weighting the regression. Firstly, the Model 1 is constructed without survey weights and with robust standard errors. The findings show that the refugee influx into the treatment area in Turkey does not have a statistically significant effect on the crime rates compared with the control area but the assault that has a negative coefficient. All of six crime types that are used in our analysis have low t-values (the highest is 1.82 for the assault.)

Furthermore, survey weighting is useful when estimating causal effects. If the sample is exogenous and the model is correctly defined, ordinary least squares (OLS) and weighted least squares (WLS) are used to estimate the consistent regression coefficients (Solon, Haider and Wooldridge, 2015). Thus, we conducted WLS, and we used the total population of each city as our weighting tool. Model 2 reports those estimates with robust standard errors. This framework supported the findings that are estimated with OLS, which is that the refugee influx into the treatment area did not significantly reduce the rate of criminal activity in that area compared with the control area. We also executed cluster models with and without the weight and found consistent results, shown in Table-3. In those calculations, standard errors are clustered with respect to the city and the total population of each city is used as a weight. These different weighting approaches yield similar results and the t-value of assaults become smaller.

The DiD method that we utilized our analysis up to now provides comparison between the treated and control areas across time and space. In some situations such as having small number of clusters (e.g., regions, municipalities or individuals) induce inconsistent standard errors (Angrist and Pischke, 2008) or creating comparison group may not represent as much as desired. Therefore, a growing literature suggests the Synthetic Control Method (SCM) might be used as an alternative. Moreover, it is stated that provinces using treatment and control regions are selected in the light of previous studies which are conducted NUTS2 that may lead to have cities different that treatment cities. Thus, we are carried on the SCM exploiting the advantages of crime data based on province to verify accuracy of treatment region.

The Synthetic Control Method

The SCM first is introduced by Abadie and Gardeazabal (2003) and then further improved in Abadie, Diamond, and Hainmuller (2010, 2015). The main goal of this econometric technique is to evaluate whether the intervention/treatment have an effect on some consequences in the treated unit, pertaining to when it would not have occurred and describe a control group called the Synthetic Control unit. The SCM is explained by non-intervention outcome for unit *i* at time *t*:

$$Y_{it}^{N} = \alpha_t + \beta_t X_i + \mu_t Z_i + \varepsilon_{it} \tag{1}$$

where α_t is a common time-dependent factor, β_t is a vector of unknown parameters, X_i is a vector of observed covariates not affected by the intervention, $\mu_t Z_i$ is a vector of unobserved time-specific common factors multiplied by a vector of unobserved unit-specific factor loadings, and ε_{it} is an unobserved temporary shock. $\mu_t Z_i$ enables the impact of unobserved unit-specific confounders to vary over time. The unit of interest is identified as unit *i*=1 and a vector of weights are defined as $S = (s_2, \ldots, s_{k+1})'$ in which k represents non-treated units, $s_k \geq 0$, and $s_2 + \cdots + s_k = 1$. A linear combination of non-treated units for any time $\sum_{k=2}^{k+1} s_k Y_{kt}$ is created with the help of S which also denotes synthetic control. This term is used as counterfactual for the intervention unit. A significant analysis and discussion conducted within the scope of this framework indicate that a S^* which have similar characteristics with S can ensure an unbiased estimator of outcome in the absence of interventionY_{1t}^{N}. In that case, vector of observed covariates and linear combination of pre-intervention outcomes are shown to be $X_1 = \sum_{k=2}^{k+1} s_k^* X_k$ and $\overline{Y_1} = \sum_{k=2}^{k+1} s_k^* \overline{Y_k}$, respectively (Abadie et al., 2010). This method aims to minimize the distance between estimated variables of the treated unit and the synthetic control unit with respect to S*. Moreover, the weights put on the estimated variables are selected to minimize the mean square predictor error of the outcome variable for the pre-intervention periods.

This method has several advantages. First, it constructs a synthetic city, which substitutes the control group and decreases the temporary nature of choosing the control group. Second, we confirm its quality by controlling the pre-treatment differences of the dependent variable between the treated and the Synthetic Control units. Finally, by creating a synthetic control for every unit (e.g., city) we can obtain a distribution of observed effects. Then we can calculate a p-value for how significant the post-treatment difference is compared to the pre-treatment relative to the whole distribution, thus conducting inference with idiosyncratic city-specific shocks.

The Synthetic Control Method Analysis Results

This part of the study discusses the findings obtained from the SCM between years 2006 and 2014. We have utilized these years because SCM gives better results when keeping the year longer.[9] As a far as we know, our study is the first attempt to use the SCM for any analysis of Turkey. The SCM is conducted for five cities which have the highest immigrant to native population ratio; Kilis (39%), Hatay (13%), Gaziantep (13%), Sanliurfa (10%), and Mardin (9%). We can reassign the treatment to the regions that did not affected by the migration wave from Syria. Thus, we construct synthetic counterfactuals creating donor pool from up to 67 cities. Subsequently, we compute the difference between each actual city and their synthetic counterparts and plot all these difference-time series together to see whether these cities stand out. If this often introduces estimated effects of a similar magnitude with DiD estimation, we will gain confidence that the estimated effect for five cities are not due to the influx of Syrian refugees. Figure-4 shows the trends in crime rates for five cities separately and their synthetic counterparts. It is seen that the synthetic control regions follow these five cities after the first Syrian refugee influx in Turkey in 2012. This implies that the refugee

[9] We also executed SCM for years between 2006-2015 and find similar results. See, Figure 10 to Figure 15 in the appendix.

influx into these cities did not significantly alter the trend of criminal activity compared with the synthetic control.[10]

[Figure-4]

[Figure-5]

[Figure-6]

[Figure-7]

[Figure-8]

[Figure-9]

Table-4 shows that t-test results from the comparison between the estimates of synthetic controls and the actual values for pre-immigration and post-immigration periods, separately. It suggests that the standard statistical tests results could not reject the null hypothesis of parallel trends; for instance, t-values of the difference between Kilis's total crime rates and the estimates from the synthetic city are -0.008 and 0.471 at pre-immigration period and post-immigration period, respectively. It means that our synthetic city is a good control group and the effect of Syrian refugees on crime is not significant. It is true for all of five cities and all crime types at those cities. It supports our main findings that point out immigrants do not have statistically significant effect on the host country's crime rates.[11]

[Table-4]

6. ROBUSTNESS CHECKS

The section of the study is concerned with robustness check using two different year intervals: 2009-2015 and 2010-2013.[12] The former is considered as a long-term analysis

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[11]We also executed SCM t-test for years between 2006-2015 and find similar results. See, Table-15 in the appendix.

[12] We did not use the data after 2015, because in Turkey incarceration rates were risen steeply because of the investigations that are related with the military coup attempt on 15th July 2016.

and the latter is considered as short-term analysis, compare to the main analysis that depend on years between 2010 and 2014. There are number of robustness exercises that carried out for each year interval to ensure the relevance of the results. We should remind that most of these robustness exercises are implemented by previous studies.

i. *Changing control regions*

The aim of our first and second robustness exercise are confirming the accuracy of the control group. For this reason, we create two additional control groups: all cities in Turkey except for our main treatment cities and all cities in Turkey except for our main treatment and control cities. We expect that the influx of refugees would have no impact on the crime rate, although the number of refugees has increased over time. Table-5 shows the first and second robustness check results obtained the Model 1 regression for main analysis.[13] We report results from the control area that includes all cities in Turkey except for our main treatment cities at Table-5A and the estimates from the control area that includes and all cities in Turkey except for our main treatment cities and control cities at Table-5B. Table-5A and Table-5B show that our results are robust. It means that the treatment area has not witnessed different trends in crime levels as compared with the control group. We should note that income generating crimes are significant and homicide in two panels and theft in panel B are statistically significantly at usual levels. For instance, for homicide the influx of refugees into the treatment area reduced criminal activity by 22.1 percentage points compared with the control area.[14] The evidence presented in this section suggests that robustness exercises consistent with baseline analysis results.

[TABLE-5]

In the Table-6, we report the analyses are conducted for the long-term, which extends years of DiD into 2009 and 2015. It illustrates that the results are in line with those of previous findings. [15] Note that only theft and homicide are significant in two

[13] We also executed same analysis for the Model 2 and find similar results. See, Table-11 in the appendix.
[14] When we us bootstrapping for estimations of standard errors, most of significant results lose the significance through out our analyses.
[15] We also executed same analysis for the Model 2 and find similar results. See, Table-12 in the appendix.

panels. It means that the influx of refugees into the treatment area reduced people's criminal activity in these types compared with the control area in the long term. In addition, the long-term regressions yield similar coefficients with our main analysis that includes years between 2010 and 2014.

[TABLE-6]

Besides, we rerun regression for the short-term that includes years between 2010 and 2013. It can be seen from the findings for short-term in Table-7 that there is no link between immigration influx and the trends of criminal rates except for homicide, which has a negative coefficient at both of new control groups and income generating crimes that has a positive coefficient whose t-value is 1.79.[16]

[TABLE-7]

ii. *Using one post-immigration year*

As the influx of refugees has increased, especially after 2012, we anticipated that our findings would show different effects than in each year are regarded separately as post-immigration periods. Thus, the other three exercises concern with reanalyzing the same regressions, setting 2012, 2013, 2014 and 2015 as separate post-immigration periods.

Table-8 exhibits robustness check results obtained the Model 1 regression for four years separately.[17] The results supported the findings that are estimated with OLS, which is that the refugee influx into the treatment area did not significantly reduce the rate of criminal activity in that area compared with the control area.

[Table-8]

iii. *Long term vs. Short term*

In this part, we used same treatment and control regions with previous literature i.e. the treatment area included 14 cities and the control area included 15 cities. With those cities, we used two different analyses: a long term, which is years between 2009 and

[16] We also executed same analysis for the Model 2 and find similar results. See, Table-13 in the appendix.
[17] We also executed same analysis for the Model 2 and find similar results. See, Table-15 in the appendix.

2015, and a short term, namely between 2010 and 2013 (some previous studies use these years for their analysis (e.g., Tumen, 2016)). Table-9 shows that the refugee influx into our sampled cities in Turkey does not have a statistically significant impact on the crime rate when compared with the control locations in the long term. One interesting finding is that only assault crime type is significant negative.

[TABLE-9]

Our short term i.e. years between 2010 and 2013 results are similar to our long-term findings. It means that when we focus on the short term, we find that the impact of refugees on the host country's crime rate are statistically insignificant in all regressions, but assault. Table-10 reports those estimates.

[TABLE-10]

CONCLUSION AND DISCUSSION

This study is the first attempt to investigate the relationship between crime rates and immigrants from the Syrian refugee influx. We apply the DiD approach that depends on a natural experiment, using the Syrian refugee influx into Turkey since 2012. Our results are based on statistics from Turkish penal institutions for the period 2009 to 2015. Our estimates suggest that the Syrian refugees did not statistically increase the crime rates in Turkey. Throughout the paper, we applied various robustness exercises and those are similar with our main findings. We should highlight that our estimates for homicide either have very low t-values or negative coefficients with high t-values. It is important because anti-immigrant sentiments usually depend on immigrants commit heinous crimes like murder or rape rather than small misdemeanors; for instance, President Trump once said "Over the years, thousands of Americans have been brutally killed by those who illegally entered our country and thousands more lives will be lost if we don't act right now".

Although we strongly believe that our findings might be helpful in clarifying the contradictory results in the literature about the effects of immigrants on crime rates thanks to the econometric advantages of the natural experiment, our study still has some shortcomings. For example, the misreporting of crimes may cause estimation problems, that is, failure of individuals to report crimes they experienced to the police may lead to lower incarceration rates. The Life Satisfaction Survey (LSS) of TurkStat, which is the micro dataset, contains one question regarding the reporting of crimes. Based on the responses to this question, in 2012, 29.4% of individuals did not report assaults they experienced that year. When respondents were asked why they did not report the crime to the security forces, 40% of them said that they did not think it would lead to any results, which is the most common answer among the respondents. In 2016-LSS, 57% of respondents did not report assaults, and 70.2% of them thought that they did not have any results. Thus, this failure to report crime may lead to the underestimation of the impact of the Syrian refugee influx on crime rates in Turkey. However, the homicide rate, which is consistent with our main conclusion, is very unlikely to suffer from the underreporting problem, which supports our conclusion.

