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Do Refugees Cause Crime?

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Abstract

The impact of immigration on crime continues to stir heated debates in public policy circles around the world whilst surveys indicate that host societies favor mitigating measures because they are concerned of what they perceive as an impingement on their security with each new wave of migration inflow. Whether there is any truth to such perceptions, however, remains a mystery for the case of developing countries since causal evidence is extremely limited. That those countries host the overwhelming majority of the global refugee population makes it paramount for researchers to supply the missing scientific link. Propelled by the magnitude of this need, this paper analyzes the impact of refugees on crime rates using the case of Turkey that hosts the world's largest refugee population within any national borders. In doing so, it uses instrumental variables, Difference-in-Differences (DiD) and Staggered DiD methods to explain if the war-fleeing Syrian refugees pushed Turkey's crime rates higher both in the short and the long-run. Controlling for various time-varying characteristics of provinces and presenting a battery of robustness checks against various identification threats, its findings show either null or negative effects of refugees on the incidence of criminal activity in the country.

Keywords: Crime, refugees, Syrians, misperceptions, Turkey.
JEL Classifications: F22, J61, J68, K42.

I. INTRODUCTION

Following waves of mass displacement due to non-ending conflicts and economic crises between 2011 and 2021, the impact of immigration on crime is now a major subject for policymakers around the world. Likewise, surveys in different contexts show crime is among natives' main concerns about receiving immigrants to their countries (Mayda 2006; Bianchi, Buonanno and Pinotti 2012). In Turkey, which has started to host the world's largest refugee population because of the Syrian civil war, the perceptions of the local population are no different. Across the country, Syrian refugees are thought to be increasing criminal activities (Nielsen, 2016). Since perceived outgroup threat is a primary source of negative emotions and attitudes towards outgroups like refugees (Yitmen and Verkuyten, 2020; Stansfield and Stone, 2018), it is crucial to provide scientific evidence whether there is any truth to such perceptions. However, the empirical literature on the nexus of immigration and crime is elusive because it mostly focuses on the case of developed countries and the role of voluntary migrants on crime while neglecting other regions where a whopping 85 percent (UNHCR, 2020) of the world's refugee population live.

Theoretical literature provides potential channels through which immigrants may cause higher crime rates in their destinations. At the macro level, they can be listed under four categories. Firstly, it may be the case if immigration causes a demographic transition like an increase in the population of people with higher potential to commit a crime such as young males (Ousey and Kubrin, 2018). Similarly, members of refugee families whose primary breadwinners are lost or have serious health problems due to armed conflicts and exhausting migration journeys (Kayaoglu, 2021) may gravitate towards criminal acts as a survival strategy. Secondly, in line with the social disorganization theory, residential turnover and population heterogeneity stemming from immigration may increase crime rates in regions that receive immigrants

(Ousey and Kubrin, 2009; Stowell et al. 2009). Thirdly, immigration into areas where there is already an intense competition for jobs may worsen the squeeze in the labor market and result in intergroup crime, a scenario that is in line with the opportunity structure theory (Messner and South, 1986). And lastly, residential segregation of immigrants or their disproportionate relocation to disadvantaged areas in the host countries (Martinez, 2002) may leave immigrant youth more vulnerable to recruitment by gangs and other criminal networks.

On the other hand, the theoretical literature also features arguments that are put forward to support just the opposite: Immigrants may cause a reduction in crime rates, too. Of those arguments, the most prominent is centered on cost of committing a crime for immigrants. It suggests that since any immigration is awash in exorbitant expenditures, both *ex-ante* and *ex-post*, immigrants' engagement in crime risks making all that spending a sunk-cost in the case of deportation, making them less likely to break bad (Butcher and Piehl, 2007). That is immigrant selection effect. A second such argument might be based on law enforcement's preparedness to fight and deter crime. For example, if a government invests in mobilizing a larger police and gendarmerie force in the face of mass immigrant inflow, then it may well manage to suppress crime not only among the foreign newcomers but also within the local community. More strikingly, as opposed to the social disorganization theory, immigrants may rather revitalize the regions they have resettled in through socio-economic contributions such as scientific discoveries, works of art, new businesses or simply by filling job and housing vacancies that are not demanded by local populations (Lee and Martinez, 2002; Sampson, 2017; Kayaoglu, 2020).

Beyond those theories, existing body of empirical research on immigrant-crime nexus[1] focuses on individual determinants of crime and macro-level determinants of crime-immigration relationship. Early findings uniformly suggest that immigration is not strongly associated with an increase in crime rates. For instance, Bianchi et al. (2012) analyze the impact of immigration on crime in Italy using a province-level panel data and conclude that immigration increases robberies only slightly and its impact on the overall crime rate is null. Chalfin (2015) confirms them with similar findings in the United States context, concluding that Mexican immigrants even have a negative impact on property crime rates in America. In rare evidence from a rather middle-income country, Ozden et al. (2018) shows that immigration significantly reduces both violent and property crime rates in parts of Malaysia. Nevertheless, researchers agree that the picture is still not complete and there is a particular need for further studies on the macro-level impact of immigration on crime rates (Ousey and Kubrin 2009; Reid et al. 2005) with the case of the world's largest refugee hosts remaining understudied.

Indeed, the literature about the effect of refugees on crime rates is extremely limited and only focuses on developed country contexts. To review them in order of publication year, one must start with Bell et al. (2013), which analyze the impact of asylum seekers in the UK in 1990s and conclude that violent crime is not affected by asylum inflows. They have found a small increase only in property crimes. Next, Gehrsitz and Ungerer (2017) examine the massive refugee influx to Germany in 2014 and 2015, suggesting that non-violent crime rates increased, mostly due to an increase in drug-related crimes, as a result. Thirdly, Amuedo-Dorantes et al. (2018) investigate the criminal engagement of refugees in the United States, writing that they could not find a statistically significant correlation between refugee settlement and local crime rates including the incidence of terrorist attacks. Finally, Huang and Kvasnicka (2019) use a

[1] See Bell and Machin (2013) and Fasani, Mastrobuoni, Owens and Pinotti (2019) for a detailed survey of the literature.

data on crimes committed by refugees against natives and show that the overall German security was not compromised because of refugees.

In an attempt to contribute to the empirical literature with much-needed insights from a developing country context where the world's largest refugee population live, this paper studies the case of Turkey. In doing so, it uses the heterogeneity in crime rates as well as refugee presence and flows across the country. It aims to explain how its crime rates are affected as more than 3.5 million war-fleeing Syrians relocated to Turkey. Nonetheless, its findings do not exclusively represent Syrians' relative inclination to commit crimes in comparison to that of the local population. Such a direct impact could be calculated only if an individual level data were available on the ethnicity of criminals in each reported case. In the absence of such metrics, this paper studies whether Syrian refugees affected the incidence of crime in Turkey either by being involved or not in an unlawful act or by impacting factors that might have ultimately altered the criminality of the native population.

Methodologically, this paper first employs a difference-in-differences (DiD) method with both local matching and focal matching strategy to explore the short-term impact of refugee inflows. Secondly, it implements a staggered DiD approach to understand their long-term impact. Results of DiD analyses conclude that the Syrian refugees have no statistically significant impact, whether in the short or the long term, on crime rates in Turkey. Finally, it uses an IV strategy to explain the impact of refugee population intensity on crime rates and present a negative impact of refugee population intensity on crime rates. When we repeat the same analyses for crime rates not per total population but per native population, these negative results turn out to be null. Thus, one can claim that refugees have lower propensity to commit crimes compared to natives, and this could be related with high deterrence costs they have in the host country such as fear of deportation.

As a result, this paper contributes to the relevant academic literature on the nexus of immigration and crime by being the first empirical research into the case of Turkey, which is not only a major developing country but also the host of the world's largest refugee population within any national borders. Moreover, the identification in this paper profoundly improves the scholar understanding of the short and long-run causal effect of refugees on the incidence of different types of crime.

II. BACKGROUND

Since 2011, the Syrian conflict has forced a total of 6.6 million people from their homeland as well as internally displacing 6.2 million others. An imminent neighbor of the war-ravaged country, Turkey is deeply affected by the humanitarian crisis next door. According to the latest official data, it hosts more than 3.5 million Syrian refugees and is now the largest-refugee hosting country in the world. Although the Turkish government has welcomed such a remarkable population of Syrian refugees[2], public opinion surveys showed that the local population in the country have started to grow increasingly more critical of its approach and

[2] On the 29 August 1961, Turkey signed the 1951 Geneva Convention which defined the 'refugee' as someone who is unable or unwilling to return to his/her country of origin owing to a well-founded fear of being persecuted for reasons of race, religion, nationality, membership in a particular social group, or political opinion. However, Turkey signed it with time and geographical limitations. This only enabled European asylum-seekers from being granted a refugee status in Turkey. Accordingly, the Law on Foreigners and International Protection[2] which is adopted in April 2013 preserved this geographical limitation in which Syrians are given the status of 'temporary protection'. And, Syrians are defined as "who have been forced to leave their country, cannot return to the country that they have left, and have arrived at or crossed the borders of Turkey in a mass influx situation seeking immediate and temporary protection". Thus, although Syrians in Turkey are internationally accepted as refugees, they are legally not entitled a refugee status and only provided a temporary protection status. In order to be in line with the international usage of the term, this paper uses 'refugee' to describe Syrians in Turkey, instead of 'Syrians under temporary protection' which is how they are referred in official documents.

policies particularly after the 2013 terror bombings[3] in the town of Reyhanli near the Syrian border. Earlier references made to the Syrian refugees such as 'guests' and 'religious brothers/sisters' have gradually lost traction. In the Syrian Barometer survey (2017), for example, 75% of the respondents argued that it is not possible to live in peace with the Syrian refugees and even a larger group (82%) said that the Syrians are not good for the Turkish economy. Moreover, 46% of them were worried that the Syrian refugees would harm them or their families. In more relevance to the subject of this paper, 60% of the respondents suggested that the Syrians damage the societal fabric in Turkey by committing crimes. Those rampant negative opinions are also boosted by populist media outlets that, at times, described Syrians outright as 'criminals' or even as 'crime machines[4]'. With the increased economic difficulties due to the Covid-19 pandemic, it would not be surprising if the native population became even more critical of Syrian refugee presence in Turkey.

