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IZA DP No. 14647

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ISSN: 2365-9793

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ABSTRACT

The Effect of 3.6 Million Refugees on Crime[1]

Most studies examining the impact of migrants on crime rates in hosting populations are in the context of economic migrants in developed countries. However, we know much less about the crime impact of refugees in low- and middle-income countries—whose numbers are increasing worldwide. This study examines this issue in the context of the largest refugee group in any country—Syrian refugees in Turkey. Although these refugees are much poorer than the local population, have limited access to formal employment, and face partial mobility restrictions, we find that total crime per person (including natives and refugees) falls due to the arrival of the refugees. This finding also applies to several types of crime; the only exception is smuggling, which increases due to the population influx. We also show that the fall in crime does not result from tighter security; we find no evidence of a change in the number of armed forces (military and civil personnel) in the migrant-hosting regions.

JEL Classification: J15, K42, D74

Keywords: refugees, crime, security, immigration-crime nexus, civil war

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[1] The usual disclaimer holds.

1. Introduction

The issues of immigration have always drawn social scientists' attention. Economists, in particular, have focused on the effects of immigration on the labor market; however, the analysis of the immigration-crime nexus has increasingly gained prominence. This paper contributes to this literature by exploiting the population influx that Turkey experienced after the Syrian Civil War onset in 2011. More specifically, our work aims at quantifying the causal impact on the commission of crimes in Turkey stemming from the arrival of more than 3.6 million Syrian refugees, a development that adds to an increasing worldwide flow of forcibly displaced populations. Indeed, the UNHCR (2021) estimates that natural disasters and conflicts have forced approximately 1 percent of the world's population to leave their places of residence, a fact that highlights the importance of assessing the socioeconomic impacts that involuntary migration brings on.

In many countries, citizens are much concerned about the migrants' impact on crime rates (see, e.g., Simon and Sikich, 2007), and Turkey is no exception. Indeed, the public opinion about the effects of Syrian refugees on crime is severely adverse. Such a situation often emerges in surveys. For instance, a study conducted by Hacettepe University showed that 62.2 percent of the participants agree with the proposition that "Syrian refugees disturb the peace and cause depravity of public morals by being involved in crimes, such as violence, theft, smuggling, and prostitution." In comparison, those who disagree account for 23.1 percent (Erdogan, 2014). Thus, our work helps to elucidate the underpinnings of a heated debate on an issue of global relevance, which, at least in public opinion, criminalizes refugees.

This study combines administrative data on provincial-level crime rates for the 2008-19 period with several complementary datasets. For the identification of the refugee effect, we employ variations in the number of incarcerated criminals and refugee stocks across Turkish provinces and over time within a difference-in-difference framework. We address the potential endogeneity in the spatial distribution of refugees using an instrumental variable, which depends on the distance of Syrian provinces to Turkish provinces, the distance of Syrian provinces to other neighboring countries, pre-war population shares of Syrian provinces, and the total number of Syrian refugees in all neighboring countries over time.

Our instrumental variable estimates show that a ten-point increase in the percentage of refugees in the provinces' population results in a statistically significant 8.1 percent drop in crime rates. Furthermore, when we distinguish between crime types, we primarily observe a negative refugee effect across them, albeit except for smuggling, a finding that concurs with numerous journalistic reports and official records.[2] Also, to strengthen our results' credibility, we conducted a battery of robustness checks, including placebo regressions based on pretreatment data and estimations of the relationship between refugee shares and variations in the presence of armed forces (military and civil personnel). Indeed, violence erupting across the border could have codetermined the spatial distribution of refugees and Turkish armed forces in the same provinces, thereby reducing crimes. Nevertheless, we find no evidence that variations in the refugee share affected armed forces' geographic allocation.

Our work contributes to the scholarship on the immigration-crime nexus by advancing an intriguing result: a negative immigration-crime relationship in a scenario remarkably adverse to the emergence of immigrant's law-abiding behaviors. Indeed, refugees had no access to the formal labor market and experienced partial mobility restrictions that likely subjected them to skill mismatch issues.[3] Furthermore, they did not self-selected into migration pursuing superior legal earnings, and, being relatively less educated and younger than natives, the Syrian refugees displayed a socioeconomic composition typically paired with a higher crime-proneness.[4] On the natives' side, there are also reasons to think that the refugees' arrival may have pushed individuals towards criminal activities. More pointedly, some studies (Ceritoğlu et al., 2017; del Carpio and Wagner, 2016; Aksu et al., 2018) show that while refugees were legally impeded to work in the formal sector, many of them took up jobs in the informal economy and ended up displacing low-skilled natives.

Also, by taking Turkey and Syria as a case study, our paper expands an essentially new line of research, namely the impact of refugees influxes on crime in developing economies. Moreover, besides palliating potential confounding pitfalls, the massive nature of the developments at issue is also novel in the academic exploration of the crime-immigration linkage.

This paper belongs to a body of research that, concerning its results, one can divide into two main categories. First, a significant majority of papers study the relationship between the two

[2] See, for instance, Karaçay (2017), and Yildiz (2017).

[3] See the European Council on Refugees and Exiles (2020) report on Turkey for a comprehensive explanation of the Syrian refugees' mobility and employment restrictions.