It is worth noting that almost 3.7 million Syrian refugees live in Turkey whose population is around 82 million. We believe that our results strongly suggest the crime trends of Turkey did not change by Syrian refugees. It demonstrates how unfounded the concerns about immigrants on the crime issue. Even though our results are robust and several previous studies found similar findings; for example, the natives have higher rates of institutionalization compared with immigrants (e.g., Butcher and Piehl, 2007), given the contentiousness of the debate, more research on the long-term effects of immigration on crime rates might still be necessary.

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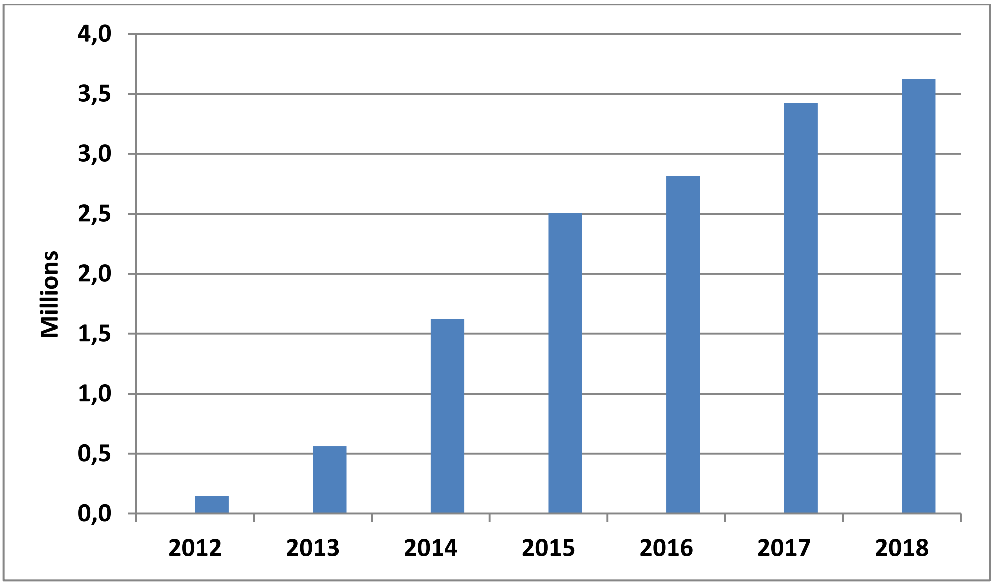
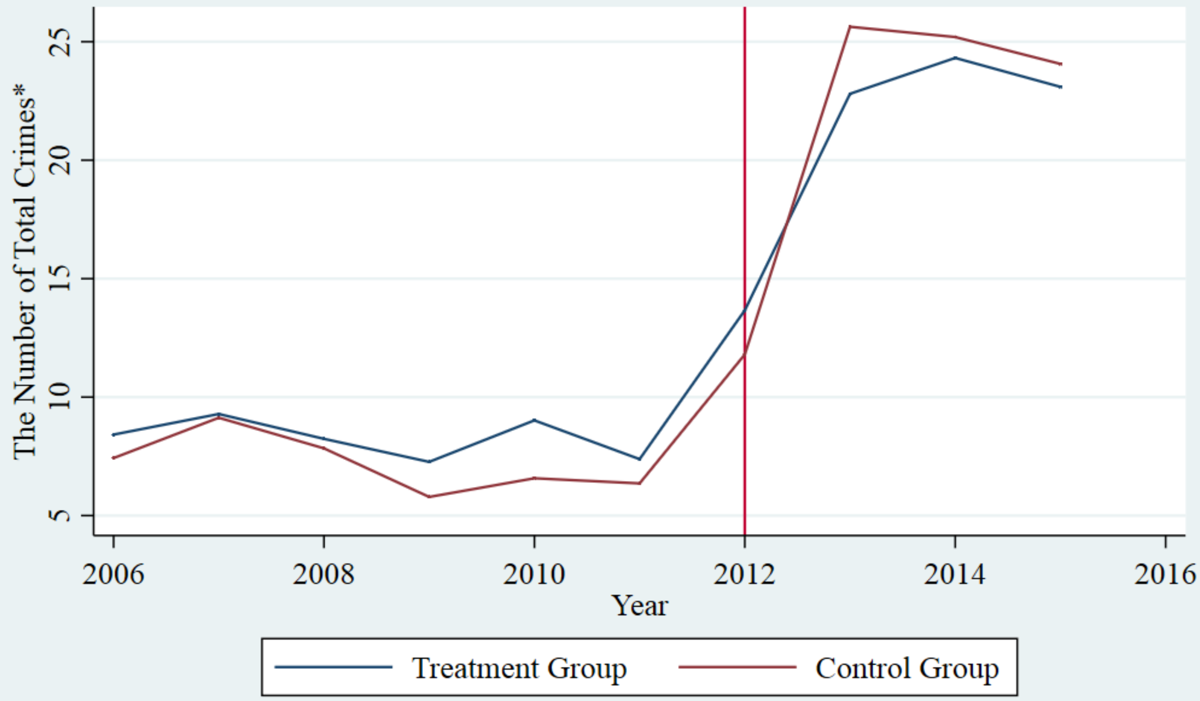
Fig. 1: Number of Registered Syrian Refugees



Source: “https://data2.unhcr.org/en/situations/syria/location/113.”

Figure 2: The Number of Total Crimes*

Treatment Area vs Control Area



*per thousand residents

Figure 3: The Map of Syrian Refugees in 2015

Treatment vs. Control

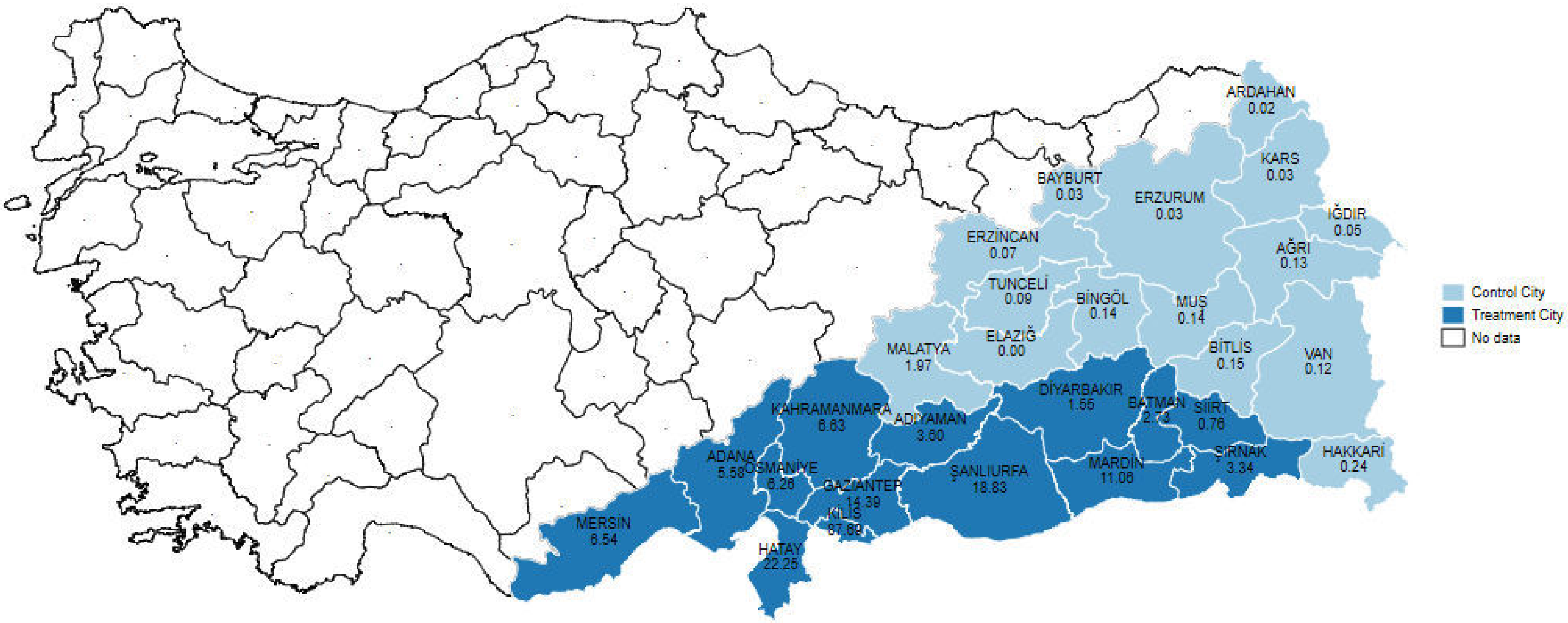
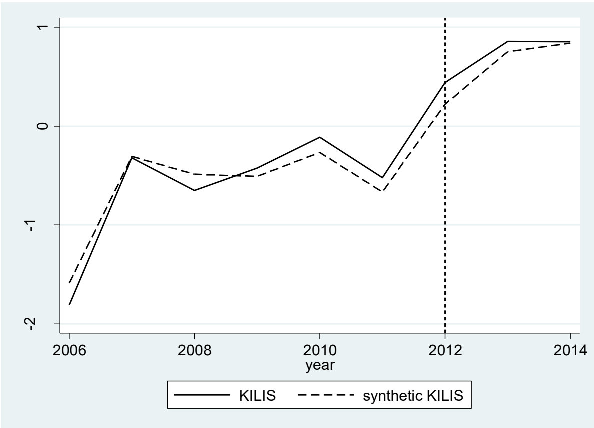


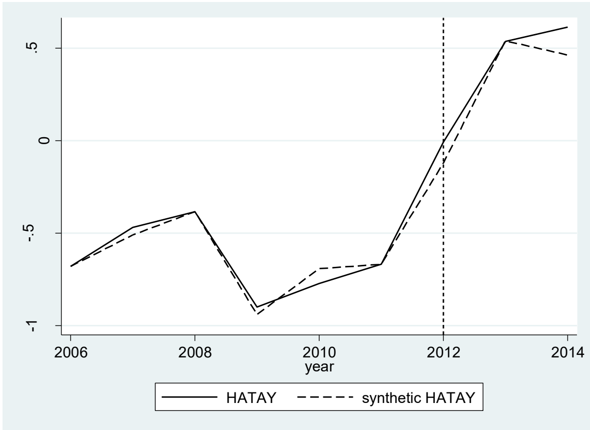
Figure 4: Synthetic Control Event Study Estimates for Total Crime

(2006-2014)

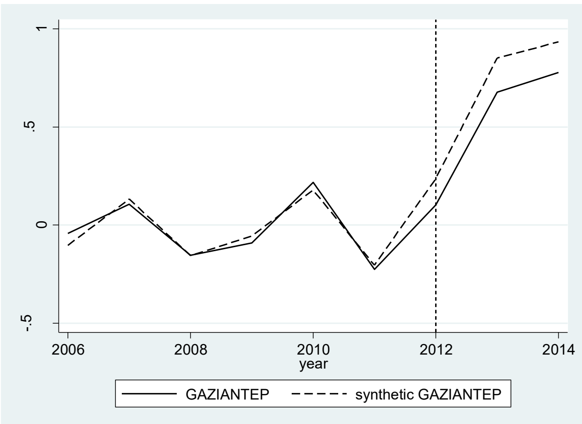
(a) SCM estimates for KILIS



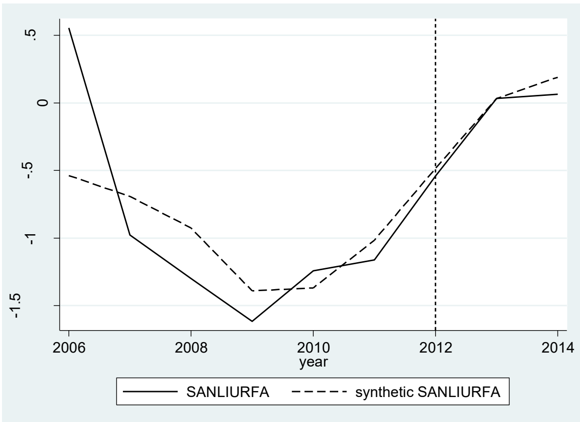
(b) SCM estimates for HATAY



(c) SCM estimates for GAZIANTEP



(d) SCM estimates for SANLIURFA



(e) SCM estimates for MARDIN

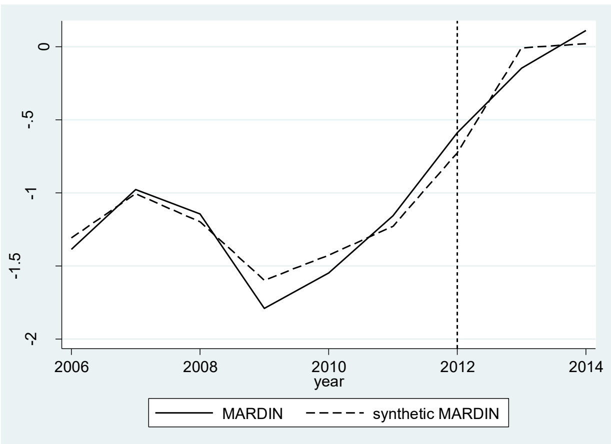
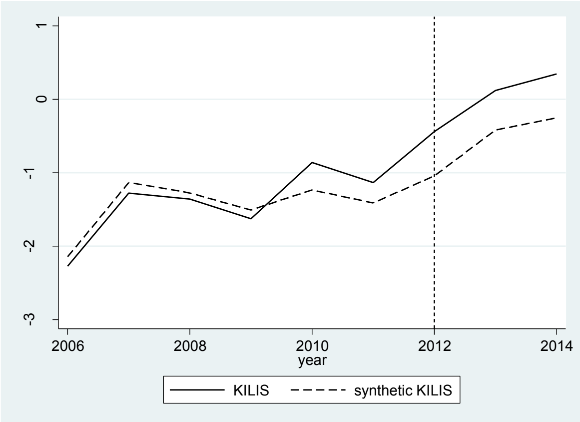