III. DATA AND STYLIZED FACTS

3.1. Syrian Refugee Population in Turkey

When a group of teenagers inspired by the 'Arab Spring' uprisings elsewhere in Middle East sprayed anti-government graffities in Daraa, southwestern Syria, in the spring of 2011, not many experts saw one of history's bloodiest conflicts was in the making. As sporadic fighting quickly turned into a full-scale war, neither Syria's neighbors nor international organizations were ready to accommodate millions of Syrians running for their lives. As ***Figure 1*** shows below, the number of Syrian refugees in Turkey increased by about 10-fold, from around 250 thousand in 2013 to 2.5 million in 2015.

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[3] For details, see: https://www.hurriyetdailynews.com/negligence-led-to-twin-car-bombings-in-turkeys-reyhanli-indictment--82264

[4] Sozcu newspaper, for example, published various articles with this view. See, for example, an article titled "Guests (!) are like crime machines" https://www.sozcu.com.tr/2016/gundem/misafirler-suc-makinesi-1230634/
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In the face of such a massive refugee inflow, Turkey readied a temporary shelter system with 14 camps in several border provinces. However, it did not take long before they proved far short of meeting the demand, paving the way for Syrians' resettlement in cities across the country. To illustrate, ***Table 1*** compares the December 2013, September 2014 and December 2014 camp and out-camp populations by province. As is seen, there is a clear upward trend in the share of Syrian refugees living in urban areas with a striking spike in out-camp refugee population during and after 2013. By the end of 2019, eventually, the total number of Syrian refugees in Turkey has reached to 3,571,030 with only 1.78% of them living in camps.

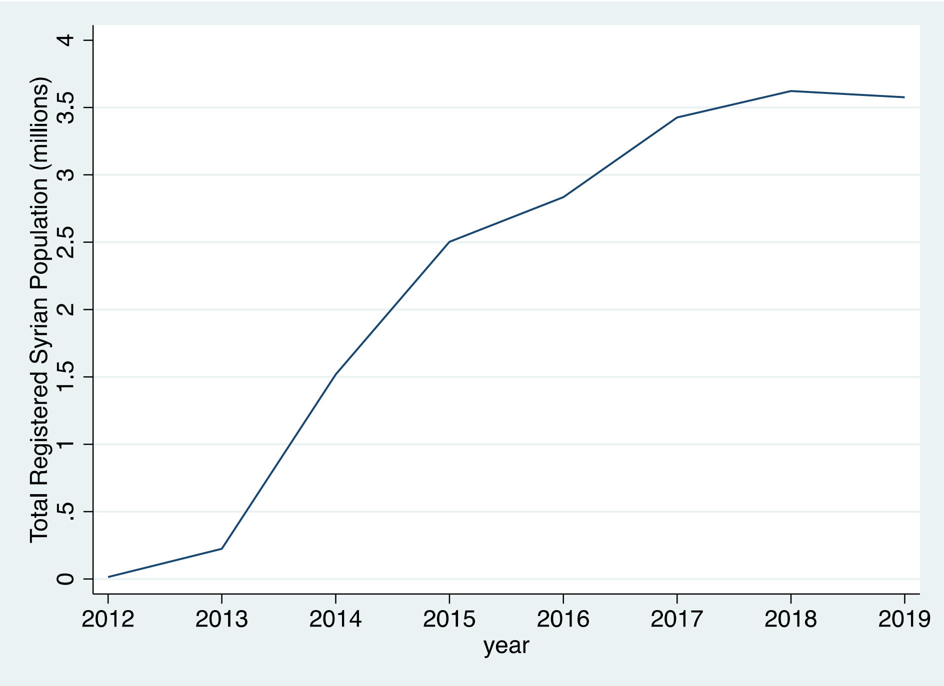


Figure 1. Registered Syrian Refugees in Turkey

In order to understand the potential role refugees can play on crime rates and interpret the findings, it is also important to know the similarities and differences between refugee and native population. ***Table 2*** compares the basic labor force and demographic characteristics of each group. Number of Syrian refugees with a work permit is very low. As a result, Syrians work incomparably more in informal jobs than natives. Additionally, the percentage of males is higher among Syrians who are also younger. The percentage of marriage is smaller among

Syrians. The 64.3% of the Syrians in Turkey are single. Lastly, there is an important education gap between natives and refugees. According to the 2019 DGMM statistics, 50.36% of them are illiterate and 92.4% have an education level below high school degree.

Table 1. Number of Registered Syrian Refugees in- and out-camps in Turkey

	December 2013		**September 2014**		**December 2014**	
	Out Camps	Total	Out Camps	Total	Out Camps	Total
Adana	4,850	16,607	35,767	46,938	79,315	90,435
Adiyaman	202	10,408	2,556	12,437	2,787	12,686
Gaziantep	110,789	145,019	177,711	210,625	290,486	326,333
Hatay	70,643	85,571	140,923	155,294	183,560	198,050
Kahramanmaras	13,830	28,877	37,210	54,027	39,476	56,749
Kilis	25,920	63,237	51,100	88,691	59,951	97,527
Malatya	0	7,195	616	7,937	1,370	8,754
Mardin	37,796	40,932	39,293	47,645	64,303	67,214
Osmaniye	8,948	18,017	15,086	24,083	15,800	22,871
Şanlıurfa	65,737	133,326	108,349	181,044	347,635	427,138
Other	8,000	8,153	18,545	18,545	372,206	372,206
Total	346,715	557,342	627,156	847,266	1,456,889	1,679,963

Source: UNHCR (2013, 2014) and AFAD (2014).
Note: DG Migration Management (DGMM) in Turkey publishes different numbers than those reported by UNHCR. Province level data by DGMM is not available for December 2013 and September 2014. Therefore, we employed UNHCR data for comparison purposes. According to DGMM yearly statistics, the total population of Syrian refugees in Turkey is 224,655 in 2013 and 1,519,286 in 2014.

This comparison of descriptive statistics between the two populations might suggest that Syrian population would have a higher potential to commit crime as it has higher shares of young and single males together with low education levels who are trapped in informal employment with long hours of work and little pay, as the literature on the individual determinants of crime suggests (Freeman 1991; Levitt 1998; Grogger 1998; Raphael and Winter-Ember 2001; Gould et al. 2002).

Table 2. Characteristics of natives and Syrian refugees

	Syrian Refugees	***Natives***[b]
Total Population	3,576,370[a]	82,002,882
Labour Force	2,150,000[e]	32,274,000
Formal Employees[c]	31,185[f]	19,134,000
Informal Employees	950,000[g]	9,604,000[d]
Male	54.20%	50.16%
Age 15-24, male	12.93%	8.10%
Age 15-24, female	9.64%	7.71%
Age 25-34, male	10.23%	7.80%
Age 25-34, female	7.37%	7.58%
Single	64.30%	44.48%
Married	34.04%	47.63%
Below High School Diploma	92.40%[h]	62.72%[i]

[a] Data from DG Migration Management of Turkey in December 2019.
[b] According to the 2018 Address Based Population Registration System.
[c] Formal employees who are registered in the Social Security System in 2019.
[d] Turkish data is obtained from Turkish Statistical Institute and calculated using the Household Labour Force Statistics.
[e] According to the announcement by the Ministry of Family, Labour and Social Services (MoFLSS) in July 2019.
[f] These are the Syrian employees who obtained the work permit. This number excludes the self-employed Syrians who are also registered in the Social Security System. The estimated number of Syrian self-employed are 50,815.
[g] Retrieved from the speech of the Head of International Labour Force Unit of MoFLSS in July 2019.
[h] DGMM 2019 statistics for all the registered Syrian refugees.
[i] TurkStat 2019 statistics for Turkish population aged above 6.

3.2. Crime Rates in Turkey

In Turkey, annual individual-level crime statistics for each of the country's 81 provinces are not publicly available. However, there are other data sources that could well inform the researchers about the crimes committed: Number of new cases opened each year at the Basic and High Criminal Courts[5] obtained from the Ministry of Justice. High Criminal Court cases include crimes such as homicide, rape, robbery, swindling, production and trading of drugs, embezzlement, bribery that have a potential to invite a prison punishment of more than 10 years. Basic Criminal Court cases, on the other hand, are related to assault, kidnapping, defamation, theft, swindling, use and purchase of drugs, forgery, maltreatment, smuggling, traffic crimes,

[5] There was Criminal Court of Peace before 2015 which is abolished after then. The cases that were reviewed in those courts are received in Basic Criminal Courts. Therefore, the data before 2015 includes the cases in both Basic Criminal Court and Criminal Court of Peace in order to have consistency in the series.

forestry crimes, crimes related with firearms and knives, threat, damage to property and so on. The latter are usually the cases where the convicted perpetrators are sentenced to less than 10 years in prison. ***Figure 2*** presents the average crime rates (number of crimes committed per each 100,000 individuals) between 2009 and 2018. The crime rate as per the number of new High Criminal Court cases opened annually is quite stable until 2016 but notably increases afterwards, which could be related to the flurry of cases filed following the 2016 thwarted coup attempt. On the other hand, the number of Basic Criminal Court cases decreases until 2016 and then similarly increases in the wake of the attempted putsch.