[4] Our data from 2021 shows that the average age among Syrian refugees is 22 years, while that of locals is 32.4 years. Moreover, the 15-24 age group represents 20.9% for Syrians, while it amounts to 15.5 for Turks. The former group comprises around 28 percent of illiterates; while for the latter group, illiterates represent 11 percent. See Loeber and Farrington D.P. (2014) for a discussion on the age-crime curve.

variables under discussion in the context of economic migrants and systematically concludes that either a null or a negative link exists between crime and immigration.[5] The second category, much sparser than the first one, comprises papers that use non-economic migrants (e.g., refugees) as their raw material and often find a positive link between immigration and crime.[6]

A clear illustration of the first category is the work by Ozden et al. (2017), who study the impact on crime rates from the arrival of on-work visa immigrants to Malaysia, concluding that immigration decreases property and violent crimes, even when no prospects of enjoying permanent residency or citizenship existed. Likewise, Maghularia and Übelmesser (2019), Bell and Machin (2013), and Jaitman and Machin (2013) arrive at similar results for developed economies.

Regarding the second category, which encompasses our paper, Bell, Fasani, and Machin (2013) found that non-economic migrants in the UK, specifically asylum seekers whom the government prevented from seeking legal employment, were more crime-prone. Similarly, Mastrobuoni and Pinotti (2015) show that recidivism rates among amnestied foreign-born criminals in Italy were much higher for individuals facing a prohibition to work versus unrestricted ones.[7] Also, Piopiunik and Ruhose (2017) quantify a sizeable positive effect from immigration on crime associated with the arrival in Germany of a wave of ethnic German immigrants. The authors' chief explanation is that the newcomers exhibited several crime-conducive socioeconomic traits and experienced a policy environment that failed to encourage law-abiding behaviors.[8] In particular, the imposition of binding mobility restrictions on immigrants and granting them immediate citizenship were counterproductive.[9] All these papers differ from ours in crucial aspects. First, none of them focuses on developing countries. Second,

[5] McDonald et al. (2013), Stowell et al. (2009), and Sampson (2008) argue that the fact that economic immigrants are likely to positively self-select along the honest-vs.-criminal dichotomy may underlie this regularity.

[6] Borjas, Grogger, and Hanson (2010) offer an interesting example that lies amid these two categories for they find a positive effect of (economic) immigration on crime rooted on increased offenses committed by locals.

[7] At the same time, Mastrobuoni and Pinotti (2015), and Baker (2015) found that immigrant legalization has a considerable negative effect on property crime.

[8] These socioeconomic traits are a disproportionately large share of males exhibiting low education levels and, as the authors label it, at a "criminal risk" age (15-25). See Loeber and Farrington D.P. (2014) for a discussion on the age-crime curve.

[9] The authors argue that receiving instantaneous citizenship lowered the immigrants' expected cost of committing crimes for the deportation threat vanished.

the magnitude of the population influxes they exploit is much lower. Third, and more importantly, their conclusions are at variance with ours.

In light of this paper's results that contradict the expectation of higher crime rates, our work calls for a more refined characterization of the immigration-crime nexus. Unfortunately, data limitations impede us from empirically investigating the mechanisms underlying our findings. However, regarding refugees' incentives, we advance a twofold hypothesis congruent with existing theoretical work.[10] First, on the expected punishment side, the reported refoulement of refugees, alongside the strengthening of the local immigration authorities' detention capacity, may have constituted a significant crime-determent device for refugees.[11] Second, regarding the availability of non-criminal rents to refugees, employment opportunities in the sizeable Turkish informal sector as well as cash transfers from humanitarian aid programs, most notably the Emergency Social Safety Net (ESSN) program,[12] may have provided enough resources to keep them away from participating in predatory activities. As to potential increases in crime commission associated with natives, evidence shows (see Aksu et al. (2018)) that an expansion of the formal sector, for its most part, countered the documented displacement of the latter from the informal sector.[13]

All in all, our research sheds new light on the responsiveness of the immigrant's crime proneness to distinct balances between the severity and certainty of punishment and labor market integration. In particular, we offer evidence that even when facing those conditions that the literature has labeled as the most criminogenic, the negative relationship between crime and immigration may persist.

[10] Mariani and Mercier (2021) expand Becker's (1968) model to analyze how self-selection shapes immigrants' incentives to engage in crime. As to economic immigrants, their pursuit of higher legal wages may suffice to keep them away from illegality. At the other end, when subject to policies that hamper their labor market integration, or when non-economic reasons drive their decision to migrate, immigrants' inclination to commit crimes may increase.

[11] See Üstübici (2019) for a detailed description of Turkish Immigration policies. As to refoulement records, see Simpson (2019) and Dalhuisen(2016).

[12] The ESSN program is an unconditional cash transfer scheme providing monthly assistance to refugees in Turkey. It was implemented nationwide in November 2016 and has become the world's largest cash transfer program that targets refugees. In fact, over 1.8 million refugees in Turkey were covered as of February 2021 (IFRC, 2021). It is funded by the European Union.

[13] Aksu et al. (2018) find that in terms of replacement of natives, the informal workers took the brunt of the Syrians' arrival. However, the authors show that via the opening of formal jobs, overall employment of native males did not change—although that of native women fell.

In the next section, we provide contextual information. Then, Section 3 presents the data used in the analysis, while Section 4 discusses the identification method and estimation. Section 5 gives the results, and Section 6 concludes.