Figure 5: Synthetic Control Event Study Estimates for Income Generating Crimes (2006-2014)

(a) SCM estimates for KILIS



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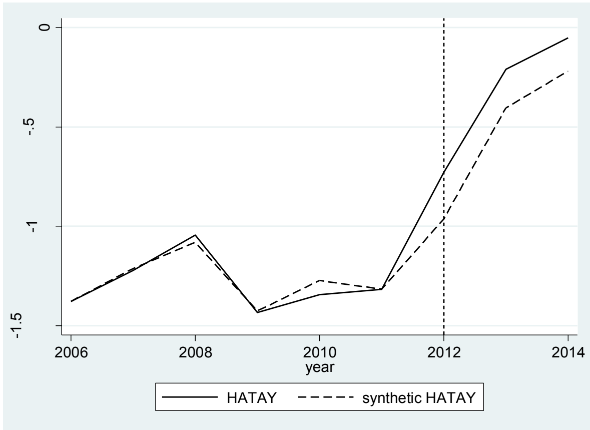
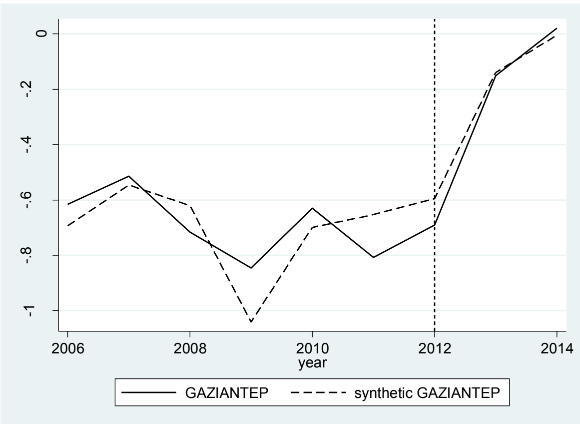


(c) SCM estimates for GAZIANTEP



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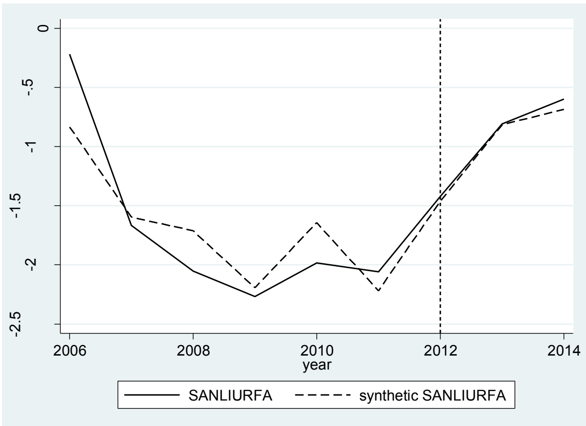

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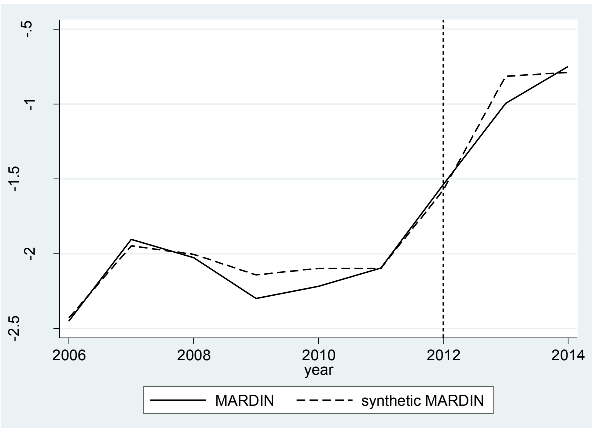
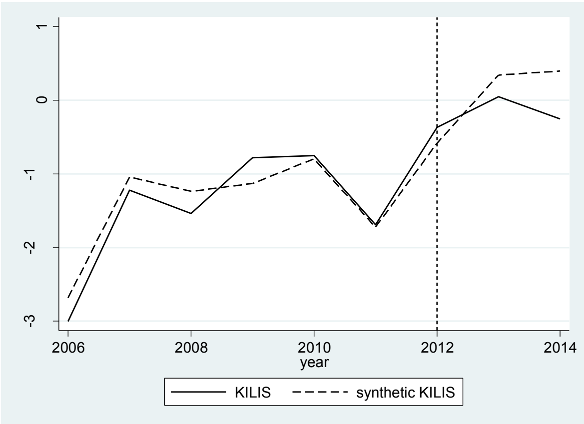
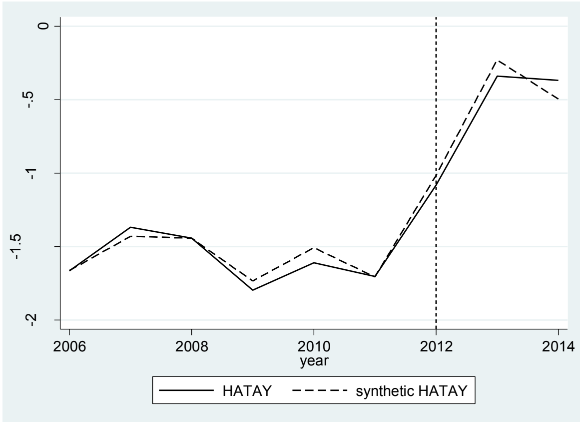


Figure 6: Synthetic Control Event Study Estimates for Non-Income Generating Crimes (2006-2014)

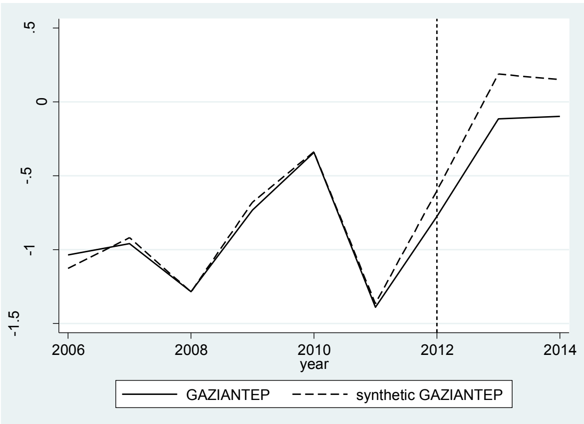
(a) SCM estimates for KILIS



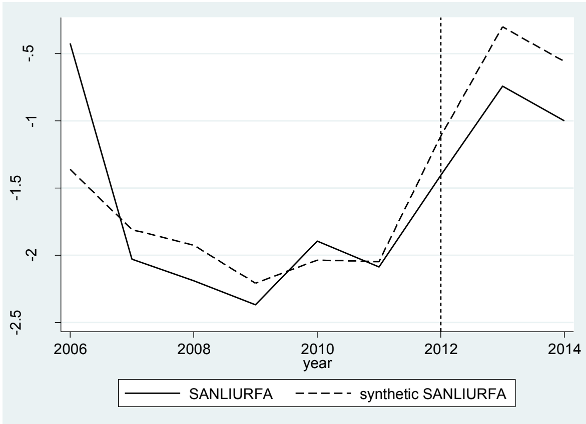
(b) SCM estimates for HATAY



(c) SCM estimates for GAZIANTEP



(d) SCM estimates for SANLIURFA



(e) SCM estimates for MARDIN

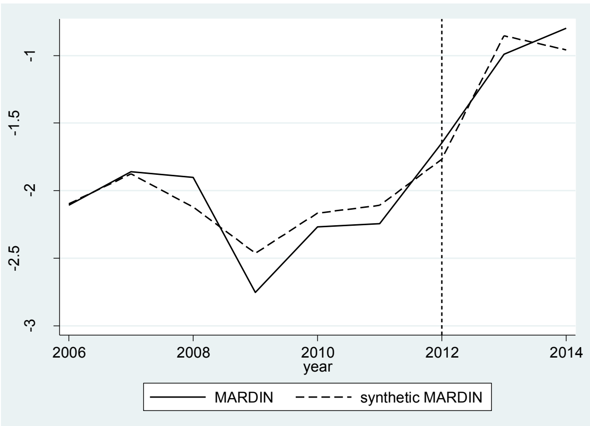
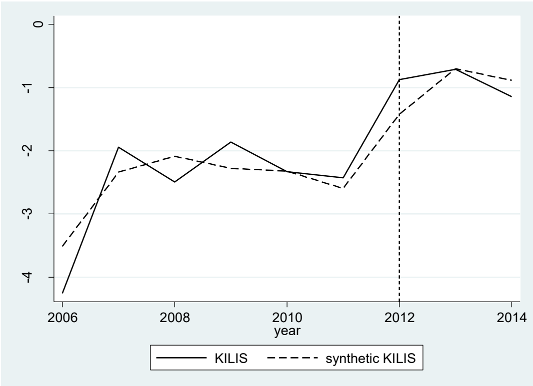


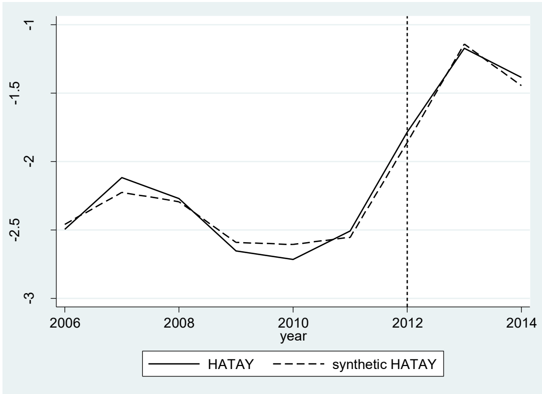
Figure 8: Synthetic Control Event Study Estimates for Assault

(2006-2014)