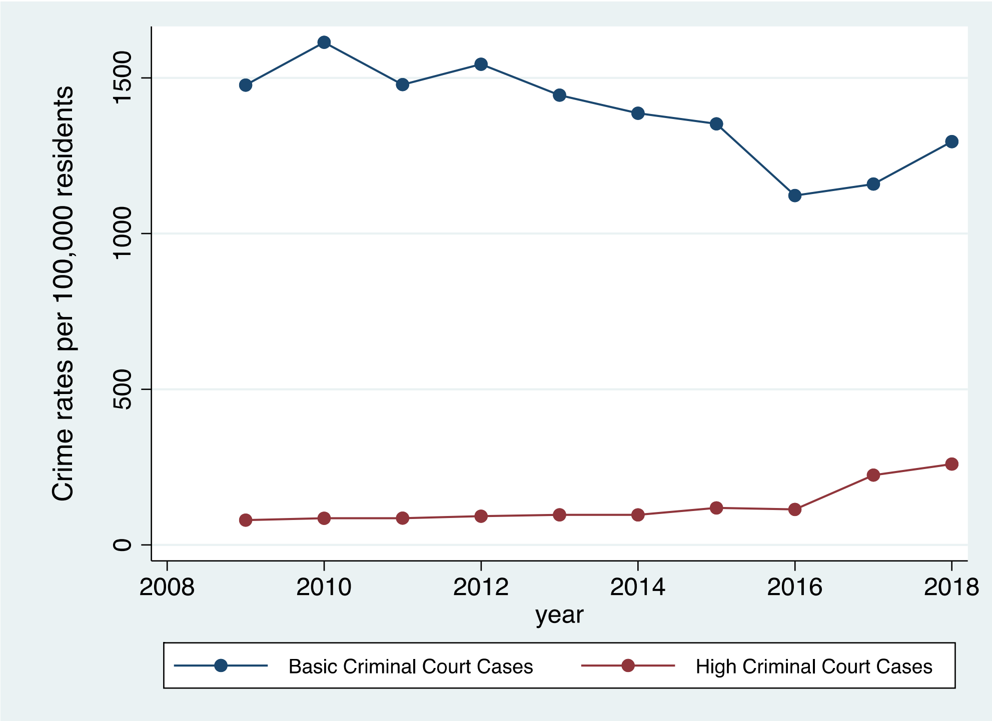


Figure 2. Average crime rates in Turkey

Figure 3a presents the correlation between new cases brought at courts each year and the relative size of the refugee population in each province from 2012 to 2018. As can be seen, there is no clear association between the two series for the new High Criminal Court cases whereas there is a negative association with the new cases at the Basic Criminal Courts. When we check how flow of Syrian refugees is associated with the changes in crime rates in ***Figure***

3b again, there is no positive relationship between the change in crime rates at High Criminal Courts and flow of Syrians into provinces. About the relationship between flow of Syrians and change in crime rates at the Basic Criminal Courts, again we have a negative correlation. Obviously, these associations do not explain the effect of refugees on crime rates because one needs to employ a careful empirical evaluation to identify the true impact. Moreover, general crime rate or conviction would not inform us about the ethnicity of criminals and victims. Therefore, we do not know whether refugees are victims or perpetrators of the crimes that have been committed.

(a) Stock of refugees vs. Stock of Crime **(b) Flow of refugees vs. Flow of Crime**

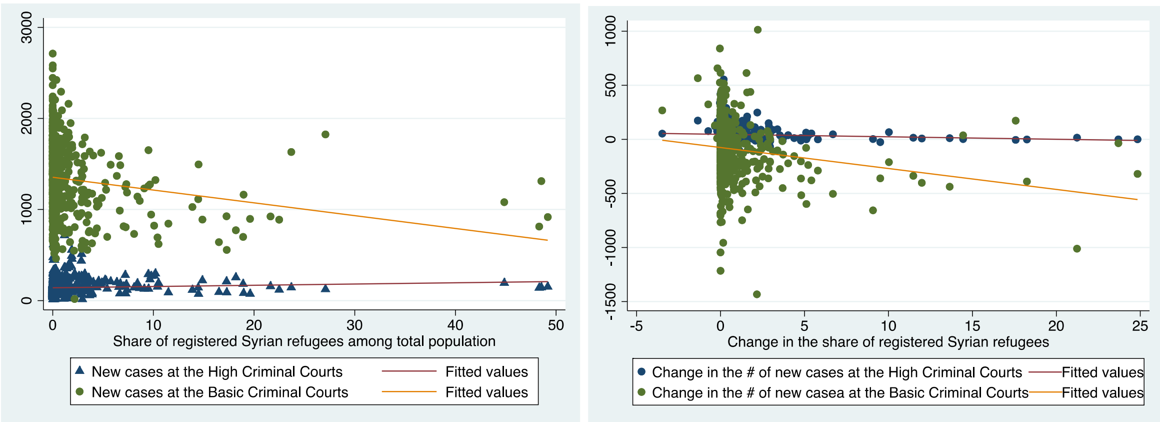


Figure 3. Refugees and Crime Rates (2012-2018)

Moreover, ***Figure 4*** below shows how the share of foreigners in Turkey (all non-Turkish residents including Syrian refugees) among total accused persons and total victims at the criminal courts evolves by the stock of foreigners over total native population between 2009 and 2018. Red dashed line represents the 45-degree line and black dashed line is denoting the year 2012 after which the Syrian refugee inflow suddenly increased. It shows that, although steadily decreasing, share of foreigners among total accused and total victims is higher than the share of foreigners before 2012. After 2012, there is an increase in both trends, however this time, shares of foreigners among both plaintiff and defendants are lower than their population share over natives. Importantly, the share of foreigners among victims is always higher than the share of foreigners among total accused persons. Although informative, this graph might also reflect discrimination in number of new cases opened in criminal courts and under-reporting of crimes committed towards Syrian refugees. And, it does not provide the particular information about the crime behavior of Syrian refugees as the data on foreigners are not provided by ethnicity or country of origin. Despite these drawbacks, the total share of foreigners among total accused was only slightly above 5 percent at maximum and the share of foreigners among total victims is below 3 percent even at the highest level. Thus, if there is any impact of Syrian refugees on native crime rates, we can claim that that effect exists mostly through the changing criminal behavior of natives after the refugee inflows but not due to refugees committing crimes themselves.

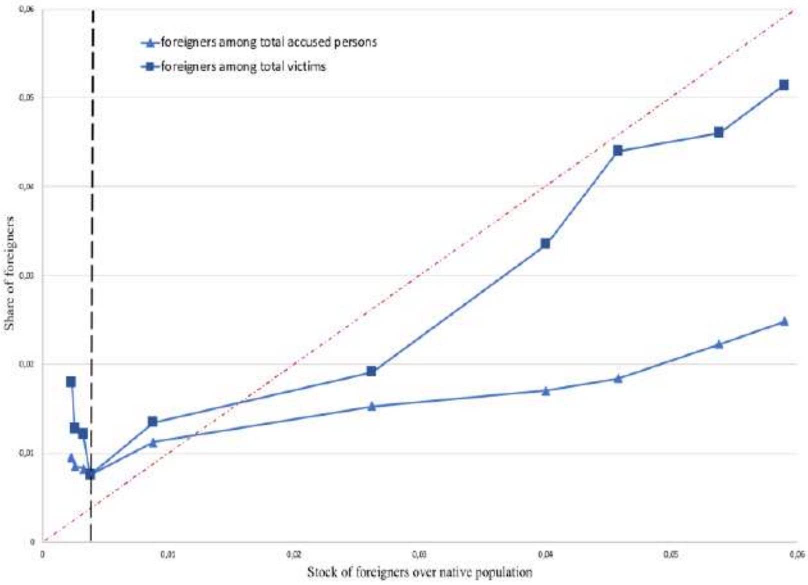


Figure 4. Share of foreigners among total accused and victims

Finally, before moving to the empirical analysis, it will be helpful to present the distribution of average refugee share and crime rates across provinces in a heat-map between 2012 and 2016 (after the treatment). We do also present the pre-treatment spatial distribution of crime rates in Appendix to ease the comparison with the post-treatment. Spatial distributions again do not show a clear association between refugee shares and crime rates.

(a) Refugee Shares

(b)Average crime per 100,000 residents, High Criminal Court Cases

(c)Average crime per 100,000 residents, Basic Criminal Court Cases

Figure 5. Spatial Distribution of Refugee Shares and Crime Rates, 2012-2016

IV. IDENTIFICATION STRATEGY

Becker (1968) and Ehrlich (1973) framework proposes a higher cost of committing a crime for refugees than local native population who, for example, do not have the risk of deportation and have better and quick access to the labor market opportunities. However, the impact of refugees on overall crime rates is ambiguous and depends on the characteristics of native population after the refugee inflows. Adopting the Becker-Ehrlich framework, the benchmark equation is constructed in this study as follows:

$$Y_{i,t} = \beta_0 + \beta_1 Refugee_{i,t} + X'\phi + \theta_i + \theta_t + \epsilon_{i,t} \tag{1}$$

In ***Equation 1***, $Y_{i,t}$ represents the crime rate in each province each year that is regressed on $Refugee_{i,t}$ (refugee share in province *i* at year *t*) together with time-varying province-specific control variables and fixed effects. Province-level fixed effects (θ_i) capture any unobserved time-invariant province characteristics. At the same time, observable characteristics of provinces are controlled with province-specific time-varying covariates, which are share of young males (aged 20-34) in total population, share of urban population, share of primary school graduates, log of real GDP per capita, unemployment rate, population density and number of police forces on patrol duty in the field. Additionally, year fixed effects (θ_t) are controlled to capture any unobserved time-specific factors that affect all provinces at the same time such as country-level macroeconomic shocks. Finally, region specific time trends are also added in some specifications to control for the persistence of such trends in crime. This model is estimated both for the new cases brought at the Basic Criminal Courts and High Criminal Courts.

OLS estimation of ***Equation 1*** will provide biased estimates due to various sources of endogeneity. There are important identification threats to understand the impact of refugees on crime rates. Firstly, there is possibly measurement error on the refugee population due to unregistered refugees and under-reporting of crime among refugee population due to security and deportation fears. Secondly, there can be refugee sorting into provinces as a response to crime rates. In other words, even if refugees do not sort in the short-run based on the pre-migration crime rates, they might choose to emigrate to other provinces in the long-run. Thirdly, there might be refugee- and crime-induced native sorting that might affect crime rates in each province. Finally, both refugee population and crime rates might respond to other factors that we are not able to control for. Thus, we have to deal with these identification threats in order to have unbiased estimates.