2. Background Information

Displacement of Syrians started after the civil Arab Spring uprisings, and Turkey received its first Syrian refugees in April 2011. Initially, the government tasked the Turkish Disaster and Emergency Management Authority (TDEMA) with humanitarian aid and emergency response, including setting up camps for the refugees. Figure 1 shows the time evolution of the number of Syrian refugees in Turkey. It follows from the figure that the speed of the refugees' arrival reached its high point in 2014 and 2015 and that the total number of them continued increasing until 2018.

As the number of refugees swelled, they started moving out of camps and into urban areas. In October 2014, the Turkish government established the Turkish Directorate General for Migration Management (TDGMM), which became responsible for registering refugees and the overall coordination of policies regarding them. Simultaneously, the Turkish government passed the *Temporary Protection Regime* for the Syrian refugees, which defined their rights to access public health, public education, and social protection. According to this, Syrians have free access to public health and education services.

As refugees started marching towards Europe in large numbers in 2015, Turkey and the EU signed an agreement on the funding and the handling of the refugee crisis, which led to the establishment of the Emergency Social Safety Net (ESSN), a program targeting refugees with funding from the EU (WFP, 2018)—discussed in more detail below. This program coped with an impressive population inflow. Indeed, The number of refugees reached 2.5 million by the end of 2015, and only 10% lived in refugee camps at this time. In the following years, refugees' arrival continued, and their number reached 3.6 million at the end of 2020, out of which only 1.6 percent of them lived in refugee camps. In fact, of the 5.5 million Syrian refugees who left their country since the onset of the civil war, 65 percent lived in Turkey at this date (UNHCR, 2020).

Syrians are, on average, younger and less educated than the local population in Turkey. Their median age is 21, compared to 31 for natives (Eryurt, 2017). The median years of education are

4.5 years and 5.1 years for Syrian men and women, whereas they are 4.8 years and 7.1 years for Turkish men (Hacettepe university Insititute of Population Studies, 2019a, 2019b).

Syrian refugees could not get official work permits before Law 8375's enactment in January 2016 (with few exceptions, primarily those who started a business). However, even after this law, the number of formally employed refugees remained low. The number of work permits issued to Syrians was 34,573 in 2018 (MoFLSS, 2019). As a result, most Syrian refugees worked in the informal sector to sustain their lives. Pinedo-Caro (2020) estimates that 813,000 Syrians were employed in 2017, and 97 percent worked informally. The Syrian module of the 2018-Turkish Demographic and Health Survey (TDHS-S) shows that among 18- to 64-year-old individuals, 60.1% of Syrian men were in paid jobs compared to 65.9% of Turkish men. Among women, the gap in paid employment is wider; only 5.8% of Syrian women were in paid jobs compared to 20.9% of Turkish women. Child labor among Syrian refugees is also high; based on the same dataset, Dayioglu, Kirdar, and Koc (2021) report that 48% of 15- to 17-year-old refugee boys worked in paid employment.

Refugees are also much poorer. Pooling the Syrian and Turkish samples of the 2018 TDHS, Dayioglu, Kirdar, and Koc (2021) report that 79 percent of Syrian households lie in the bottom quintile of the wealth index they generate using 21 different household assets. WFP (2016) reports, based on the Pre-Assistance Baseline (PAB) survey conducted before the launch of ESSN, that 28.6 percent of Syrian refugees that resided outside camps were food insecure, and 93 percent were below the national poverty line. In part, their poverty is due to the lower employment among refugees, but refugees also work in worse jobs that pay less. As reported above, they are much more likely to work informally. In addition, Pinedo-Caro (2020) reports that although the majority of Syrian men work long hours (76 percent of Syrians worked more than 45 hours per week, the maximum legal number of working hours in Turkey), they earned 1,300 TL per month on average in 2017, which was 7 percent below the minimum wage in that year.

It is also important to note that several aid programs have targeted Syrian refugees in Turkey. The most salient one has been the Emergency Social Safety Net (ESSN) program, first implemented in November 2016, which reached 1.8 million refugees as of February 2021 (IFRC, 2021). The amount of pay in this unconditional cash transfer program is sizeable. For the average Syrian household with six members (based on the 2018-Demographic and Health Survey of Turkey), the monthly payment is 720 TL (around USD 105)—which is roughly equal to 55% of the average monthly labor earnings of Syrian men in Turkey (as estimated by ILO).

Furthermore, Aygun et al. (2021) estimate that the monthly payment is about 36% of the average monthly consumption value of the refugee households in the nationally representative micro-level dataset used in this study and that these cash transfers substantially alleviate extreme poverty and reduce a family's need to resort to harmful coping strategies.

3. Data

The data we use on crime rates come from the Turkish Statistical Institute (TURKSTAT). This dataset enumerates convicts received into prison by type of crime and the province where the crime occurred. We use the data on overall crime and ten different categories of crimes: assault, crimes involving firearms and knives, homicide, robbery, smuggling, theft, sexual crimes, kidnapping, defamation, use and purchase of drugs, and production and commerce of drugs.[14] Our outcome variables are crime rates per 100K inhabitants (including natives and refugees) of each province in the corresponding year. The crime data include both convicted Turkish citizens and foreigners.