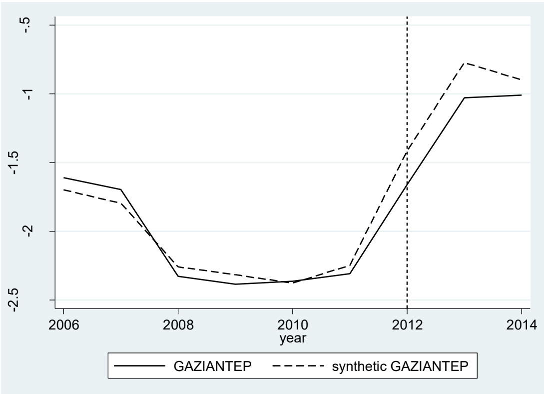
(a) SCM estimates for KILIS



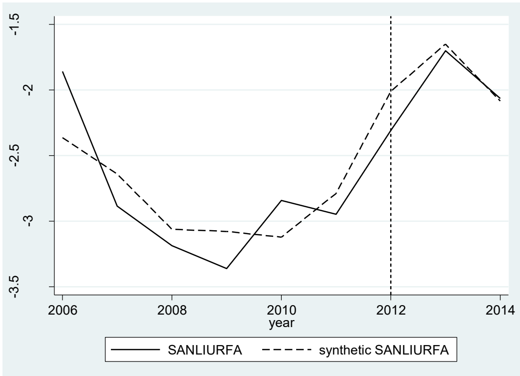
(b) SCM estimates for HATAY



(c) SCM estimates for GAZIANTEP



(d) SCM estimates for SANLIURFA



(e) SCM estimates for MARDIN

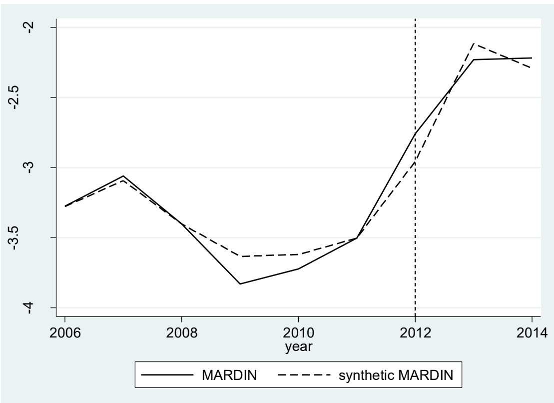
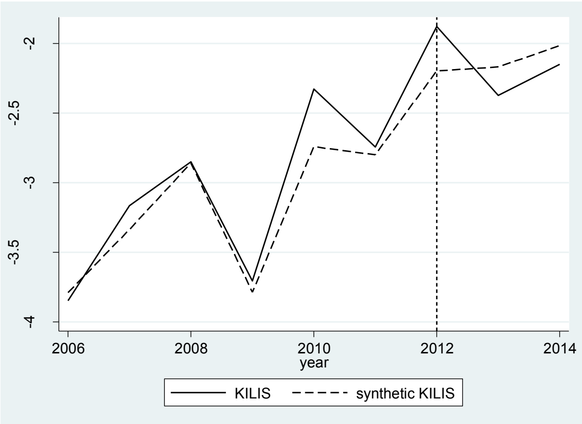


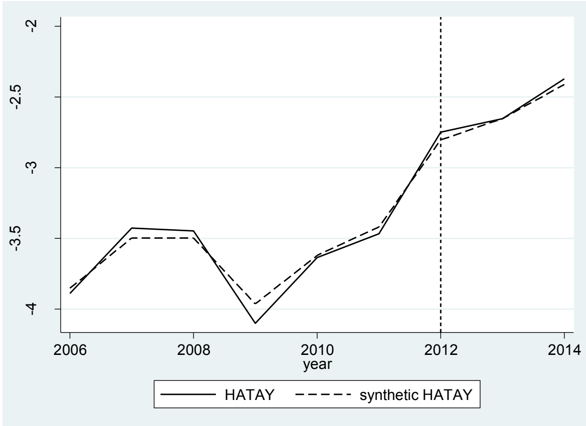
Figure 8: Synthetic Control Event Study Estimates for Homicide

(2006-2014)

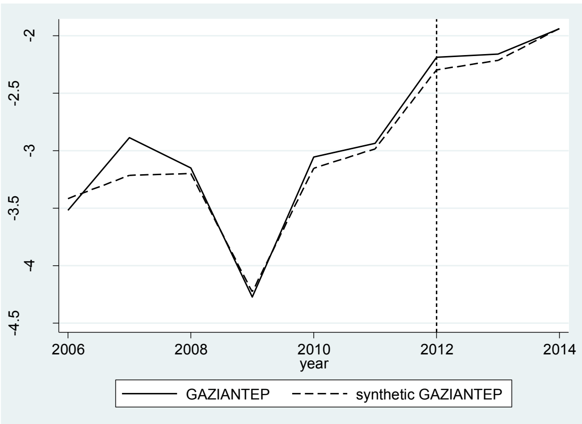
(a) SCM estimates for KILIS



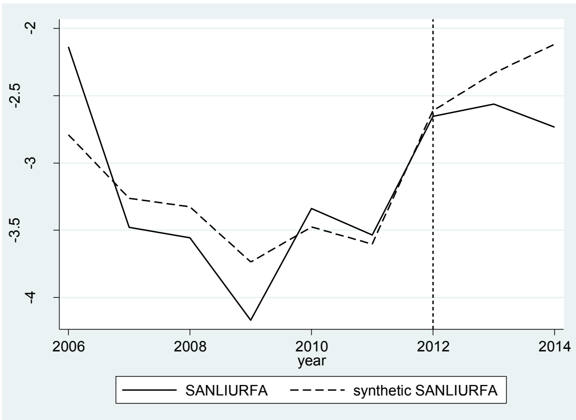
(b) SCM estimates for HATAY



(c) SCM estimates for GAZIANTEP



(d) SCM estimates for SANLIURFA



(e) SCM estimates for MARDIN

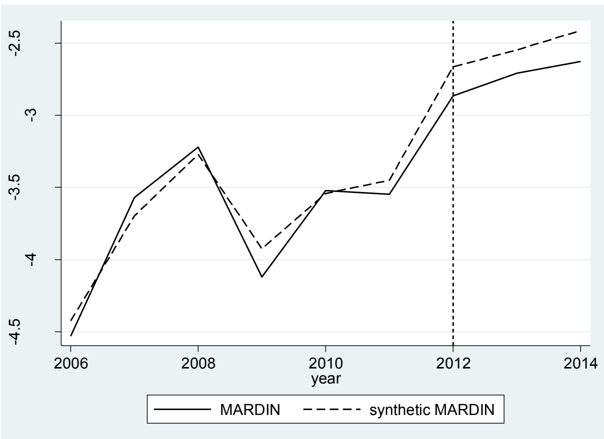
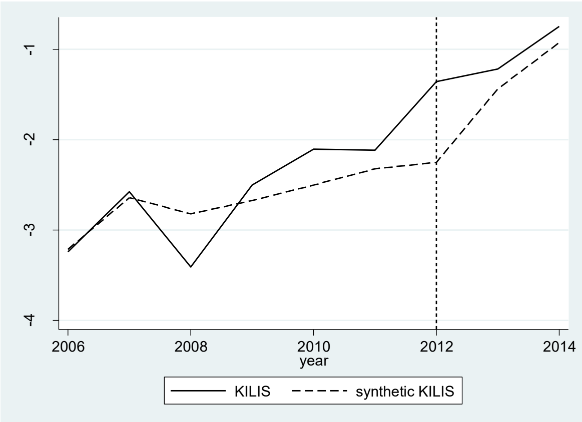


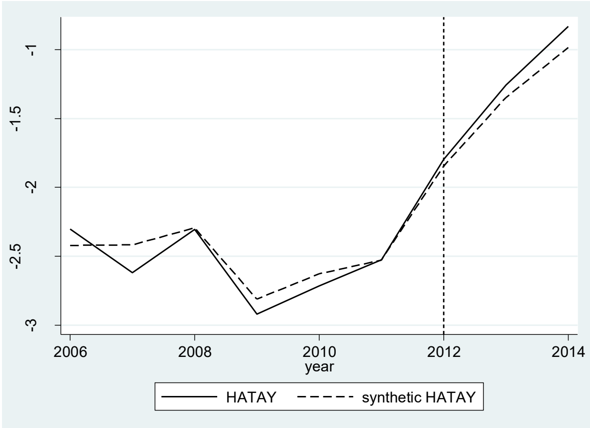
Figure-9: Synthetic Control Event Study Estimates for Theft

(2006-2014)

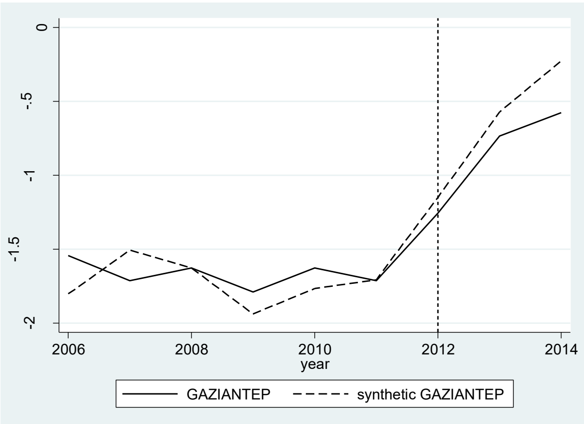
(a) SCM estimates for KILIS



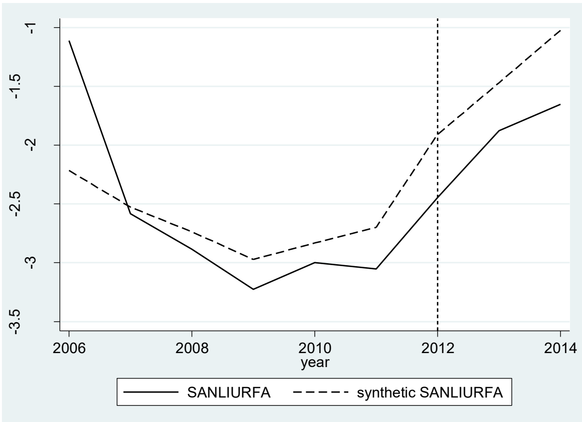
(b) SCM estimates for HATAY



(c) SCM estimates for GAZIANTEP



(d) SCM estimates for SANLIURFA



(e) SCM estimates for MARDIN

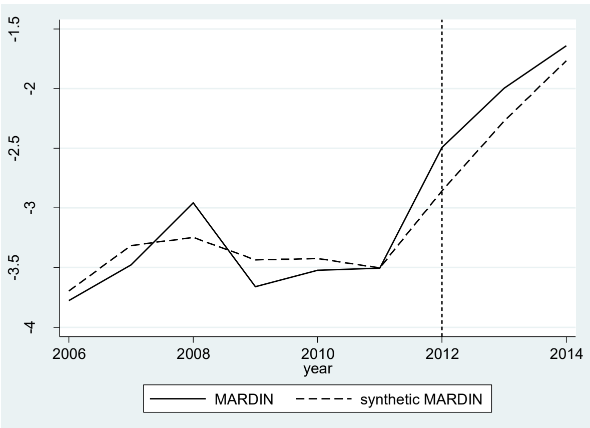
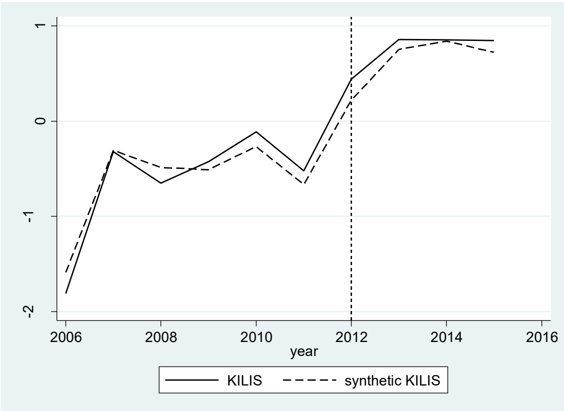


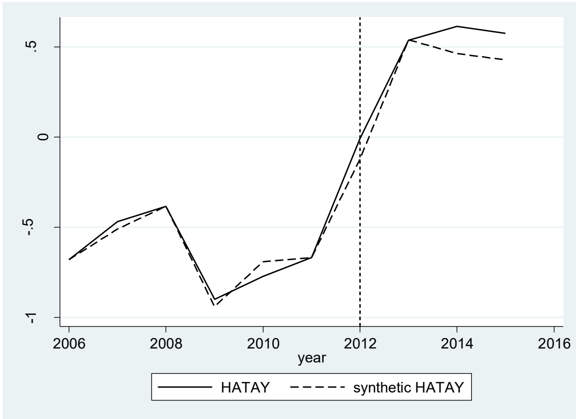
Figure-10: Synthetic Control Event Study Estimates for Total Crime

(2006-2015)