Moreover, Aydemir and Borjas (2011) argue that measurement error particularly bias OLS estimates in specifications with many fixed effects. Measurement error in the share of refugee population variable is addressed by including province and year fixed effects in our regression equations assuming the following relationship exists between observed and unobserved refugee shares:

$$Intensity^{*}_{i,t} = \mu_i + \mu_t + Refugees_{i,t} \tag{2}$$

,where dependent variable is *ln((unregistered refugees + registered refugees)/total population)*. $Refugees_{i,t}$ is the share of registered Syrian refugees each year in each province standardized by the total population at year t. However, this definition would be endogenous due to potential in-out migration of natives if there is refugee-induced native sorting at the province-level (Borjas 2006; Card 2007; Lonsky 2021). We directly test for the native sorting at province level using ***Equation 3*** by conducting the Card (2007) specification with the modification suggested by Peri and Sparber (2011). If this exists then even IV coefficients will be biased. We found no impact of refugees on native sorting across provinces. Still, I used share of Syrians as % of native population in each province at the base year 2012 and found that it does not alter the results.

$$\frac{N_{i,t} - N_{i,t-1}}{P_{i,t-1}} = \alpha + \beta(\frac{Refugees_{i,t} - Refugees_{i,t-1}}{P_{i,t-1}}) + \mathbf{X}_{i,t}\gamma + \lambda_i + \mu_t + \epsilon_{i,t} \tag{3}$$

There is also possibility for refugees to sort based on the pre-existing crime rates and this would downward bias our OLS estimates. The following specification is used to test for the refugee sorting:

$$\triangle Intensity_{2012-2018} = CrimeRate_{2012} + X'_{i,2012}\beta + \lambda_r + \xi_i \tag{4}$$

, where $Crime_{i,2009}$ is crime rate in 2012, $Intensity_{2012-2018}$ is the level change in refugee shares in each province between 2012 and 2018, and $X_{i,2012}$ are other initial conditions in each province and θ_r is region-level fixed effects. We find that there is no immigrant sorting.

However, we might still have an endogeneity problem due to refugee sorting in post-immigration period. This is addressed with Difference-in-Differences (DiD) specification in the short-run analysis and both with a staggered DiD and IV specification in the analysis of long-run impact of refugees on crime rates.

Importantly, increased and continuing refugee inflows in Turkey and internal movements of refugees inside the country resulted in changing treatment status for provinces in different years in the long-term. Therefore, to be safe from these internal validity threats, this paper first focuses on the short-term effect of refugees on crime rates. Given these population changes of

Syrian refugees in outside camp regions, we use January 2012 as the treatment starting period because the number of refugees who migrated between May 2011 and December 2011 were negligible and they were also hosted in refugee camps established in border provinces. Thus, the period between January 2009 and January 2012 are used as pre-treatment years and between January 2012 to January 2014 are considered as post-treatment period in our short-term impact analysis. Long-term impact is analyzed using the whole period with a staggered DID approach of Callaway and Sant'Anna (2020) because treatment timing varies across provinces as shown in Section 6.

In addition to testing the impact of hosting refugees above a threshold both in the short-run and long-run using DiD approach, I also analyze the impact of treatment intensity on crime rates. As refugee shares in each province in the treatment group differ due to either immigration/emigration of Syrian refugees and with the continuing inflows of refugees into Turkey, both treatment intensity and treatment timing is not homogenous. Therefore, an instrumental variables regression methodology is implemented to understand the role of treatment intensity on crime rates. Descriptive statistics of both dependent and control variables are provided in ***Table 3*** for pre- and post-refugee periods.

Table 3. Descriptive Statistics

(a) Post-refugee period: 2012-2018

	Mean	Std. Dev.	Min	Max
High Criminal Court Cases (per 100,000)	143.268	90.319	12.796	716.672
Basic Criminal Court Cases (per 100,000)	1329.257	392.576	17.265	2711.746
Share of refugees in total population	.017	.052	0	.492
Share of young males (aged 20-34)	12.326	1.894	9.922	26.395
Share of urban population (%)	75.699	18.871	35.18	100
Share of primary school graduates	.252	.054	.113	.387
Log of real GDP per capita	9.981	.412	8.865	11.280
Unemployment rate	9.280	4.760	3.4	28.3
Population density	124.76	310.77	11.059	2899.87
Number of Police Forces on Patrol Duty	2987.489	4783.099	406	39779

Number of observations:567. Data sources: Ministry of Justice Statistics, Ministry of Interior Affairs, Turkish Statistical Institute (TurkStat).

(b) Pre-refugee period: 2009-2011

	Mean	Std. Dev.	Min	Max
High Criminal Court Cases (per 100,000)	83.878	26.551	37.187	180.934
Basic Criminal Court Cases (per 100,000)	1523.347	389.433	659.372	3067.495
Share of refugees in total population	0	0	0	0
Share of young males (aged 20-34)	12.859	1.965	10.108	25.827
Share of urban population (%)	63.739	13.798	31.94	98.98
Share of primary school graduates	.304	.074	.139	.460
Log of real GDP per capita	9.348	.368	8.345	10.347
Unemployment rate	10.520	3.947	4.2	26.5
Population density	116.227	282.81	10.320	2622.06
Number of Police Forces on Patrol Duty	2542.193	4427.499	358	38140

Number of observations:243. Data sources: Ministry of Justice Statistics, Ministry of Interior Affairs, Turkish Statistical Institute (TurkStat).

V. SHORT-RUN IMPACT OF REFUGEES ON CRIME RATES

The advantage of the natural experiment setting offered by the Syrian influx in Turkey, which was largely unexpected, and the immense migration movements enabled us to use the Difference-in-Differences (DiD) strategy to find the causal impact of refugees on crime. This specification assumes that refugees cannot self-select into treatment provinces in the short-term as the extent of civil war was unexpected and sudden for Syrians. Thus, a basic DiD strategy is employed where the treatment region is compared with the rest of provinces in East and Southeast Regions in Turkey (local match) because these provinces share similar cultural and social backgrounds with the treatment provinces that are in the same regions. However, as Kahn-Lang and Lang (2019) argues, DiD is more plausible when compared groups are not only similar in pre-treatment trends but also in levels. In other words, parallel pre-trends are insufficient evidence to claim the parallel trends assumption between treated group and unobservable counterfactual. Moreover, there is threat of spillover effect between local matches and treated provinces in longer terms therefore we use this local match only in the short-term impact analysis. Therefore, statistically proximate comparison group (Focal Matching) is constructed with propensity score matching. Average treatment effect on the treated (ATET) is estimated using the following equation:

$$Y_{i,t} = \alpha + \beta \times D_i + \delta \times Post_t + \theta \times (D_i \times Post_t) + X'\phi + \epsilon_{i,t} \quad (5)$$

, where Y_{it} is the crime rate in province *i* and year *t*. Given the refugee inflows each year, we consider January 2013 as the start of the treatment. More specifically, pre-treatment periods are 2009-2012, and post-treatment period is from January 2012 to January 2013. Although refugee migration started in 2012, their population was quite small and were hosted in refugee camps. And, only one province (namely, Kilis) had a refugee population above 1 percent in 2012. Therefore, short-run (1 year) impact of refugees are analyzed separately with and without Kilis, and as you will see coefficient estimates are statistically insignificant in all specifications. Moreover, four years in the pre-treatment period enables us to check the parallel trends assumption and construct statistical comparison groups.

In a panel data setting, one can also use a two-way fixed effects (TWFE) specification, as in ***Equation 6***, to estimate the coefficient of interest more precisely with the inclusion of time-varying province specific control variables. In this canonical DID specification, D_i is a dummy variable equaling to 1 for treated provinces which have a share of refugees in the total population above 1 percent at the end of 2013 according to DGMM administrative statistics on registered Syrian refugees. Treated provinces are Adiyaman, Gaziantep, Kahramanmaras, Kilis, Osmaniye and Sanliurfa. As is seen in ***Figure 5***, these are provinces close to or actually on the Turkish-Syrian border, and refugee population in these provinces were quite persistent in the long-run although we observe out-migration of refugees towards western provinces most notably to Istanbul, particularly after 2014.

$$Y_{i,t} = \alpha + \delta^{DiD} D_{i,t} + X'_{i,t}\beta + \lambda_i + \gamma_t + \epsilon_{i,t} \tag{6}$$

Since we have panel data, error terms are likely to have within group correlation which might cause Type 1 error (Bertrand et al. 2004). We therefore used clustered standard errors at province level, together with year and province fixed effects, to address both heteroskedasticity and serial correlation problem (Furquim et al. 2020; Liang and Zeger 1986). ***Table 4*** presents the ATET estimates from *Equation 6* and ***Figure 6*** shows the trends in crime rates for multiple comparison groups. As can be seen from the results, refugees do not increase crime rates in all the comparisons when we include control variables into estimations. It is even found that provinces with refugee shares among total population is above 1 percent (treatment provinces) in 2013 had a decrease both in the High and Basic Criminal Court cases in the short-run. We checked if these results are robust by performing a placebo treatment test where we excluded all the post-treatment periods and checked if these results stay the same when we use 2010 or 2011 as treatment years. Also, as can be seen in Figure 7 and Figure 12, Kilis started to host a refugee share above 1 percent in year 2012. Therefore, we also repeated the DiD regressions when Kilis is excluded from the sample. All the coefficients are still statistically insignificant.