We use several supplementary province-level datasets to generate our control variables for the 2008-19 period. First, we employ data on exports and imports (in USD; TurkStat, 2021a). Second, we use gross domestic product per capita data in USD (TurkStat, 2021b). Third, we use the gross domestic product at current prices by economic activity branches (TurkStat, 2021c) to generate the shares of different sectors in GDP (agriculture, industry, and services). Fourth, we use data on age dependency ratio by provinces provided by TurkStat (2018d), on the average size of households across provinces (TurkStat, 2021e), and population by province and age group (TurkStat, 2018f) to create age groups. Finally, we use data on attained education levels for the population over 15 years of age provided by TurkStat (2018g) to construct education categories. In addition, we use one dataset that provides information at the NUTS-2 region level; the number of armed forces (military and civil personnel) comes from Turkey's Household Labor Force Surveys.

The control variables include the logarithm of trade volume, the logarithm of GDP per capita, the shares of different sectors in GDP (agriculture, industry, and services), age dependency

[14] The total crime rate that we use includes – in addition to these nine categories of crime – swindling, forgery, bad treatment, embezzlement, bribery, traffic crimes, forestry crimes, opposition to the bankruptcy and enforcement law, opposition to the military criminal law, threat, damage to property, prevention of performance, contrary to the measures for family protection and other crimes.

ratio, average household size, shares of five age brackets, and shares of six education categories. The age dependency ratio is the number of people in the "0-14" and "65 and over" age groups per 100 people in the "15-65" age group. The age groups are 15-24, 25-34, 35-44, 46-54, and 55-64. The education categories are (i) illiterate, (ii) literate but no diploma, (iii) primary school or primary education graduates, (iv) junior high school and middle school equivalent vocational school graduates, (v) high school and high school equivalent vocational school graduates, and (vi) graduates from university and higher education institutions. Each sub-group in the age category indicates the group's share within the population aged 15-64. Similarly, each sub-group in the education category shows the share of the specific group over "15 years of age and over".

The number of Syrian refugees used for this study comes from different sources. The figure for 2013 comes from the Disaster and Emergency Management Presidency of Turkey (AFAD). Erdogan (2014) provides the refugee numbers for 2014, and the Ministry of Interior Directorate General of Migration Management provides information on the number of Syrian refugees for 2015 to 2019. The number of refugees in this analysis starts from 2013 since the number of Syrian refugees in Turkey for 2012 is unavailable at the province level. Using these numbers and the province populations obtained from TurkStat, we generate the percentage of Syrian refugees in each province over time.

Although the data on crime rates covers the years 2006-19, GDP per capita and trade volume are the only variables available for this period. Hence, we restrict our analysis to the years 2008-19 – although we check the robustness of our findings using the crime data for the more extended period of 2006-19 but with a much shorter list of control variables. In addition, our analysis excludes the data for 2012 because the data on the distribution across provinces of refugees is not available for this year. Hence, we have 11 years of data over 81 provinces, resulting in 891 observations.

Table 1 provides descriptive statistics. The average number of crimes per 100,000 people is about 196 across provinces and years. The variation in this variable is also significant, ranging between 17 and 531. Of the ten subcategories of crime that we focus on, the most frequent are assault and theft. Smuggling and the use and purchase of drugs display more variation across province-year observations; their standard errors are larger than their means, unlike for all other variables. Many of the control variables also display significant variation across observations, indicating large socioeconomic differences across provinces in Turkey and the importance of accounting for these variables.

4. Identification Method and Estimation

To estimate the impact of the refugee inflow on crime rates, we use a difference-in-differences methodology where we compare the provinces with high refugee intensity with those with low refugee intensity before and after the arrival of refugees. In particular, we use the following equation,

$$c_{pt} = \alpha + \beta\, R_{pt} + X_{pt}\Gamma + \delta_p + \theta_t + \mu_{p't} + \varepsilon_{pt}, \tag{1}$$

where c_{pt} denotes the crime rate in province p at time t, R_{pt} is the percentage of refugees in the total population (natives and refugees) of province p at time t, and X_{pt} stands for other province-time level characteristics at time t (presented in Table 1 and explained in the previous section). Province fixed effects and time fixed effects are shown by δ_p and θ_t, respectively. In order to account for potential differences in pre-existing trends across regions, we allow the time effects to vary across regions using various region-year interactions ($\mu_{p't}$): (i) five region-specific time trends, (ii) twelve NUTS-1 region-specific time trends, (iii) fixed effects for interactions of five regions with years, (iv) fixed effects for interactions of twelve regions with years. Finally, α stands for the constant term and ε_{pt} represents the error term.

A potential identification problem is that refugees' settlement patterns could correlate with the crime rates across provinces. Refugees might not choose their location of residence based on the crime rates; however, if they choose them based on economic and employment conditions, we might still expect their settlement patterns to be associated with crime rates. Therefore, we use an instrumental variable approach to generate an exogenous variation in the settlement patterns of refugees.