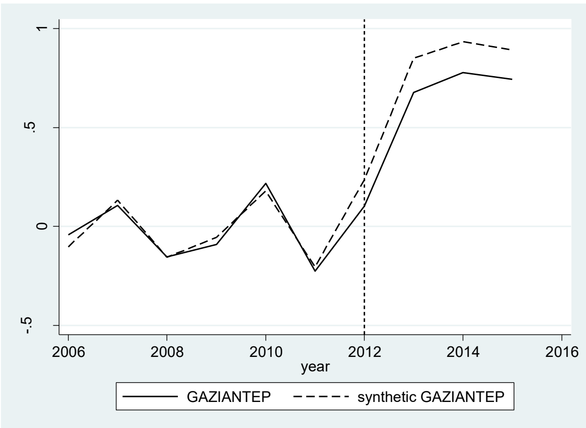
(a) SCM estimates for KILIS



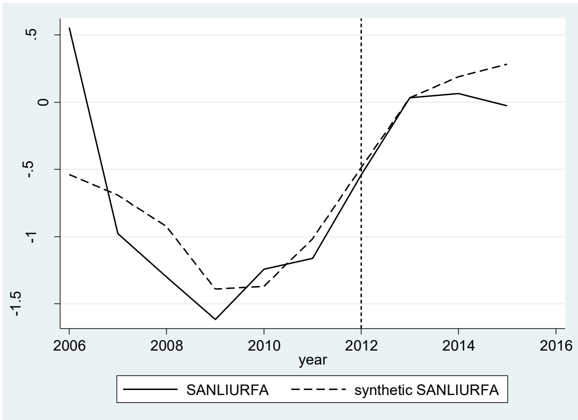
(b) SCM estimates for HATAY



(c) SCM estimates for GAZIANTEP



(d) SCM estimates for SANLIURFA



(e) SCM estimates for MARDIN

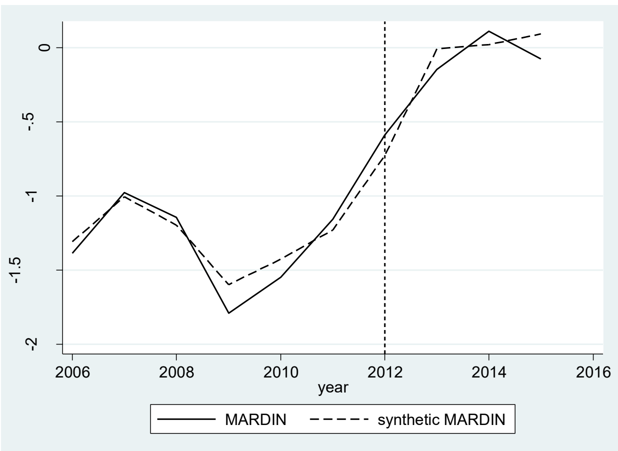
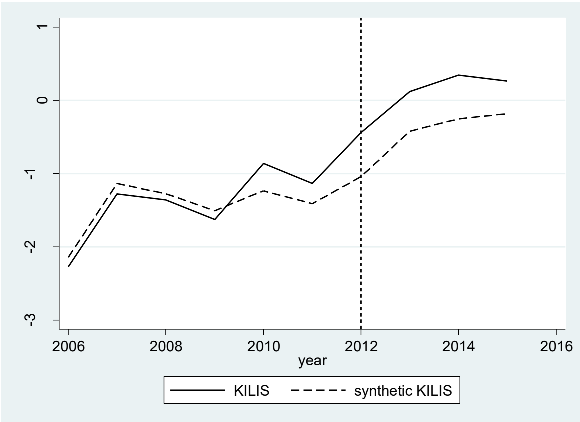
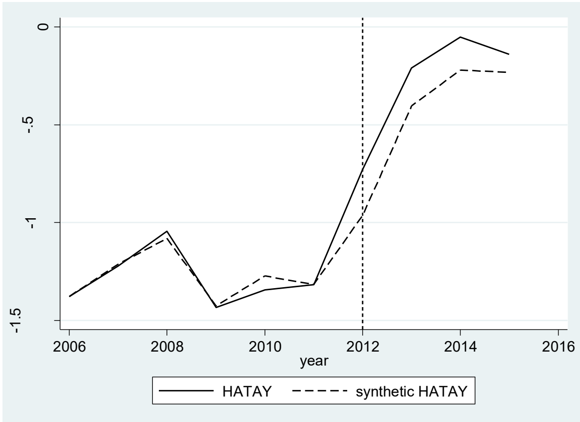


Figure-11: Synthetic Control Event Study Estimates for Income Generating Crimes (2006-2015)

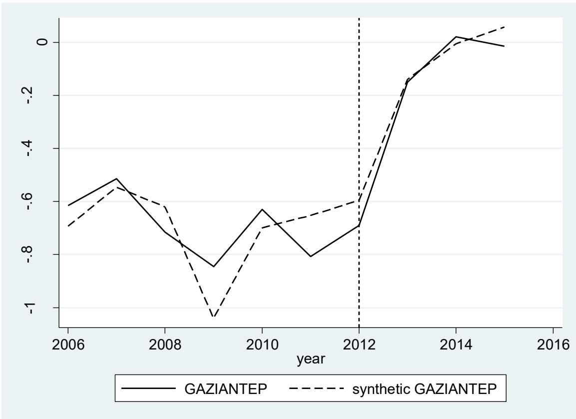
(a) SCM estimates for KILIS



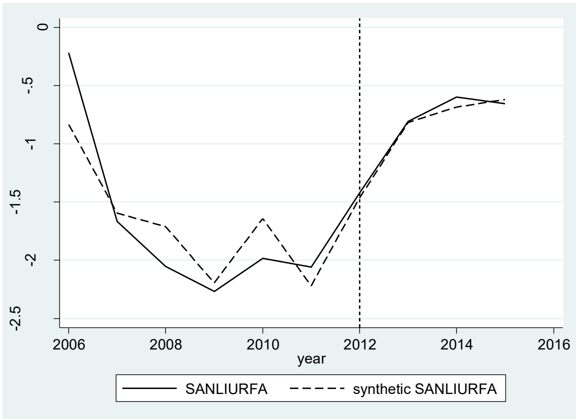
(b) SCM estimates for HATAY



(c) SCM estimates for GAZIANTEP



(d) SCM estimates for SANLIURFA



(e) SCM estimates for MARDIN

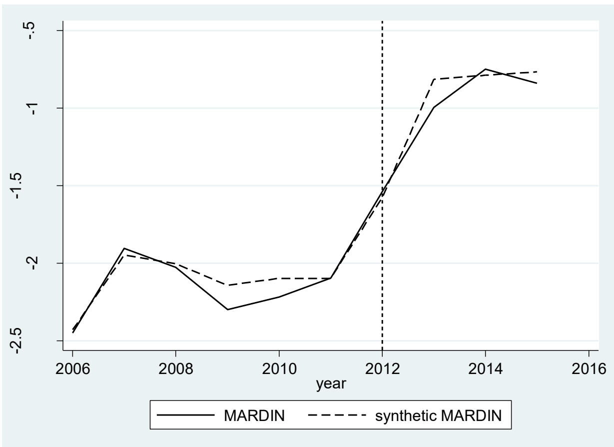
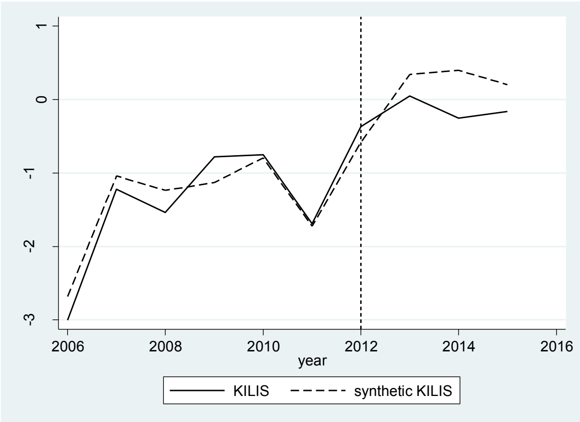
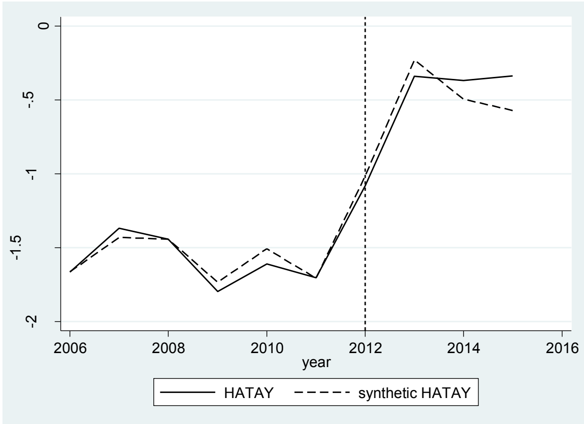


Figure-12: Synthetic Control Event Study Estimates for Non-Income Generating Crimes (2006-2015)

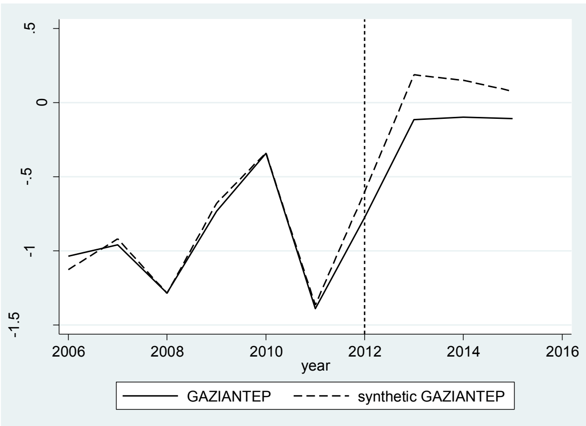
(a) SCM estimates for KILIS



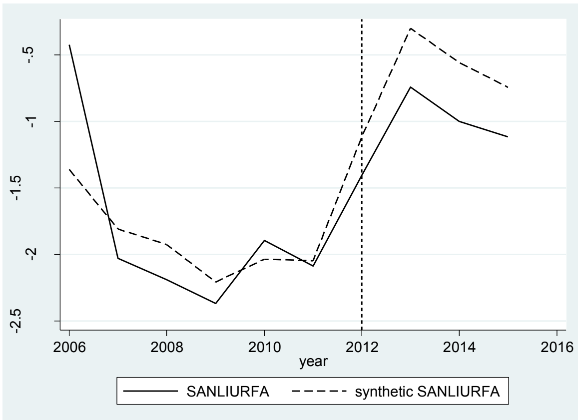
(b) SCM estimates for HATAY



(c) SCM estimates for GAZIANTEP



(d) SCM estimates for SANLIURFA



(e) SCM estimates for MARDIN

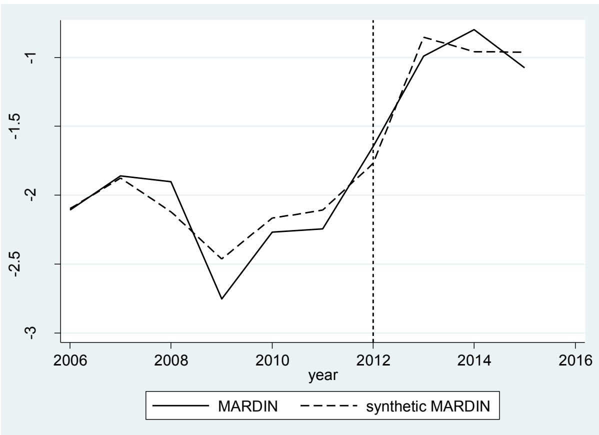
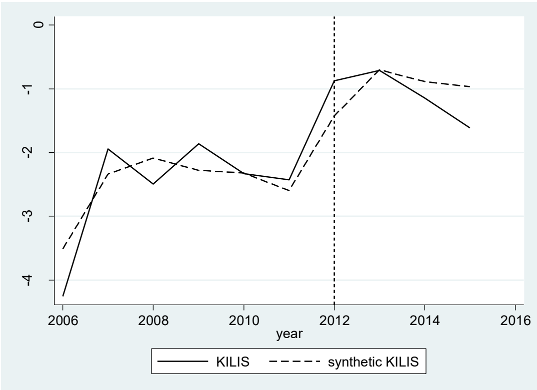