Table 4. Short-run (1-year) Impact of Refugees on Crime Rates

(a) High Criminal Court Cases

	(1) ALL	(2) ALL	(3) Local Match	(4) Local Match	(5) Focal Match	(6) Focal Match
δ^{DiD}	5.347 (7.600)	5.360 (8.209)	4.897 (10.208)	-7.749 (10.068)	1.096 (8.817)	-5.941 (8.673)
Controls	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	405	405	130	130	145	145
R-squared	0.807	0.812	0.725	0.759	0.859	0.880

(b) Basic Criminal Court Cases

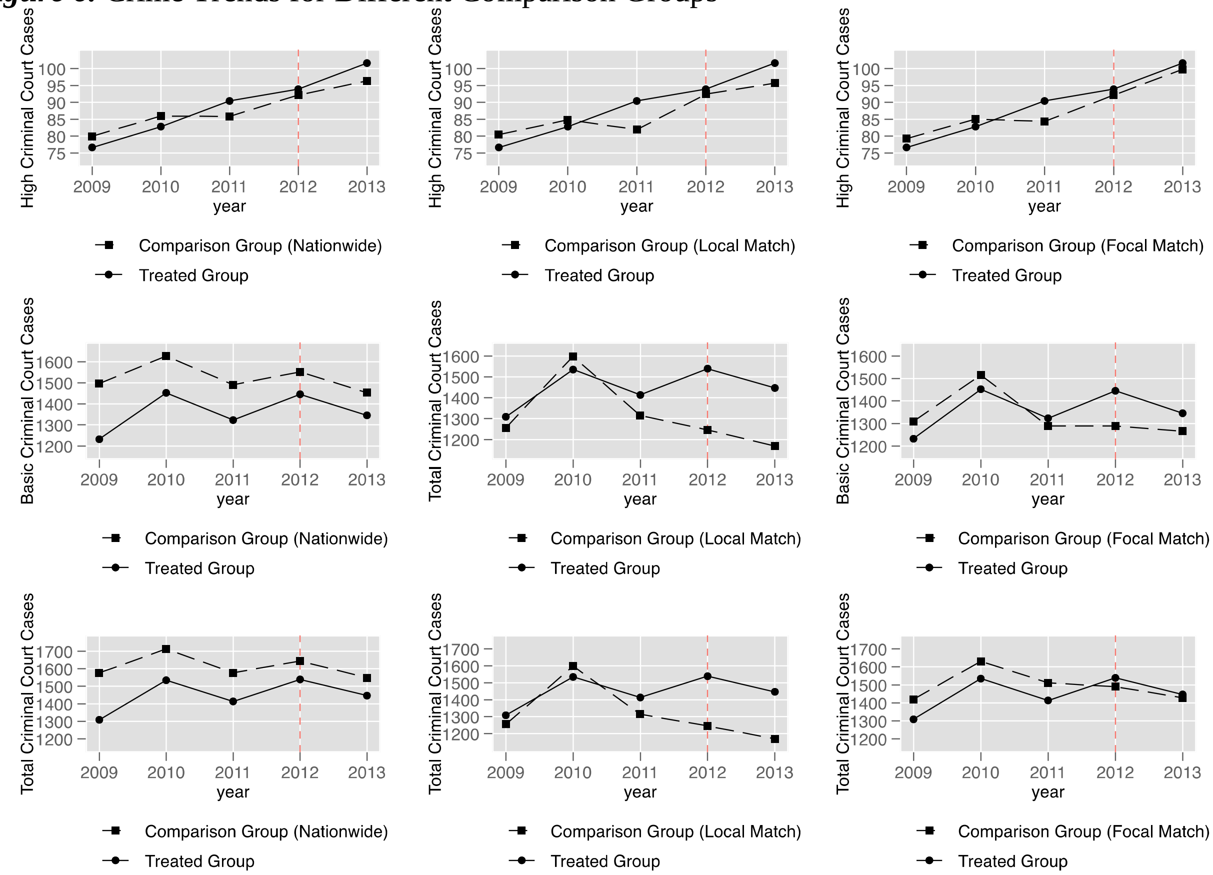
	(1) ALL	(2) ALL	(3) Local Match	(4) Local Match	(5) Focal Match	(6) Focal Match
δ^{DiD}	71.253 (102.49)	103.78 (100.28)	177.282 (111.72)	145.933 (109.29)	67.387 (107.78)	48.452 (95.137)
Controls	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	405	405	130	130	140	140
R-squared	0.862	0.881	0.851	0.873	0.843	0.872

(a) Total Criminal Activity

	(1) ALL	(2) ALL	(3) Local Match	(4) Local Match	(5) Focal Match	(6) Focal Match
δ^{DiD}	76.60 (107.43)	109.140 (105.88)	182.18 (117.29)	138.184 (112.64)	82.988 (123.40)	95.236 (143.91)
Controls	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	405	405	120	130	140	140
R-squared	0.867	0.884	0.849	0.871	0.787	0.821

Robust standard errors clustered at province level in parentheses.
* p<0.05, ** p<0.01, *** p<0.001

Figure 6. Crime Trends for Different Comparison Groups



VI. LONG-RUN IMPACT OF REFUGEES ON CRIME RATES

6.1. Staggered DID method

Short-term and long-term effects of refugees on crime rates might differ substantially because the impact might depend on the length of exposure for a given province. Thus, we use share of Syrian refugee population and other province characteristics from January 2009 to January 2017 to understand the long-term impact of refugee exposure on crime rates. In our case, there is a staggered treatment adoption across provinces as can be seen in the ***Figure 7***. Our post-treatment period in the long-term analysis starts from January 2012 and ends in January 2017. We preferred not to include the years after 2016 because the botched coup attempt on July 15, 2016 has a clear upward impact on court cases as shown in ***Figure 2***.

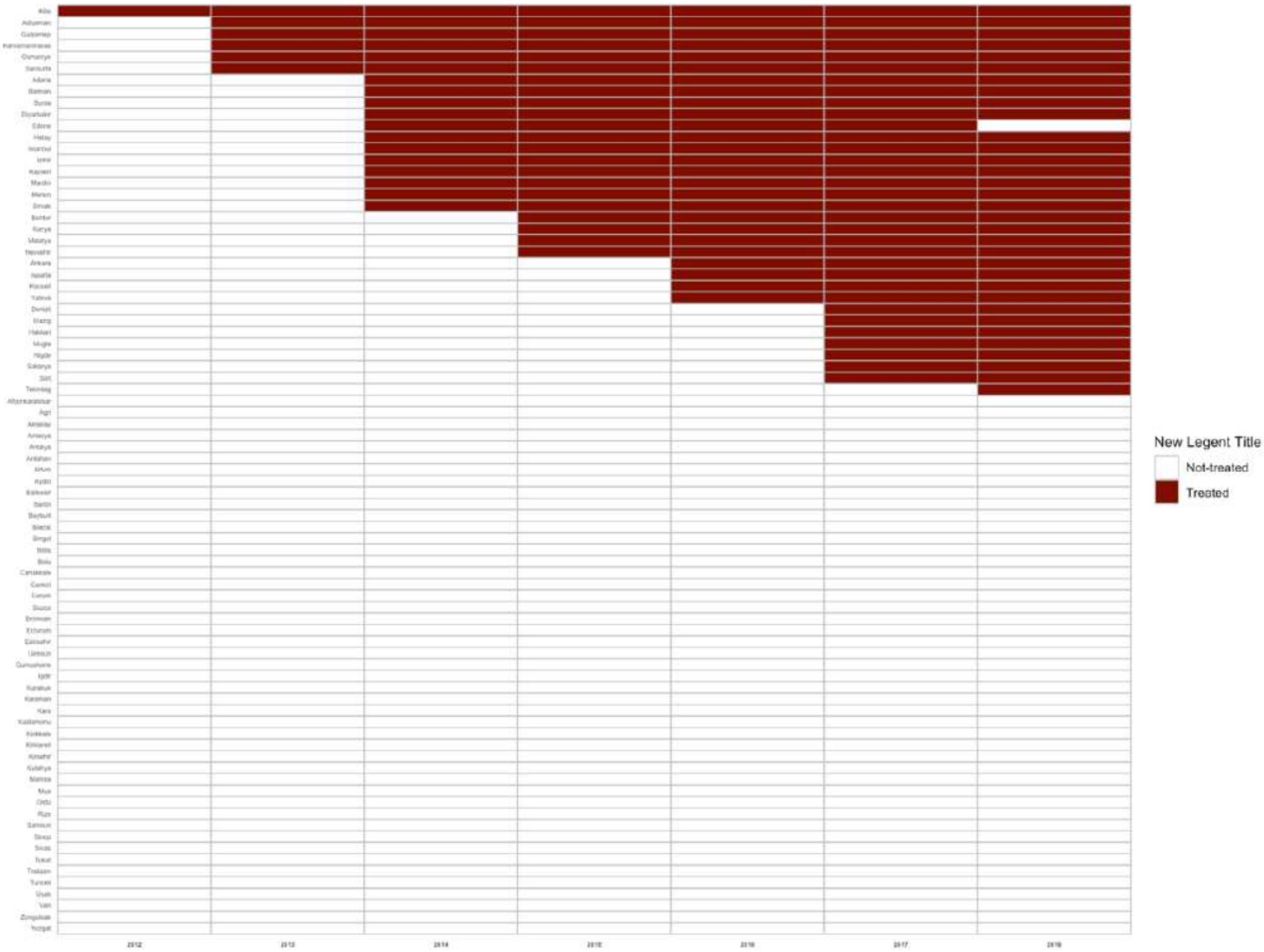


Figure 7. Staggered Treatment Timing Across Provinces

A recent growing literature shows that a two-way fixed effects (TWFE) linear regression or event study regressions can provide severely biased estimates in DiD with multiple time periods particularly in cases where the treatment intake is not homogenous across units (see Athey and Imbens 2018; Borusyak and Jaravel 2017; de Chaisemartin and D'Haultfouille 2020; Goodman-Bacon 2018; Sun and Abraham 2020; Callaway and Sant'Anna 2020).

In this section, we employ the semi-parametric DID estimation technique of Callaway and Sant'Anna (2020). There are five treatment starting periods in our setting which are denoted by g with ($g \in \{2012, 2013, 2014, 2015, 2016\}$). There are also provinces which are 'never-treated'. So, 'never-treated' provinces and 'not-yet-treated' provinces can act as different comparison groups. Using the notation in Callaway and Sant'Anna (2020), $G_{i,g}=1$ if the province i is first treated at time g, and zero otherwise. Since there can be provinces which take the treatment in the same time period, we can refer to all those belonging to the same 'group' of 'cohort' of treated. Thus, it is a dummy variable showing treatment switching on for each province. C_i=1 is a dummy denoting the 'never-treated' comparison group. Moreover, there is staggered treatment intake which is denoted by treatment dummy variables $D_{i,t}$ for t=2009, 2010,…,2016 ,and $D_{i,t}$=1 implies $D_{i,t+1}$=1, $D_{i,t+2}$=1 and so on. In other words, there is no switching-off once a province is treated.