We employ the distance-based instrument used by Aksu et al. (2018), an extension of the instrument used by del Carpio and Wagner (2016). The del Carpio-Wagner instrument distributes the yearly number of Syrian refugees in Turkey across Turkish provinces according to the distance of each Turkish province from each Syrian province and the pre-war population shares of Syrian provinces. Noting that many Syrian refugees left for other bordering countries of Syria—Lebanon, Jordan, and Iraq—Aksu et al. (2018) also accounts for the distance of each Syrian province to these countries. The instrument is defined as follows,

$$I_{p,t} = \sum_{s=1}^{13} \frac{\left(\frac{1}{d_{s,T}}\right)\pi_s}{\left(\frac{1}{d_{s,T}}+\frac{1}{d_{s,L}}+\frac{1}{d_{s,J}}+\frac{1}{d_{s,I}}\right)} \frac{T_t}{d_{p,s}}, \tag{2}$$

where $I_{p,t}$ stands for the expected number of refugees in province p at time t (the instrument) and $d_{s,T}$, $d_{s,L}$, $d_{s,J}$, and $d_{s,I}$ stand for the distance of Syrian provinces to the closest border entry in Turkey, Lebanon, Jordan, and Iraq, respectively. In equation (2), π_s is the pre-war population share of Syrian province s, $d_{p,s}$ is the distance of Turkish province p to Syrian province s, and T_t stands for the total number of Syrian refugees in the bordering four countries.

This instrument is different from that of del Carpio and Wagner in two ways. First, we reweight the pre-war population shares of Syrian provinces according to their distance from the four countries. For instance, while the pre-war population share of Aleppo is 0.21, with the scaling in equation (2), its pre-war population share (for Turkey) increases to 0.45. Second, instead of allocating the number of refugees in Turkey, it allocates the total number of refugees in the four neighboring countries. Hence, this instrument accounts for the potential endogeneity of the level and timing of Syrian refugees entering Turkey, as there are different countries to choose from for the potential refugees. In addition, this extension makes the first-stage regression stronger because a disproportionate amount of refugees in Turkey originate from Syrian provinces that border Turkey, such as Aleppo and Idlib, than provinces that border the other three neighboring countries.

Regarding the instrument, finally, we discuss why distance matters. As shown in Figure 2, even in 2019, refugees are still concentrated in the regions bordering Syria—although, over time, their presence in the industrialized cities in western Turkey increased. The primary reason is that the border region is the entry point of the refugees, where camps were established immediately after their arrival. Since the government initially conceived them as temporary, it mounted the camps in areas close to the border. Moreover, even after leaving the camps for urban areas, many refugees preferred to stay in provinces closest to their original residence in Syria, where many family members still resided.[15] Finally, Syrian refugees in Turkey are supposed to use the health and educational facilities in the province they are registered. Although the local authorities do not strictly enforce this, it might have created some inertia against further movement.

The assumption for the validity of our instrument is that the trends in crime outcomes in the absence of the refugee shock, conditional on region and time fixed effects and a set of covariates, are uncorrelated with our distance-based instrument. This assumption could fail, for instance, if our instrument is correlated with the unobserved trends in economic and

[15] In fact, they can visit their family members on certain occasions like religious holidays.

employment conditions, hence with the unobserved trends in crime outcomes. When we use time-region interactions ($\mu_{p't}$), our instrument relies on a weaker independence assumption. For instance, when we use region-year fixed effects, we assume that distance does not correlate with unobserved trends in crime outcomes—within the country's five regions—a more plausible assumption. We leave the presentation of support for this identification assumption to the Robustness Check subsection (as its interpretation requires a comparison with the main results, given in the next section).

5. Results

We provide our estimates of the refugee impact on crime in Table 2 for the OLS estimates and Table 3 for the 2SLS estimates. In each table, five different specifications are used that differ according to how we account for pre-existing trends. Column (1) provides the estimates for the baseline specification with no controls for potential pre-existing trends (only province and time fixed effects are used). On the other hand, potential pre-existing trends are accounted for via 5 region-specific linear time trends in column (2), 12 NUTS-1 regions specific linear time trends in column (3), fixed effects for 5 region-year interactions in column (4), and fixed effects for 12 region-year interactions in column (5).

Before we start presenting our results, we will discuss the first-stage regression results in our 2SLS estimation. As shown in the bottom part of Table 3, the first stage coefficients of the instrument are statistically significant at the 1 percent level for all five specifications. In addition, the partial R-squared is quite high at about 0.7, and the F-statistics are above the suggested levels in the literature for all five specifications.

The OLS results in Table 2 show that while the coefficients of refugee effect on all crimes (given in the first row) are negative across all specifications, they are not statistically significant at the conventional levels. The 2SLS coefficients on the refugee impact on all types of crimes are larger in absolute value than the corresponding OLS estimates. Moreover, the negative 2SLS coefficient in column (1) with the baseline specification is statistically significant at the 10 percent level. While the coefficients with other specifications are similar in magnitude, they are not statistically significant due to larger standard errors. Quantitatively, the coefficient in the first column indicates that a 10-point increase in the percentage of refugees in the population decreases the crime rate by 16 from a baseline level of 196—implying an 8.1 percent drop. The fact that the 2SLS estimates are more negative than the OLS estimates suggests that the provinces that the refugees settle in would have more positive time trends in the absence of the refugee shock—controlling for the covariates.