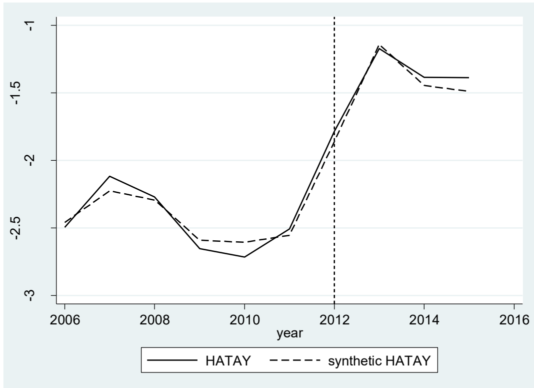
Figure-13: Synthetic Control Event Study Estimates for Assault

(2009-2015)

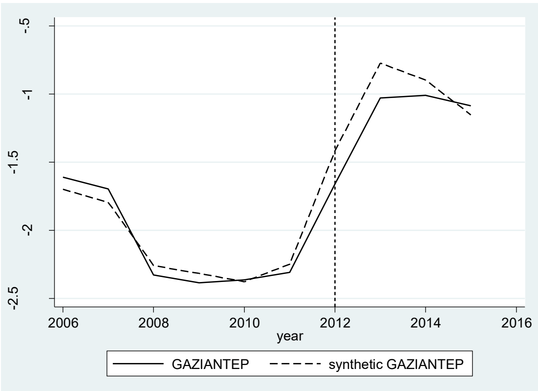
(a) SCM estimates for KILIS



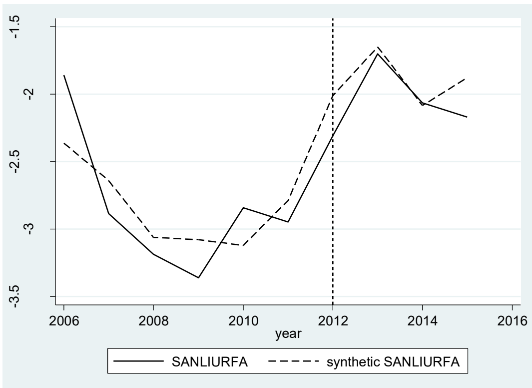
(b) SCM estimates for HATAY



(c) SCM estimates for GAZIANTEP



(d) SCM estimates for SANLIURFA



(e) SCM estimates for MARDIN

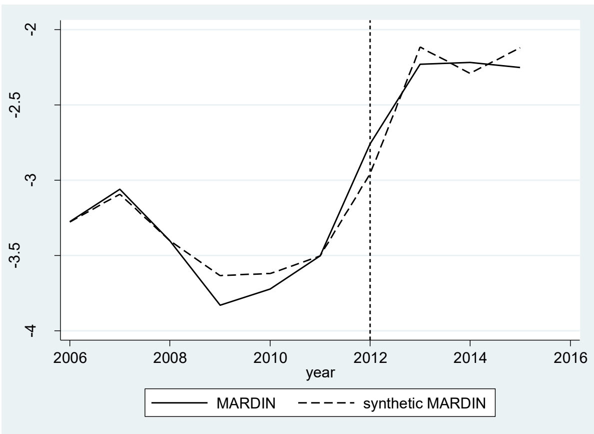
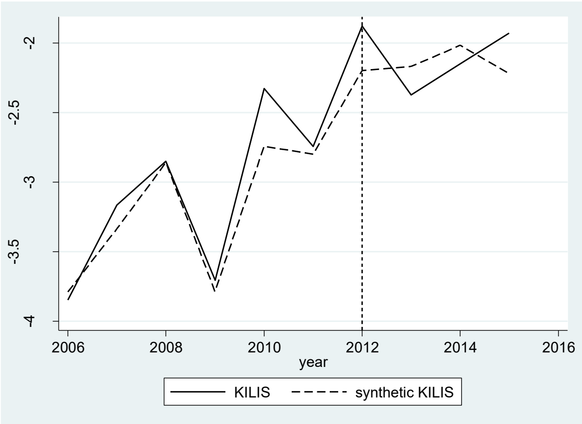


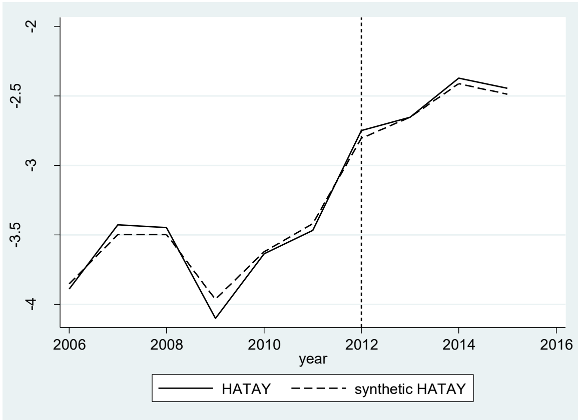
Figure-14: Synthetic Control Event Study Estimates for Homicide

(2006-2015)

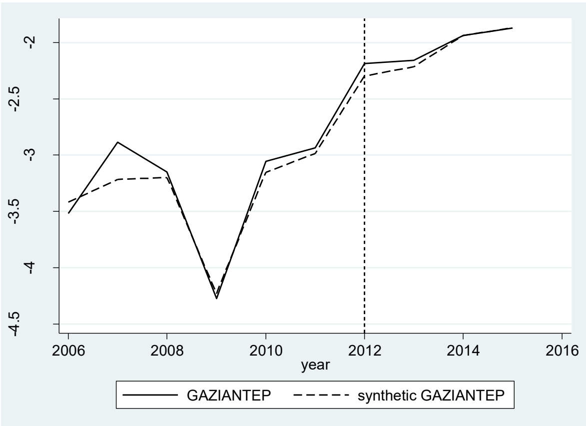
(a) SCM estimates for KILIS



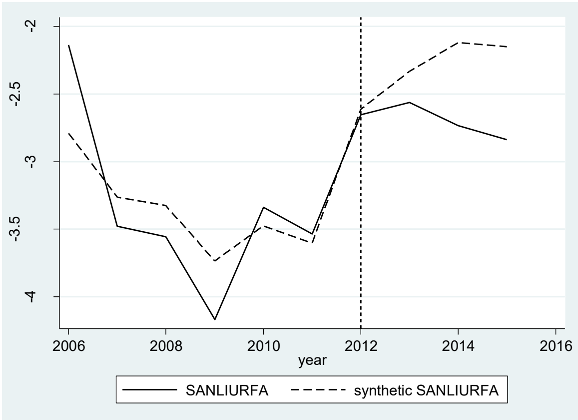
(b) SCM estimates for HATAY



(c) SCM estimates for GAZIANTEP



(d) SCM estimates for SANLIURFA



(e) SCM estimates for MARDIN

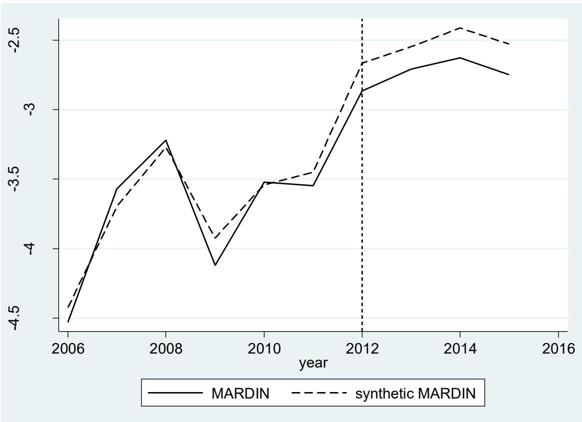
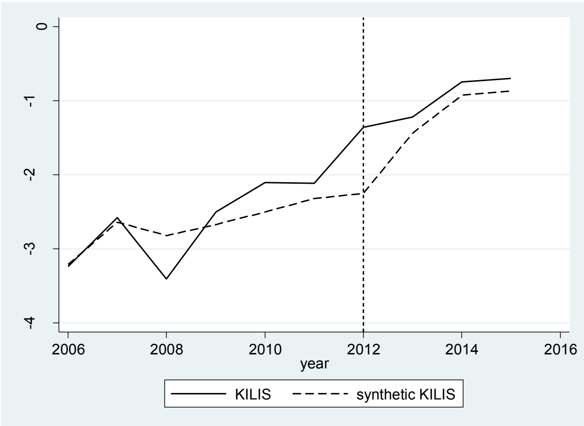


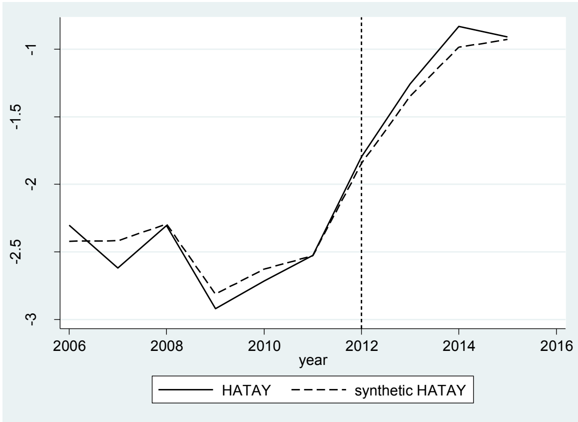
Figure-15: Synthetic Control Event Study Estimates for Theft

(2006-2015)

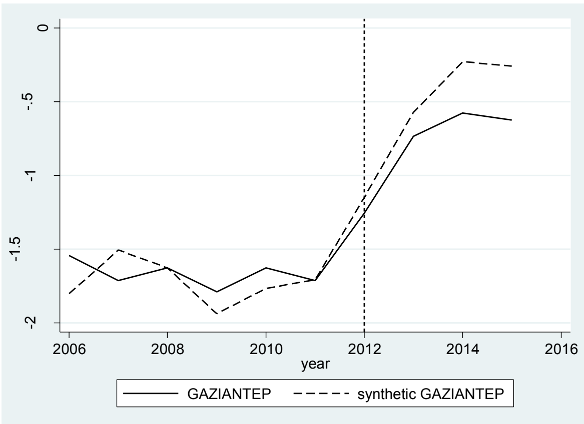
(a) SCM estimates for KILIS



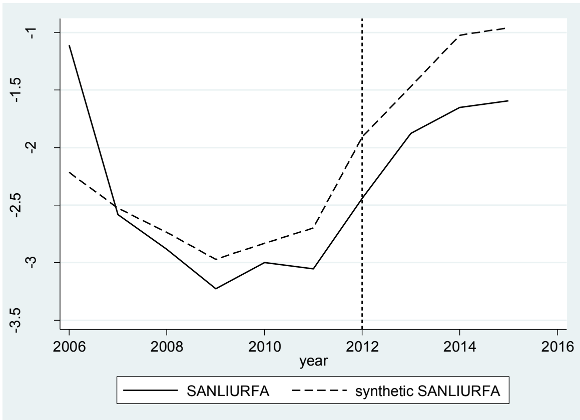
(b) SCM estimates for HATAY



(c) SCM estimates for GAZIANTEP



(d) SCM estimates for SANLIURFA



(e) SCM estimates for MARDIN

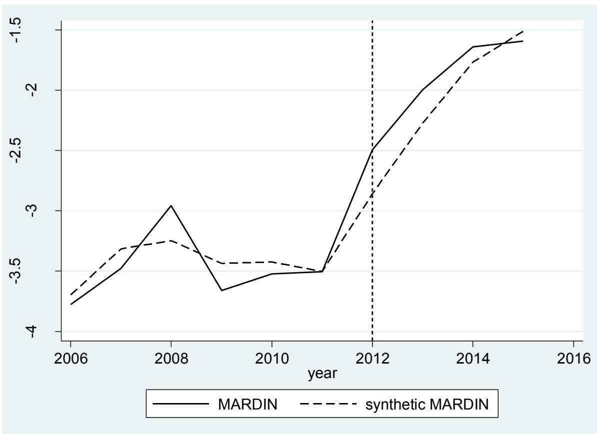


Table-1: Summary statistics of variables for the treatment and control groups between 2010 and 2014.