Moreover, $Y_{it}(g)$ is the crime rate for a province i at time t if that specific province becomes treated at time g. $Y_{it}(0)$ is the untreated potential outcome of a province and Y_{it} is the observed outcomes for province i at time t. Thus, for those provinces that are never-treated, the observed outcome is equal to their untreated potential outcome ($Y_{it}=Y_{it}(0)$) but, for those that are treated, the observed outcome is their potential outcome when they were 'not-yet-treated' and is their potential outcome when they join the 'treated'group G_i at time t (in other words, $Y_{it}=\mathbf{1}\{G_i>t\}Y_{it}(0)+\mathbf{1}\{G_i\leq t\}Y_{it}(G_i)$). Thus, we will estimate the group-time average treatment effects $ATET(g,t)=E[Y_t(g)-Y_t(0)|G=g]$. This implies that $ATET$ ($g=2014$, $t=2015$) is the average treatment effect at year 2015 for those provinces that become treated at year 2014. Callaway and Sant'Anna (2020) show that parallel trends assumption is identified based on either 'never-treated' or 'not-yet-treated' units and is even more plausible when conditioned on pre-treatment covariates. Moreover, since there are many group-time ATETs, we show here an overall effect of taking the treatment for all defined groups in an event-study type presentation. Group-time ATETs are presented in Figure A3 and Figure A4 in the Appendix.

Figure 8 shows the aggregate group-time ATETs for the High Criminal Court cases. As can be seen, there is not an increase in High Criminal Court cases after the treatment intake, and the pre-trends are followed in the post-treatment period. When we look at the cohort specific ATETs on High Criminal Court cases, as presented in ***Figure 9***, we see that there is even a slight decrease in those cases for the group which had a refugee share above 1 percent after 2014 or 2015. Overall, there is no impact of refugees on High Criminal Court cases in the long-run.

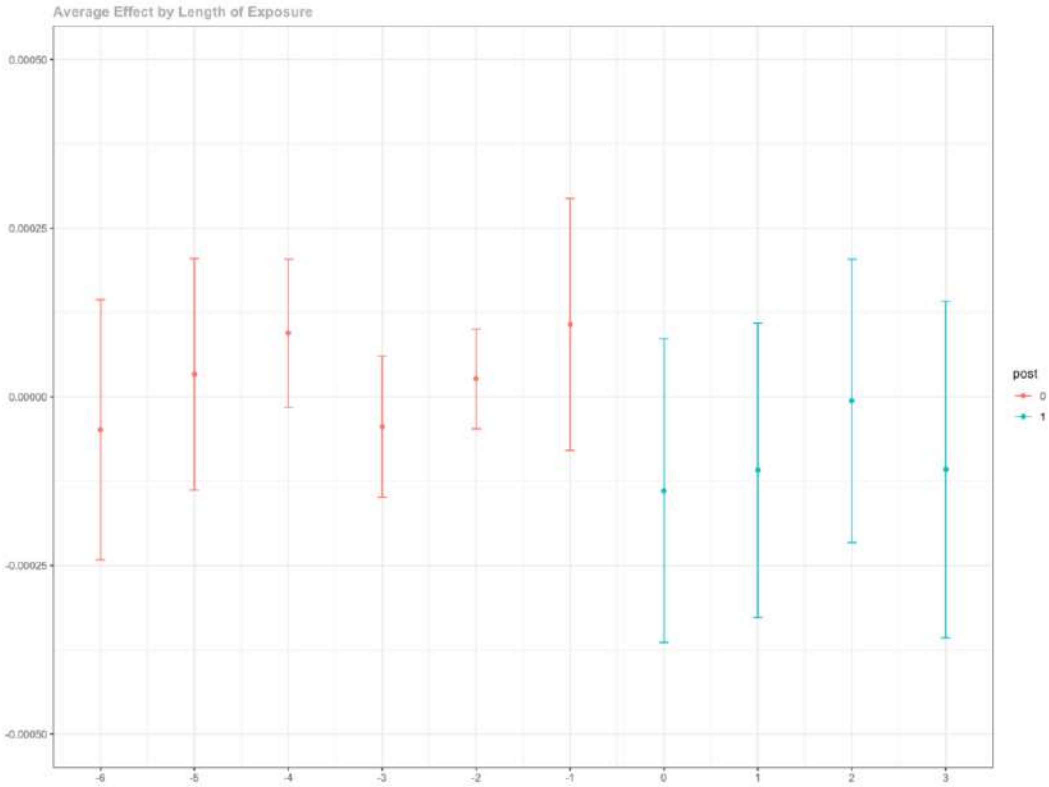


Figure 8. Aggregate group-time average treatment effects for High Criminal Court Cases

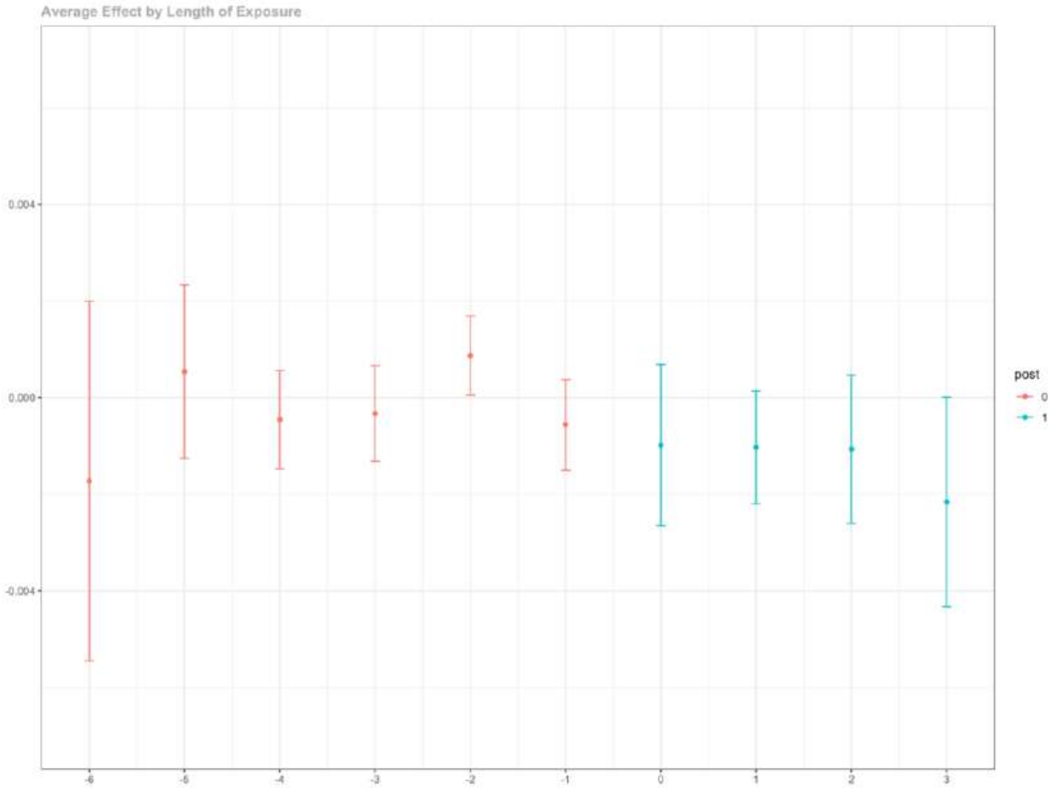


Figure 9. Aggregate group-time average treatment effects for Basic Criminal Court Cases

We performed the similar analysis for the Basic Criminal Court cases. ***Figure 9*** presents the aggregate group-time ATETs. Again, we do not see any deteriorating impact of refugees on Basic Criminal Court cases. There is even a slight decrease in the number of Basic Criminal Court cases after 3 years of hosting refugees. ***Figure A4*** in the Appendix presents the group-specific ATETs and it is clear again that there is no long-term impact of refugees on the number of Basic Criminal Court cases.

6.2. Impact of Treatment Intensity on Crime Rates

The analysis above shows that Syrian refugees do not have an impact on Syrian refugees both in the short and long term when we did not pay attention to the treatment intensity across provinces. However, share of refugee population is extensively varying across treated provinces as can be seen in the ***Figure 12*** below, where exact share of refugees in each province is provided. Therefore, this section analyzes the impact of refugee intensity on crime rates.