When we examine the migrant effect by the type of crime, we find evidence of a conclusive negative effect (that holds across all specifications) on assaults, sexual crimes, kidnapping, and defamation. Quantitatively, a 10-point increase in the percentage of refugees in the population decreases assaults by about 4 to 6 (about 15-20 percent), sexual crimes by about 1.1 to 1.4 (about 22-30 percent), kidnapping by about 0.6 to 1.2 (20-40 percent), and defamation by about 0.9 to 1.1 (about 25 percent).

For homicide, the specifications in columns (1), (2), and (4) provide evidence of a negative refugee impact, whereas the other two do not. Since all specifications pass the placebo test in Table 2, no reason exists to prefer any specification to the others, and we conclude that suggestive evidence of a negative impact of the refugee shock on homicides exists. For thefts, the specifications in columns (1), (3), and (5) present evidence of a negative effect. Moreover, the negative effects in the two other specifications are just marginally statistically insignificant and similar in absolute magnitude. Hence, overall, the results suggest a negative refugee impact on thefts. Quantitatively, a 10-percent rise in the percentage of refugees decreases homicides by about 0.8-1.5 (by 10-20 percent) and thefts by about 4 to 6 (by 15-25 percent).

For one crime type, the refugee impact is positive. Specifications (1) to (3) show evidence that smuggling increases with the arrival of refugees. The coefficients in specifications (4) and (5) are marginally statistically insignificant and slightly lower. Overall, the results suggest that a 10-percent rise in the refugee percentage increases smuggling crimes per 1000 people by about two units (close to 40 percent). In other words, this effect is also quantitatively large.

5.1 Potential Channel via Armed Forces

An increase in the number of armed forces (military and civil personnel) in the migrant-receiving locations could in part explain our findings that the arrival of migrants did not increase crime. To examine this issue, we first check whether the government increased the number of armed forces in the migrant-dense regions. Since we do not have data on the number of police officers and gendarmerie, we use data on the number of all armed forces (including the military personnel) from the Household Labor Force Surveys of Turkey, as explained in the Data Section.

Panel (A) of Table 5 shows the results of regressing the logarithm of the number of armed forces on the migrant ratio and the list of control variables, which now also includes the logarithm of the native population as a control variable because the dependent variable is in levels. From these results, it follows that no evidence exists of an increase in the number of armed forces. In other words, it does not seem like the government responded to the refugee shock by adjusting the allocation of armed forces across regions.

Second, we examine how the refugee shock altered the number of armed forces per capita (including natives and refugees). Panel (B) of Table 5 shows suggestive evidence of a decline in the dependent variable due to the migrant shock. All the coefficients are negative and similar in magnitude, and they are either marginally statistically significant or significant at the 10 percent level. In essence, these findings imply that a rise in the number of armed forces is not the underlying reason for the absence of a rise in crime rates in refugee-receiving regions.

Finally, we introduce the number of armed forces per capita to our main regression equation as a control variable. Table A1 in the Appendix provides the results. We leave this as a robustness check because the data on the per capita armed forces is available at the NUTS-2 region level—which requires clustering of the standard errors at this level, decreasing the precision of our estimates. In fact, with this additional control, the coefficient estimates change very little; however, as expected, the standard errors are larger.

5.2 Robustness Checks

This subsection presents the results of placebo regressions that support the identification assumption by measuring the impact of refugees when no effect is supposed to come about. For this purpose, we act as if the refugees in 2019 arrived in 2011. More specifically, we restrict our data to the pre-shock period 2008–2011. Then we assign the 2019 distribution of our instrument and the refugee-to-native ratio across provinces to 2011 and run a 2SLS regression. If the instrument were correlated with unobserved pre-shock trends in crime outcomes—contrary to the identification assumption—this regression would yield a statistically significant coefficient for the refugee intensity which is instrumented.

Table 4 presents the results of this placebo regression. We find no evidence of a correlation between the instrument and the pre-existing time trends (after accounting covariates) for any specification for the overall crime rate. Moreover, the magnitudes of the coefficients are much smaller than the coefficients we estimate in Tables 2 and 3. For some subcategories of crime that we report a refugee impact, statistical evidence of a correlation emerges. However, in these cases, the placebo coefficients are much smaller than the actual coefficients in Table 3 (sexual crimes, defamation) or have the opposite sign (theft). Hence, Table 4 provides strong support for our identification assumption.

6. Conclusion

In this paper, we examine the causal link between immigration and crime in the context of the arrival in Turkey of 3.6 million Syrian refugees. For this purpose, we combine administrative data on crime rates for the 2008-19 period with several complementary datasets and use the spatial distribution of refugees across provinces within an IV difference-in-differences methodology to estimate the effect of interest.

We find suggestive statistical evidence that the refugee shock reduced the aggregate crime rate. Quantitatively, the estimated effect is large: a 10-point increase in the percentage of refugees in the population decreases our measure of crime rate by 8.1 percent. When we examine the effects by crime type, we find conclusive statistical evidence of a negative effect of the refugee shock on assaults, sexual crimes, kidnapping, and defamation. Our analysis also points to a negative impact of the refugee shock on homicides and thefts. On the other hand, in line with anecdotal information, we find a positive impact of the arrival of refugees for one crime type: smuggling.

We also find that the reduction in crime rates with the arrival of refugees does not result from an increased presence of armed forces (civilian and military personnel) in the refugee-hosting regions. On the contrary, we find suggestive evidence of a decrease in the per capita number of armed forces when the resident population includes native and refugee populations.