Treatment Group					
Variable Names	Obs	Mean	Std. Dev.	Min	Max
Theft	70	0.20	0.16	0.02	0.75
Assault	70	0.17	0.13	0.01	0.50
Homicide	70	0.06	0.03	0.01	0.16
Nonincome-generating crimes	70	0.46	0.33	0.07	1.29
Income-generating crimes	70	0.48	0.34	0.10	1.58
Total crime	70	1.10	0.72	0.20	3.12
Lawyers/counselors	70	0.48	0.23	0.11	1.06
Having less then higher degree	70	586.77	44.28	492.03	651.91
Having higher degree	70	53.50	18.39	20.18	99.15
Per capita GDP	70	5621.72	1256.91	3629.52	8792.06
Total employment	70	0.01	0.00	0.00	0.01
Housing price	70	139.11	30.63	102.92	221.06
Participants in Quran courses	70	6.08	6.07	0.15	23.56
Control Group					
Variable Names	Obs	Mean	Std. Dev.	Min	Max
Theft	75	0.14	0.12	0	0.56
Assault	75	0.20	0.20	0.00	1.11
Homicide	75	0.06	0.03	0	0.18
Nonincome-generating crimes	75	0.49	0.43	0.03	2.15
Income-generating crimes	75	0.33	0.22	0.02	1.20
Total crime	75	1.00	0.69	0.06	3.15
Lawyers/counselors	75	0.42	0.23	0.10	0.95
Having less then higher degree	75	611.84	55.63	495.24	730.55
Having higher degree	75	59.03	24.81	18.25	133.73

Per capita GDP	75	5569.40	1614.51	3189.17	9750.98
Total employment	75	0.03	0.01	0.01	0.04
Housing price	75	129.20	20.77	103.54	179.54
Participants in Quran courses	75	8.06	8.11	0.23	29.02

Notes 1: The crime dataset used in this study came from statistics of Turkish penal institutions for the time period 2010 to 2014.

All variables' summary statistics are expressed considering their definitions in the study.

Notes 2: Nonincome-generating crimes are a homicide, assault, sexual crimes, kidnapping, defamation, bad treatment, prevention of performance, traffic crimes, forestry crimes, crimes related to firearms and knives, criminal threats, damage to property, and contrary to the measures for family protection. The income-generating crimes consisted of theft, smuggling, opposition to cheque laws, swindling, the use and purchase of drugs, the production, and sale of drugs, forgery, embezzlement, and bribery. Total crime is generated by aggregating all crimes types in two groups; nonincome-generating crimes and income-generating crimes.

Table-2: The number of different types of crimes in treatment and control groups for the period from 2010 to 2014

Crime[3]	2010-2011[2]		2012-2014	
	Treatment Group	Control Group	Treatment Group	Control Group
Theft	3,018	677	7,859	3,614
Assault	2,471	840	11,478	4,449
Homicide	1,226	495	4,183	1,530
Nonincome-generating crimes	8,756	2,428	29,211	10,551
Income-generating crimes	8,851	2,563	32,721	8,822
Total Crime	19,186	5,596	72,254	23,858

[1]Since Syrian refugees started to come into Turkey at the beginning of 2012, a year interval is constituted around this cutoff date.

[2] The dataset includes only the civilian population.

Table-3: Results of the impact of the refugee influx on crime rates.

Crimes	Model 1	R^2	Observation	Model 2	R^2	Observation
Assault	-0.225* (0.124)	0.95	145	-0.138 (0.084)	0.97	145
Theft	0.024 (0.127)	0.94	144	-0.025 (0.084)	0.97	144
Homicide	-0.125 (0.153)	0.80	143	0.003 (0.112)	0.88	143
Non-income generating crimes	-0.088 (0.145)	0.93	145	-0.040 (0.118)	0.95	145
Income generating crimes	-0.067 (0.111)	0.93	145	0.041 (0.092)	0.96	145
Total crime	-0.091 (0.117)	0.92	145	0.003 (0.086)	0.96	145

***ρ<0.01, ** ρ <0.05 and *ρ<0.01.

Notes: All models include control variables: employment rate, house price, the proportion of lawyer, the proportion of participants in Quran courses, real GDP per capita, high school degree or lower, higher degree than high school diploma per thousand residents, year and city dummies. Model 1 is conducted without survey weights but with robust standard errors. Model 2 is conducted with robust standard errors and survey weights. We also performed cluster models with and without the weight and obtained similar results in Table-3. Although standard errors are clustered with respect to the city, crimes are weighted by the total population of each city.

Nonincome-generating crimes are Nonincome-generating crimes are a homicide, assault, sexual crimes, kidnapping, defamation, bad treatment, prevention of performance, traffic crimes, forestry crimes, crimes related to firearms and knives, criminal threats, damage to property, and contrary to the measures for family protection. The income-generating crimes consisted of theft, smuggling, opposition to cheque laws, swindling, the use and purchase of drugs, the production, and sale of drugs, forgery, embezzlement, and bribery.

Table-4: Synthetic Control Method t-test Results

Crime Type	Pre-immigrant	Post-immigrant
Total Crime	t statistic	t statistic
Kilis	-0.008	0.471
Hatay	0.005	0.303
Gaziantep	0.031	-0.505
Sanlıurfa	0.092	-0.061
Mardin	-0.272	0.094
Homicide		
Kilis	0.360	-0.041
Hatay	-0.134	0.200
Gaziantep	0.222	0.406
Sanlıurfa	-0.011	-1.957
Mardin	-0.128	-1.895
Assault		
Kilis	-0.069	0.373
Hatay	-0.040	0.130
Gaziantep	0.002	-0.702
Sanlıurfa	-0.017	-0.498
Mardin	-0.305	0.170
Theft		
Kilis	0.145	1.007
Hatay	-0.388	0.260
Gaziantep	0.793	-0.607
Sanlıurfa	0.061	-1.506
Mardin	-0.350	0.640
Non-income generating crimes		
Kilis	-0.141	-0.713
Hatay	-0.193	-0.047
Gaziantep	-0.024	-0.708
Sanlıurfa	0.210	-1.269
Mardin	-0.333	0.125
Income generating crimes crimes		
Kilis	0.116	1.730
Hatay	-0.121	0.657
Gaziantep	0.239	-0.096
Sanlıurfa	-0.023	0.135
Mardin	-0.432	-0.102

Table-5: Results of robustness exercises for model 1 (2010-2014)

	Assault	Theft	Homicide	Non-income generating crimes	Income generating crimes	Total crime
A. All Turkey except the treatment region						
Refugee effect (T = 1 and P = 1)	-0.080	-0.023	-0.187**	0.038	0.068	0.045
	(0.059)	(0.059)	(0.082)	(0.092)	(0.053)	(0.070)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.95	0.94	0.83	0.91	0.93	0.91
Observations	405	404	403	405	405	405
B. All Turkey except the treatment and original control regions						
Refugee effect (T = 1 and P = 1)	-0.018	-0.089	-0.221***	0.093	0.090*	0.093
	(0.056)	(0.061)	(0.082)	(0.095)	(0.053)	(0.072)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.96	0.95	0.85	0.91	0.94	0.92
Observations	330	330	330	330	330	330

***ρ<0.01, ** ρ <0.05 and *ρ<0.01.

Notes: All models include control variables: employment rate, house price, the proportion of lawyer, the proportion of participants in Quran courses, real GDP per capita, high school degree or lower, higher degree than high school diploma per thousand residents, year and city dummies. Model 1 is conducted without survey weights but with robust standard errors. We also performed cluster models with and without the weight and obtained similar results in Table-5. Although standard errors are clustered with respect to the city, crimes are weighted by the total population of each city.

Nonincome-generating crimes are Nonincome-generating crimes are a homicide, assault, sexual crimes, kidnapping, defamation, bad treatment, prevention of performance, traffic crimes, forestry crimes, crimes related to firearms and knives, criminal threats, damage to property, and contrary to the measures for family protection. The income-generating crimes consisted of theft, smuggling, opposition to cheque laws, swindling, the use and purchase of drugs, the production, and sale of drugs, forgery, embezzlement, and bribery.

Table-6: Results of robustness exercises -time variation in refugee intensity for model 1 (2009-2015)

	Assault	Theft	Homicide	Non-income generating crimes	Income generating crimes	Total crime
A. All Turkey except the treatment region						
Refugee effect (T= 1 and P = 1)	-0.097*	-0.052	-0.182**	0.016	0.039	0.027
	(0.056)	(0.055)	(0.077)	(0.089)	(0.051)	(0.068)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.95	0.95	0.82	0.92	0.93	0.91
Observations	486	485	484	486	486	486
B. All Turkey except the treatment and original control regions						
Refugee effect (T= 1 and P = 1)	-0.011	-0.105*	-0.222***	0.092	0.056	0.089
	(0.053)	(0.057)	(0.080)	(0.094)	(0.051)	(0.071)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.96	0.95	0.85	0.92	0.95	0.92
Observations	396	396	396	396	396	396

***ρ<0.01, ** ρ <0.05 and *ρ<0.01.

Notes: : All models include control variables: employment rate, house price, the proportion of lawyer, the proportion of participants in Quran courses, real GDP per capita, high school degree or lower, higher degree than high school diploma per thousand residents,year and city dummies. Model 1 is conducted with robust standard errors and survey weights. We also performed cluster models with and without the weight and obtained similar results in Table-6. Although standard errors are clustered with respect to the city, crimes are weighted by the total population of each city.

Nonincome-generating crimes are Nonincome-generating crimes are a homicide, assault, sexual crimes, kidnapping, defamation, bad treatment, prevention of performance, traffic crimes, forestry crimes, crimes related to firearms and knives, criminal threats, damage to property, and contrary to the measures for family protection. The income-generating crimes consisted of theft, smuggling, opposition to cheque laws, swindling, the use and purchase of drugs, the production, and sale of drugs, forgery, embezzlement, and bribery.

Table-7: Results of robustness exercises -time variation in refugee intensity for model 1 (2010-2013)

	Assault	Theft	Homicide	Non-income generating crimes	Income generating crimes	Total crime
A. All Turkey except the treatment region						
Refugee effect (T= 1 and P = 1)	-0.077	-0.009	-0.201**	0.065	0.078	0.054
	(0.062)	(0.064)	(0.090)	(0.095)	(0.055)	(0.073)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.95	0.92	0.81	0.90	0.92	0.89
Observations	324	323	322	324	324	324
B. All Turkey except the treatment and original control regions						
Refugee effect (T= 1 and P = 1)	-0.021	-0.080	-0.230**	0.125	0.100*	0.103
	(0.057)	(0.066)	(0.090)	(0.097)	(0.056)	(0.074)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.96	0.93	0.84	0.91	0.93	0.90
Observations	264	264	264	264	264	264

***ρ<0.01, ** ρ <0.05 and *ρ<0.01.

Notes: All models include control variables: employment rate, house price, the proportion of lawyer, the proportion of participants in Quran courses, real GDP per capita, high school degree or lower, higher degree than high school diploma per thousand residents, year and city dummies. Model 1 is conducted without survey weights but with robust standard errors. We also performed cluster models with and without the weight and obtained similar results in Table-7. Although standard errors are clustered with respect to the city, crimes are weighted by the total population of each city.

Nonincome-generating crimes are Nonincome-generating crimes are a homicide, assault, sexual crimes, kidnapping, defamation, bad treatment, prevention of performance, traffic crimes, forestry crimes, crimes related to firearms and knives, criminal threats, damage to property, and contrary to the measures for family protection. The income-generating crimes consisted of theft, smuggling, opposition to cheque laws, swindling, the use and purchase of drugs, the production, and sale of drugs, forgery, embezzlement, and bribery.

Table-8: Results of robustness exercises -time variation in refugee intensity for model 1 (2009-2015)

	Assault	Theft	Homicide	Non-income generating crimes	Income generating crimes	Total crime
A. Post-immigration period: 2012						
Refugee effect (T= 1 and P = 1)	-0.065 (0.175)	0.041 (0.162)	-0.057 (0.191)	0.047 (0.198)	-0.001 (0.124)	0.027 (0.154)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.95	0.9	0.80	0.87	0.94	0.88
Observations	87	86	85	87	87	87
B. Post-immigration period: 2013						
Refugee effect (T= 1 and P = 1)	-0.380** (0.168)	0.137 (0.196)	-0.190 (0.249)	0.036 (0.188)	-0.032 (0.146)	0.012 (0.162)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.97	0.94	0.78	0.94	0.96	0.93
Observations	87	86	86	87	87	87
C. Post-immigration period: 2014						
Refugee effect (T= 1 and P = 1)	-0.376** (0.151)	-0.148 (0.165)	-0.115 (0.231)	-0.010 (0.189)	-0.140 (0.184)	-0.016 (0.152)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.96	0.96	0.85	0.93	0.94	0.94
Observations	87	86	86	87	87	87
D. Post-immigration period: 2015						
Refugee effect (T= 1 and P = 1)	-0.402** (0.177)	-0.209 (0.162)	-0.069 (0.250)	0.001 (0.207)	-0.221 (0.195)	-0.063 (0.168)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R2	0.96	0.96	0.85	0.93	0.95	0.94
Observations	87	86	86	87	87	87

***ρ<0.01, ** ρ <0.05 and *ρ<0.01.

Table-9: Results of the impact of the refugee influx on crime rates (2009-2015).