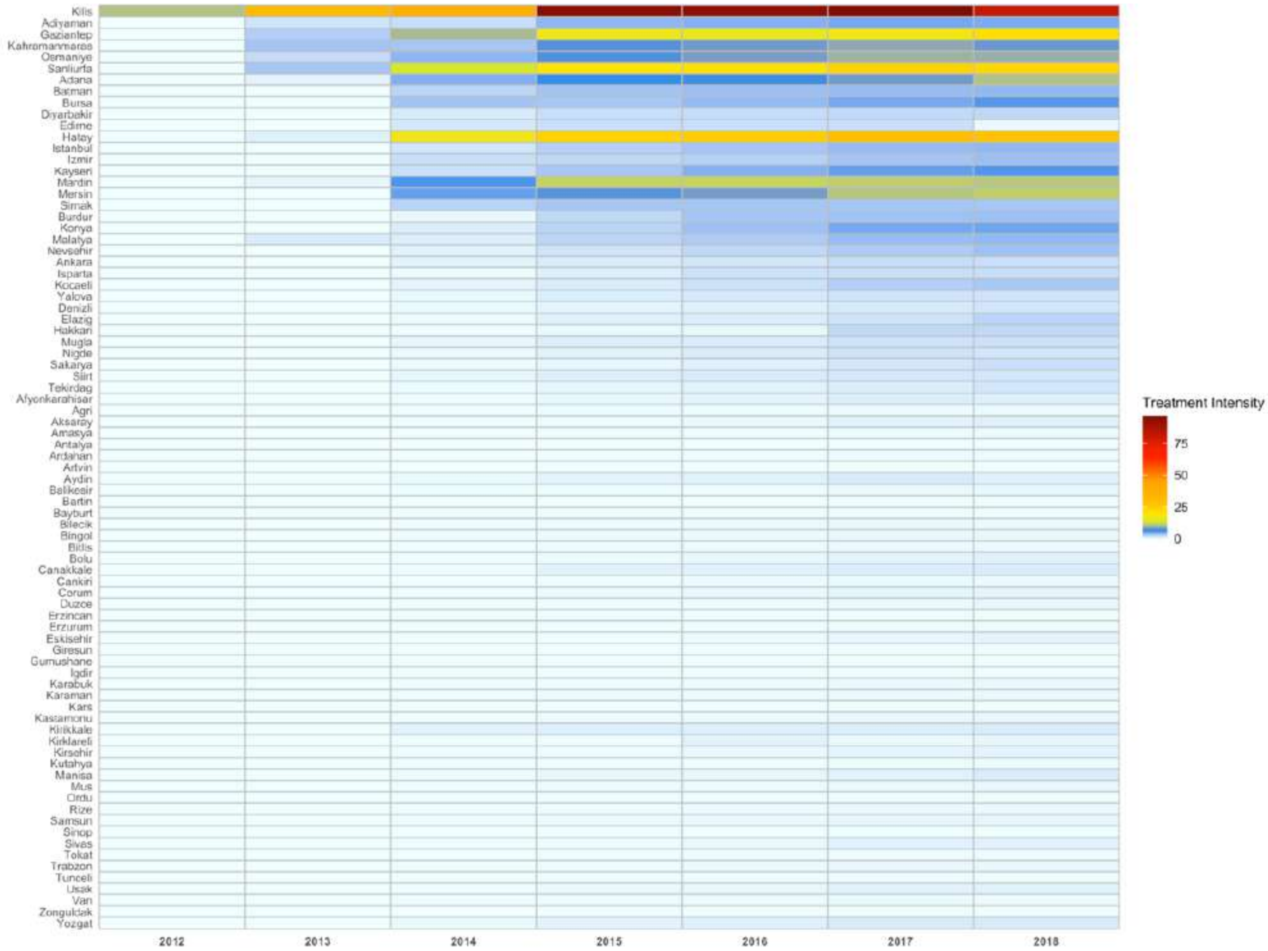


Figure 12. Refugee Share Across Provinces

The following specification is used to capture the impact of treatment intensity:

$$Y_{i,t} = \alpha + \delta Intensity^{*}_{i,t} + X'_{i,t}\beta + \lambda_i + \gamma_t + \epsilon_{i,t} \tag{7}$$

, where $Intensity^{*}_{i,t}$ is the measurement error corrected refugee share in each province at each year from 2012 to 2018. Province-specific time-varying control variables are share of male population aged 20-34, share of urban population, share of primary school graduates, log of GDP per capita, unemployment rate, population density and number of police forces on patrol duty. Province fixed-effects do control for the time-invariant province specific factors. Year fixed-effects are added to the model to control for year specific shocks that equally affect all provinces. However, estimating this equation through OLS would cause bias because, as

Borjas, Freeman and Katz (1996) argue, refugee inflows can cause native emigration or refugees themselves self-select into provinces with different crime rates and this would result in selection bias. ***Table A1***, ***Table A2*** and ***Table A3*** in the Appendix shows that there are neither refugee-induced native migration across provinces nor selection bias due to refugee sorting. Still, IV strategy is employed with the following instruments to control for any endogeneity issue left unsolved. Our instrument is:

$$w_{i,t} = \sum_j \frac{OriginGovernorate_{j,2013} \times SyrianRefugees_t}{distance_{i,j}} \tag{10}$$

, where ***j*** refers to the Syrian Governorates, ***i*** stands for the Turkish provinces and ***t*** is year. Worldwide out-camp population of Syrian refugees in a specific year ($SyrianRefugees_t$) is obtained from UNHCR statistics and is used to calculate the instrument because it does not depend on local factors and it addresses several issues raised by Jaeger et al. (2018). We also used the information about the total share of Syrian refugees in Turkey according to their origin governorate in Syria ($OriginGovernorate_{j,2013}$). These fractions are important because it is not only the distance that matters for refugee's decisions to migrate to Turkey but also the governorate they were living in Syria. Those who were in regions ruled by the Assad regime or further south in the country had extra difficulties to migrate first to the north of the Syria which was ruled by the opposition groups. And, $distance_{i,j}$ is the shortest driving distance in kilometers between Turkish province *i* and Syrian governorate *j* which is obtained from Google Maps.

For robustness of our IV specification, we first did a direct test of immigrant sorting following the specification suggested by Halla, Wagner and Zweimüller (2017):

$$\triangle Intensity_{2012-2018} = CrimeRate_{2012} + X'_{i,2012}\beta + \lambda_r + \xi_i \tag{9}$$

X is vector of other initial conditions measured in 2012 and λ_r is region fixed effects. 2012 is the base year not because this is the initial year of the provincial data on refugee distribution that is available but because the refugee inflow into Turkey started after April 2011 and increased particularly after 2013 as presented in ***Figure 1***. Moreover, refugee movements in 2011 were mostly hosted in refugee camps. This also implies that refugee distribution at the base year is likely to be exogenous, i.e. uncorrelated with the error term conditional on control variables. Furthermore, sharp increase in the refugee population during and after 2012, as presented in ***Table 1***, might result in native sorting that can cause bias in our results. Therefore, we have also directly tested for the refugee-induced native sorting. Reviewing Card (2007) and other methods offered in the literature, Peri and Sparber (2011) suggest the following specification:

$$\frac{(N_{i,t} - N_{i,t-1})}{Pop_{i,t-1}} = \alpha + \beta(\frac{F_{i,t} - F_{i,t-1}}{Pop_{i,t-1}}) + \phi_i + \lambda_t + \epsilon_{i,t} \tag{10}$$

, where $N_{i,t}$ is number of natives in province i and year t, $F_{i,t}$ is number of refugees in province i and year t, and $Pop_{i,t-1}$ is total population in province i in year t-1. So, the dependent variable is native net flow while the key explanatory variable is refugee net inflow. Thus, if $\beta > 0$ it implied that natives' inflow to province i in response to the refugee inflow and vice versa. Sa (2014) argues that OLS estimate of this equation would lead to upward bias due to omitted variable bias. Therefore, IV is used using the same instrument in our main regression analysis. Results of immigrant and native-sorting tests are presented in the Appendix in ***Table A1***, ***Table A2*** and ***Table A3*** which show that there are no such sources of biases in our IV estimates.

Table 5. Impact of Refugee Shares on Crime Rates

(a) High Criminal Court Cases

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Share of refugees	-0.232**	-0.292***	-0.397*	-0.225**	-0.345***	-0.653**
	(0.070)	(0.081)	(0.163)	(0.070)	(0.083)	(0.206)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	No	Yes	Yes	No	Yes	Yes
Region-specific time trends	No	No	Yes	No	No	Yes
Obs	567	567	567	567	567	567
Adj R-squared	0.681	0.725	0.778	0.627	0.677	0.730
Mean of dep. variable	0.143	0.143	0.143	0.143	0.143	0.143
Std dev of dep. variable	0.090	0.090	0.090	0.090	0.090	0.090
Kleibergen-Paap rk Wald F-stat.				235.8	279.3	190.3
Anderson-Rubin chi-sq. test p-val.				0.002	0.000	0.001

(b) Basic Criminal Court Cases

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Share of refugees	-1.802***	-2.046***	-1.416***	-1.454***	-1.973***	-1.266**
	(0.341)	(0.393)	(0.370)	(0.389)	(0.477)	(0.402)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	No	Yes	Yes	No	Yes	Yes
Region-specific time trends	No	No	Yes	No	No	Yes
Obs	567	567	567	567	567	567
Adj R-squared	0.493	0.569	0.605	0.405	0.495	0.526
Mean of dep. variable	1.329	1.329	1.329	1.329	1.329	1.329
Std dev of dep. variable	0.393	0.393	0.393	0.393	0.393	0.393
Kleibergen-Paap rk Wald F-stat.				235.8	279.3	190.3
Anderson-Rubin chi-sq. test p-val.				0.000	0.000	0.001

† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors in parentheses, clustered at the province level. Time-varying control variables are share of male population aged 20-34, share of urban population, share of primary school graduates, log of GDP per capita, unemployment rate, population density and number of police forces on patrol duty.

Table 5 above presents both OLS and IV results of *Equation 7*. As can be seen, there is a statistically significant and negative impact of refugee shares on both the number of High Criminal Court cases and Basic Criminal Court cases. This is the case in all specifications where we included control variables and region-specific time trends in a step-wise manner. Moreover, first-stage F-statistics is well above the threshold of 104.7 to obtain a valid inference as suggested by Lee et al. (2020). The IV coefficient from the full specifications (column 6 of ***Table 5a*** and ***Table 5b***) suggest that a 1 percentage point increase in the share of refugees in a province decreases the High Criminal Court cases by 0.65 percentage points, and decreases the Basic Criminal Court cases by about 1.27 percentage points.

VII. CONCLUSION

This paper provides the much-needed causal evidence about the impact of refugees on crime rates in a developing country context. Besides, it is the first such scholarly work analyzing the case of Turkey in regards to the nexus of crime and immigration. Turkey makes an especially interesting example since it hosts the largest refugee population on any national territory worldwide. In doing so, the paper uses the number of new cases brought at the Basic and High Criminal Courts as a proxy for the number of crimes committed each year. The geographical distribution of Syrian refugees across the country from 2012 to 2018 and the quasi-experimental setting of the refugee inflows has allowed it to draw scientific conclusions.