Our case study comprises a series of features that render our results intriguing. Indeed, the empirical research that finds a positive immigration-crime nexus conceives the imposition of partial mobility impediments and restrictions to accessing the legal labor market on the newcomers as the driving force behind their results. In light of this observation, the Turkish scenario poses a breeding ground for increases in crime derived from the Syrian's arrival. As a potential explanation, we hypothesize that the existence of a significant local informal sector, humanitarian aid programs targeting refugees via cash transfers (in particular, the ESSN program), plus a palpable threat of refoulement shied refugees away from illegal behaviors.

On the other hand, as Borjas et al. (2010) demonstrate, population influxes may propel natives into criminal activities via worsening overall conditions in the host economy's labor market. Given that Syrians ended up displacing a significant number of native informal workers(see Ceritoğlu et al., 2017; del Carpio and Wagner, 2016; Aksu et al., 2018), the refugees, in principle, could have sparked an indirect crime increase. However, as Aksu et al. (2018) demonstrate, employment and wages of natives in the formal sector increased with the arrival of Syrian refugees, leaving overall native male employment conditions primarily intact. Such a fact likely suppressed the potential rise in crime among natives.

In this manner, and given the impressive scale and abrupt nature of the phenomenon we study, our results serve to characterize further a regularity found in papers focusing on either more sluggish or less dramatic immigration episodes, namely a negative immigration-crime relationship. More precisely, we conclude that even when it comes to non-economic migrants, the proper balance between expected punishments and job opportunities may serve to curb their incentives to carry out crimes.

Due to data limitations, we cannot empirically test the above hypothesis, let alone provide an estimation of what elements counted the most to produce a negative immigration-crime link. Thus, as more data becomes available, future research may pin down the sensitivity of crime committed by refugees to policy changes. Also importantly, as the Syrian refugee crisis drags on, it will be possible to test whether second-generation immigrants are more crime-prone than the original ones, a result introduced by Morenoffand Astor (2006), Hagan et al. (2008), and Bucerius (2011). Likewise, it will be possible to contribute to a series of papers showing that individuals exposed to extreme violence or criminal cultures are more prone to commit violent crimes themselves (Damm and Dustmann (2014), Carvalho and Soares (2016), Aliprantis (2017), Sviatschi (2018) and Couttenier et al. (2019)). Finally, if distinguishing detained criminals' nationality becomes eventually viable, one could test whether the Syrians arrival affected the number of crimes committed by locals, which lies at the center of other paper's analyses (Borjas, Grogger, and Hanson, 2010).

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Tables and Figures

Table 1: Descriptive Statistics

	Mean	St. Dev.	Min.	Max.	No Obs.
Dependent Variables (Rate per 100,000 people)					
All Crimes	195.918	104.460	16.944	530.835	891
Assault	28.307	18.319	0.398	111.887	891
Crimes related with firearms and knifes	5.496	3.560	0.000	23.931	891
Homicide	8.058	4.522	0.000	28.504	891
Robbery	6.625	5.997	0.000	32.116	891
Smuggling	5.311	8.696	0.000	133.113	891
Theft	25.342	19.214	0.000	102.206	891
Sexualcrimes	5.021	4.078	0.000	18.607	891
Kidnapping	3.009	2.659	0.000	16.028	891
Defamation	4.094	3.000	0.000	19.459	891
Use and Purchase of Drugs	3.400	4.766	0.000	36.788	891
Production and Commerce of Drugs	9.993	9.788	0.000	60.426	891
Control Variables					
Log GDP per capita	8.935	0.353	7.911	9.939	891
Average Household Size	3.853	1.068	2.600	8.400	891
Average Dependency Ratio * 100	51.376	10.038	35.930	91.650	891
Log Trade Volume	19.427	2.476	0.000	26.215	891
Shares of Education Groups					
Illiterate	0.072	0.049	0.012	0.310	891
No Degree	0.070	0.038	0.019	0.242	891
Primary School	0.438	0.082	0.141	0.609	891
Middle School	0.093	0.052	0.014	0.343	891
High School	0.212	0.040	0.105	0.316	891
University	0.115	0.042	0.024	0.281	891
Shares of Age Groups					
Age: 15-24	0.264	0.054	0.181	0.444	891
Age: 25-34	0.231	0.025	0.182	0.299	891
Age: 35-44	0.203	0.018	0.133	0.247	891
Age: 45-54	0.170	0.029	0.083	0.216	891
Age: 55-64	0.131	0.035	0.048	0.218	891
Shares of Sectors in GDP					
Agriculture	0.169	0.085	0.001	0.469	891
Industry	0.268	0.111	0.052	0.615	891
Services	0.563	0.085	0.343	0.812	891

Notes: The data cover 81 provinces of Turkey over the years 2008 to 2019 (except 2012). The rates of the 11 sub-categories of crime do not add up to the overall crime rate because some crime types are not included. This is because either these crimes were not reported consistently over the years or they were rare.