Crime	Model 1	R^2	Observation	Model 2	R^2	Observation
Assault	-0.240** (0.116)	0.95	174	-0.164** (0.077)	0.97	174
Theft	-0.020 (0.121)	0.95	173	-0.068 (0.081)	0.97	173
Homicide	-0.126 (0.139)	0.79	172	-0.035 (0.112)	0.88	172
Nonincome-generating crimes	-0.124 (0.138)	0.93	174	-0.117 (0.112)	0.95	174
Income-generating crimes	-0.079 (0.113)	0.94	174	0.037 (0.099)	0.96	174
Total crime	-0.123 (0.114)	0.93	174	-0.039 (0.084)	0.96	174

***ρ<0.01, ** ρ <0.05 and *ρ<0.01.

Notes: All models include control variables: employment rate, house price, the proportion of lawyer, the proportion of participants in Quran courses, real GDP per capita, high school degree or lower, higher degree than high school diploma per thousand residents, year and city dummies. Model 1 is conducted without survey weights but with robust standard errors. Model 2 is conducted with robust standard errors and survey weights. We also performed cluster models with and without the weight and obtained similar results in Tabl-9. Although standard errors are clustered with respect to the city, crimes are weighted by the total population of each city.

Nonincome-generating crimes are Nonincome-generating crimes are a homicide, assault, sexual crimes, kidnapping, defamation, bad treatment, prevention of performance, traffic crimes, forestry crimes, crimes related to firearms and knives, criminal threats, damage to property, and contrary to the measures for family protection. The income-generating crimes consisted of theft, smuggling, opposition to cheque laws, swindling, the use and purchase of drugs, the production, and sale of drugs, forgery, embezzlement, and bribery.

Table-10: Results of the impact of the refugee influx on crime rates (2010-2013).

Crimes	Model 1	R^2	Observation	Model 2	R^2	Observation
Assault	-0.203 (0.144)	0.95	116	-0.059 (0.093)	0.97	116
Theft	0.070 (0.143)	0.93	115	0.068 (0.096)	0.97	115
Homicide	-0.096 (0.167)	0.78	114	0.002 (0.130)	0.86	114
Non-income generating crimes	-0.037 (0.162)	0.91	116	0.111 (0.117)	0.94	116
Income generating crimes	-0.053 (0.107)	0.93	116	0.033 (0.091)	0.96	116
Total crime	-0.066 (0.131)	0.91	116	0.065 (0.093)	0.95	116

***ρ<0.01, ** ρ <0.05 and *ρ<0.01.

Notes: All models include control variables: employment rate, house price, the proportion of lawyer, the proportion of participants in Quran courses, real GDP per capita, high school degree or lower, higher degree than high school diploma per thousand residents, year and city dummies. Model 1 is conducted without survey weights but with robust standard errors. Model 2 is conducted with robust standard errors and survey weights. We also performed cluster models with and without the weight and obtained similar results in Table-10. Although standard errors are clustered with respect to the city, crimes are weighted by the total population of each city.

Nonincome-generating crimes are Nonincome-generating crimes are a homicide, assault, sexual crimes, kidnapping, defamation, bad treatment, prevention of performance, traffic crimes, forestry crimes, crimes related to firearms and knives, criminal threats, damage to property, and contrary to the measures for family protection. The income-generating crimes consisted of theft, smuggling, opposition to cheque laws, swindling, the use and purchase of drugs, the production, and sale of drugs, forgery, embezzlement, and bribery.

Table11: Results of robustness exercises for model 2 (2010-2014)

	Assault	Theft	Homicide	Non-income generating crimes	Income generating crimes	Total crime
A. All Turkey except the treatment region						
Refugee effect (T= 1 and P = 1)	0.012 (0.047)	-0.001 (0.048)	-0.051 (0.063)	0.152 (0.083)	0.233*** (0.055)	0. 032*** (0.065)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.96	0.96	0.90	0.93	0.95	0.92
Observations	405	404	403	405	405	405
B. All Turkey except the treatment and original control regions						
Refugee effect (T= 1 and P = 1)	0.015 (0.048)	-0.027 (0.052)	-0.087 (0.066)	0.192 (0.086)	0.222*** (0.055)	0.226*** (0.067)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.97	0.97	0.91	0.93	0.94	0.93
Observations	330	330	330	330	330	330

***ρ<0.01, ** ρ <0.05 and *ρ<0.01.

Notes: All models include control variables: employment rate, house price, the proportion of lawyer, the proportion of participants in Quran courses, real GDP per capita, high school degree or lower, higher degree than high school diploma per thousand residents, year and city dummies. Model 2 is conducted with robust standard errors and survey weights. We also performed cluster models with and without the weight and obtained similar results in Table-11. Although standard errors are clustered with respect to the city, crimes are weighted by the total population of each city.

Nonincome-generating crimes are Nonincome-generating crimes are a homicide, assault, sexual crimes, kidnapping, defamation, bad treatment, prevention of performance, traffic crimes, forestry crimes, crimes related to firearms and knives, criminal threats, damage to property, and contrary to the measures for family protection. The income-generating crimes consisted of theft, smuggling, opposition to cheque laws, swindling, the use and purchase of drugs, the production, and sale of drugs, forgery, embezzlement, and bribery.

Table-12: Results of robustness exercises -time variation in refugee intensity for model 2

	Assault	Theft	Homicide	Non-income generating crimes	Income generating crimes	Total crime
A. All Turkey except the treatment region						
Refugee effect (T= 1 and P = 1)	0.006	-0.028	-0.059	0.141*	0.190***	0.187***
	(0.047)	(0.049)	(0.061)	(0.082)	(0.056)	(0.065)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.96	0.97	0.89	0.93	0.93	0.93
Observations	486	485	484	486	486	486
B. All Turkey except the treatment and original control regions						
Refugee effect (T= 1 and P = 1)	0.039	-0.032	-0.083	0.205**	0.187***	0.229***
	(0.047)	(0.054)	(0.065)	(0.085)	(0.058)	(0.067)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.96	0.97	0.90	0.94	0.94	0.93
Observations	396	396	396	396	396	396

***ρ<0.01, ** ρ <0.05 and *ρ<0.01.

Notes: All models include control variables: employment rate, house price, the proportion of lawyer, the proportion of participants in Quran courses, real GDP per capita, high school degree or lower, higher degree than high school diploma per thousand residents, year and city dummies. Model 2 is conducted with robust standard errors and survey weights. We also performed cluster models with and without the weight and obtained similar results in Table-12. Although standard errors are clustered with respect to the city, crimes are weighted by the total population of each city.

Nonincome-generating crimes are Nonincome-generating crimes are a homicide, assault, sexual crimes, kidnapping, defamation, bad treatment, prevention of performance, traffic crimes, forestry crimes, crimes related to firearms and knives, criminal threats, damage to property, and contrary to the measures for family protection. The income-generating crimes consisted of theft, smuggling, opposition to cheque laws, swindling, the use and purchase of drugs, the production, and sale of drugs, forgery, embezzlement, and bribery.

Table-13: Results of robustness exercises -time variation in refugee intensity for model 2 (2010-2013)

	Assault	Theft	Homicide	Non-income generating crimes	Income generating crimes	Total crime
A. All Turkey except the treatment region						
Refugee effect (T= 1 and P = 1)	0.043	0.032	-0.061	0.177**	0.260***	0.218***
	(0.049)	(0.051)	(0.069)	(0.085)	(0.058)	(0.068)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.97	0.95	0.88	0.92	0.93	0.90
Observations	324	323	322	324	324	324
B. All Turkey except the treatment and original control regions						
Refugee effect (T= 1 and P = 1)	0.049	-0.004	-0.102	0.204**	0.265***	0.239***
	(0.049)	(0.052)	(0.069)	(0.089)	(0.057)	(0.069)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.97	0.96	0.90	0.93	0.93	0.91
Observations	264	264	264	264	264	264

***ρ<0.01, ** ρ <0.05 and *ρ<0.01.

Notes: All models include control variables: employment rate, house price, the proportion of lawyer, the proportion of participants in Quran courses, real GDP per capita, high school degree or lower, higher degree than high school diploma per thousand residents, year and city dummies. Model 2 is conducted with robust standard errors and survey weights. We also performed cluster models with and without the weight and obtained similar results in Table-13. Although standard errors are clustered with respect to the city, crimes are weighted by the total population of each city.

Nonincome-generating crimes are Nonincome-generating crimes are a homicide, assault, sexual crimes, kidnapping, defamation, bad treatment, prevention of performance, traffic crimes, forestry crimes, crimes related to firearms and knives, criminal threats, damage to property, and contrary to the measures for family protection. The income-generating crimes consisted of theft, smuggling, opposition to cheque laws, swindling, the use and purchase of drugs, the production, and sale of drugs, forgery, embezzlement, and bribery.

Table-14: Results of robustness exercises-time variation in refugee intensity for model 2 (2010-2015)

	Assault	Theft	Homicide	Non-income generating crimes	Income generating crimes	Total crime
A. Post-immigration period: 2012						
Refugee effect (T= 1 and P = 1)	-0.047	0.080	0.004	0.109	-0.007	0.046
	(0.104)	(0.121)	(0.161)	(0.137)	(0.103)	(0.106)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.97	0.96	0.86	0.91	0.96	0.93
Observations	87	86	85	87	87	87
B. Post-immigration period: 2013						
Refugee effect (T= 1 and P = 1)	-0.210	0.094	-0.058	0.157	0.053	0.092
	(0.136)	(0.136)	(0.214)	(0.160)	(0.131)	(0.137)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.98	0.98	0.87	0.95	0.97	0.96
Observations	87	86	86	87	87	87
C. Post-immigration period: 2014						
Refugee effect (T= 1 and P = 1)	-0.292	-0.140	0.096	-0.003	0.053	0.068
	(0.116)	(0.111)	(0.169)	(0.182)	(0.154)	(0.132)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.98	0.98	0.92	0.94	0.97	0.96
Observation	87	86	86	87	87	87
D. Post-immigration period: 2015						
Refugee effect (I = 1 and D = 1)	-0.343***	-0.234*	-0.001	-0.073	-0.039	-0.022
	(0.124)	(0.126)	(0.192)	(0.214)	(0.183)	(0.145)
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.97	0.98	0.91	0.94	0.97	0.96
Observations	87	86	86	87	87	87

***ρ<0.01, ** ρ <0.05 and *ρ<0.01.

Table-15: Synthetic Control Method t-test Results (2006-2015)

Crime Type	Pre-immigrant	Post-immigrant
Total Crime	t statistic	t statistic
Kilis	-.008	.662
Hatay	.004	.483
Gaziantep	.030	-.667
Sanlıurfa	.092	-.549
Mardin	-.271	-.080
Homicide		
Kilis	.359	.558
Hatay	-.133	.278
Gaziantep	.221	.307
Sanlıurfa	-.010	-3.091**
Mardin	-.128	-2.769**
Assault		
Kilis	-.068	-.365
Hatay	-.039	.267
Gaziantep	.001	-.645
Sanlıurfa	-.017	-.967
Mardin	-.305	.030
Theft		
Kilis	.145	1.013
Hatay	-.388	.254
Gaziantep	.792	-.925
Sanlıurfa	.061	-1.874
Mardin	-.350	.472
Non-income generating crimes		
Kilis	-.140	-1.121
Hatay	-.193	.188
Gaziantep	-.023	-.906
Sanlıurfa	.210	-1.75
Mardin	-.332	.027
Income generating crimes crimes		
Kilis	.115	2.065
Hatay	-.121	.743
Gaziantep	.238	-.172
Sanlıurfa	-.023	.095
Mardin	-.432	-.170

***ρ<0.01, ** ρ <0.05 and *ρ<0.01.