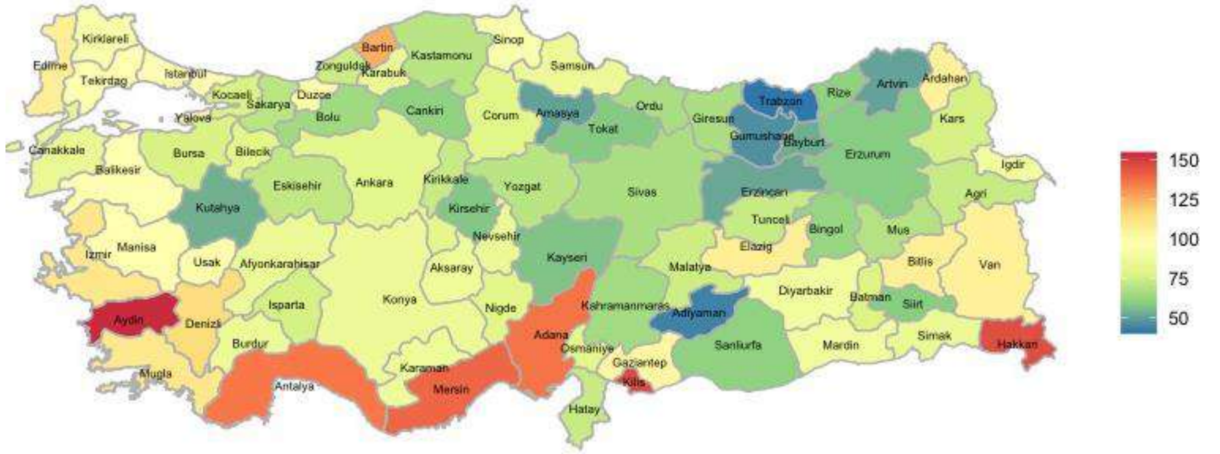
More specifically, this paper looks first at the short-term (1-year) impact of refugees on crime rates by employing a Difference-in-Differences (DiD) method with a two-way fixed effects regression framework both with local and focal matching. Official data show that different Turkish provinces started hosting refugee populations in different years. Besides, the refugee share (treatment intensity) is also not homogenous across provinces. In the light of such information, to investigate their long-term impact, this paper first performs a Staggered DiD method and then analyzes the impact of treatment intensity with an Instrumental Variables (IV) method.

All the analyses show that crime rates did not increase after refugee inflows, irrespective of their size. A null effect or a negative impact on both the number of High Criminal Court cases and Basic Criminal Court cases per 100,000 residents is found. When the same analyses are repeated using the number of High Criminal Court cases and Basic Criminal Court cases per 100,000 natives as the dependent variable, these negative effects vanish and a null effect is found. Therefore, it will not be wrong to argue that the Syrian refugees decreased the number of crimes per 100,000 residents because their propensity to commit a crime is lower than the native population. This could be related to the higher deterrence costs for refugees either due to risk of deportation or greater probability of incarceration. Clarifying the exact mechanisms behind this negative impact of Syrian refugee intensities in the long-run on the incidence of crime in Turkey begets further studies.

VIII. APPENDIX

Figure A1. Spatial Distribution of Refugee Shares and Crime Rates, 2009-2011

(a)Average crime per 100,000 residents, High Criminal Court Cases



(b)Average crime per 100,000 residents, Basic Criminal Court Cases

Figure A3. Group-time average treatment effects for High Criminal Court Cases

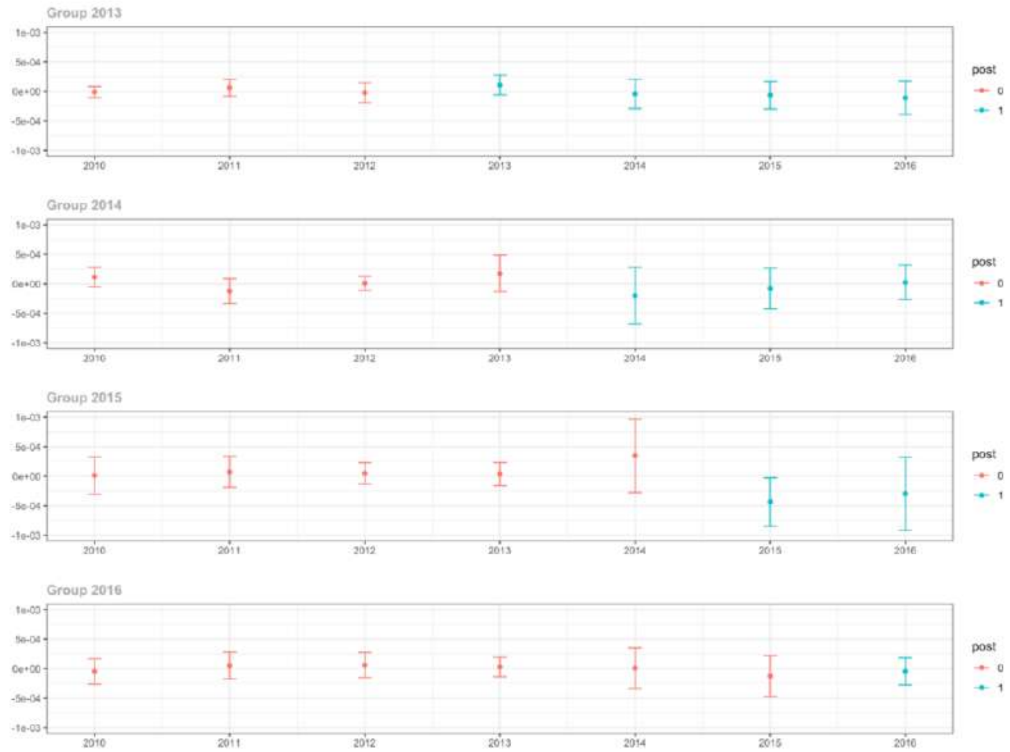


Figure A4. Group-time average treatment effects for Basic Criminal Court Cases

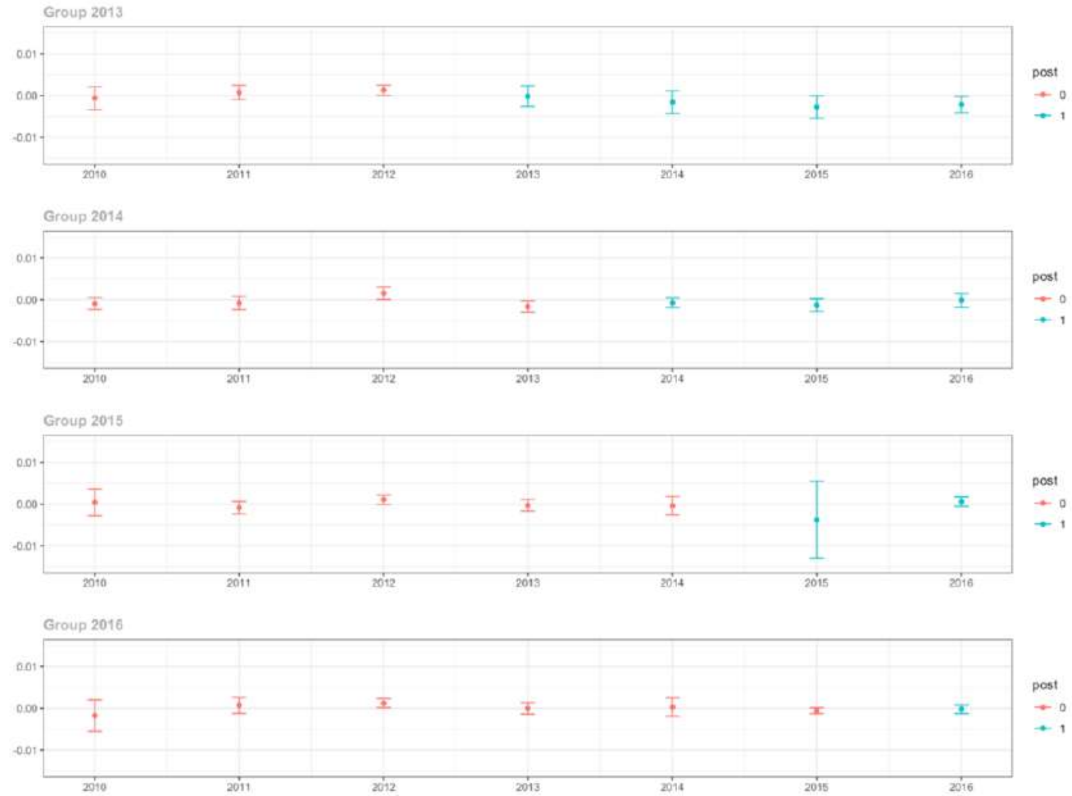


Table A1. Direct Test of Immigrant Sorting

	(1)	(2)	(3)	(4)
High Criminal Court Cases in 2012	.270	.264		
	(.212)	(.337)		
Basic Criminal Court Cases in 2012			.037	.027
			(.024)	(.026)
Initial controls (in 2012)	Yes	Yes	Yes	Yes
Region Fixed Effects	No	Yes	No	Yes
Obs	81	81	81	81
R-squared	.229	.498	.248	0.502
Mean of dep. variable	.027	.027	.027	.027
Std dev of dep. variable	.054	.054	.054	.054

† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robust standard errors in parentheses. Dependent variable is the level change in the share of refugees between 2012 and 2018. Initial control variables are share of male population aged 20-34, share of urban population, share of primary school graduates, log of GDP per capita, unemployment rate, population density and number of police forces on patrol duty.

Table A2. Direct Test of Native Mobility due to Share of Refugee Stock using IV regressions

	in-migration	out-migration	net migration rate
Refugee Share (stock)	-0.0113	-0.0505	0.0351
	(0.0739)	(0.0702)	(0.0368)
Year Fixed Effects	Yes	Yes	Yes
Observations	648	648	648
R-sq	0.241	0.128	0.125
First-stage F-stat	231.89	231.89	231.89

Clustered standard errors in parentheses.
* p<0.05, ** p<0.01, *** p<0.001

Table A3. Direct Test of Native Mobility due to Net Refugee Flows using IV regressions

	in-migration	out-migration	net migration rate
Refugee Share (flow)	-8.311	7.311	-15.22
	(4.805)	(5.970)	(10.17)
Year Fixed Effects	Yes	Yes	Yes
Observations	648	648	648
R-sq	0.221	0.066	0.125
First-stage F-stat	623.98	623.98	623.98

Clustered standard errors in parentheses.
* p<0.05, ** p<0.01, *** p<0.001

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