Table 2: Refugee Effect on Various Types of Crime, OLS Estimates

	(1)	(2)	(3)	(4)	(5)	Mean
All	-84.883	-75.279	-27.085	-93.779	-36.512	195.918
	(61.452)	(75.689)	(80.349)	(81.466)	(95.619)	
Assault	-41.853***	-46.364***	-32.578**	-49.041***	-33.806*	28.307
	(14.208)	(15.731)	(14.605)	(16.367)	(17.070)	
Crimes related with firearms and knifes	2.516	3.260	4.444	3.335	4.255	5.496
	(3.921)	(3.053)	(3.386)	(3.349)	(4.085)	
Homicide	-13.424***	-15.468***	-10.294***	-15.095***	-10.170**	8.058
	(3.541)	(3.746)	(3.574)	(4.151)	(4.308)	
Robbery	0.026	2.044	2.629	1.914	2.777	6.625
	(5.615)	(5.843)	(6.833)	(6.446)	(8.234)	
Smuggling	16.837*	17.062	15.776	14.964	17.582	5.310
	(9.778)	(10.833)	(14.678)	(11.908)	(17.187)	
Theft	-20.181*	-24.017	-32.598*	-26.749	-33.007	25.342
	(11.131)	(16.555)	(19.126)	(18.099)	(22.134)	
Sexual Crimes	-11.320***	-10.066***	-7.795**	-10.309***	-8.238**	5.021
	(2.669)	(2.827)	(3.088)	(3.168)	(3.475)	
Kidnapping	-7.785***	-7.937***	-4.278**	-8.734***	-4.779**	3.009
	(1.931)	(2.511)	(1.890)	(2.879)	(2.399)	
Defamation	-5.997***	-5.117**	-4.258	-6.631**	-5.721*	4.094
	(1.921)	(2.546)	(2.639)	(2.888)	(3.155)	
Use and Purchase of Drugs	6.102	8.946	4.954	8.511	4.701	3.400
	(5.239)	(5.774)	(7.924)	(5.859)	(8.893)	
Production and Commerce of Drugs	4.021	-0.852	-12.587	-3.096	-15.326	9.993
	(12.170)	(9.569)	(13.072)	(10.373)	(15.462)	
Observations	891	891	891	891	891	
Controls for						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	
5-Region Linear Time Trends	No	Yes	Yes	Yes	Yes	
NUTS1 Linear Time Trends	No	No	Yes	Yes	Yes	
5-Region-Year Fixed Effects	No	No	No	Yes	Yes	
NUTS1-Year Fixed Effects	No	No	No	No	Yes	

Notes: The sample includes 81 provinces for each year from 2008 to 2019 (except 2012), therefore the number of observations is 891. The dependent variable is the rate for various types of crimes given above, where the denominator includes both natives and refugees. Each cell shows the estimates for the key variable of interest -- the ratio of migrants to population (migrants+natives) -- in a separate OLS regression of the dependent variable on the key variable of interest, a set of province-specific control varibles, a set of geographical-area and year specific control variables as indicated above. Province-specific control variables include the logarithm of trade volume, the logarithm of GDP per capita, GDP sector shares, age dependency ratio, average household size, shares of five age categories, and shares of six education categories. The age dependency ratio is the number of people in the ”0-14” and ”65 and over” age groups per 100 people in the ”15-65” age group. GDP sector shares include the shares of agriculture, industry, and services. The age groups are 15-24, 25-34, 35-44, 46-54, and 55-64. The education categories are (i) illiterate, (ii) literate but no diploma, (iii) primary school or primary education graduates, (iv) junior high school and middle school equivalent vocational school graduates, (v) high school and high school equivalent vocational school graduates, and (vi) university and higher educational institution graduates. Each sub-group in the age category indicates the share of that group within the population aged 15-64. Similarly each sub-group in education category shows the share of the specific group over “15 years of age and over”. Standard errors, given in parentheses, are clustered at the province level. *, **, or *** indicates significance at the 10%,

Table 3: Refugee Effect on Various Types of Crime, 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)	Mean
All	-157.282*	-147.620	-114.552	-175.252	-140.377	195.918
	(89.023)	(113.301)	(128.815)	(119.168)	(138.970)	
Assault	-45.920***	-54.363***	-40.617**	-59.091***	-43.956**	28.307
	(15.977)	(18.722)	(19.714)	(19.046)	(19.601)	
Crimes related with firearms and knifes	0.486	2.451	3.586	3.229	3.522	5.496
	(5.317)	(4.150)	(5.211)	(4.079)	(5.158)	
Homicide	-12.622***	-14.732***	-7.559	-14.871***	-7.539	8.058
	(3.918)	(4.266)	(5.940)	(4.853)	(6.196)	
Robbery	-7.820	-4.765	-4.102	-5.507	-4.785	6.625
	(9.105)	(10.439)	(11.529)	(11.132)	(12.464)	
Smuggling	20.524**	21.732**	23.043*	17.081	21.701	5.310
	(8.101)	(9.593)	(13.726)	(10.896)	(16.390)	
Theft	-36.520**	-40.660	-55.126*	-46.601	-60.569*	25.342
	(17.233)	(26.999)	(30.421)	(29.089)	(33.007)	
Sexual Crimes	-14.575***	-13.147***	-11.358**	-13.890***	-12.218***	5.021
	(3.266)	(3.739)	(4.464)	(4.000)	(4.439)	
Kidnapping	-9.372***	-10.165***	-6.388**	-11.744***	-7.788**	3.009
	(2.715)	(3.562)	(3.029)	(3.947)	(3.365)	
Defamation	-9.057***	-9.275**	-9.445**	-10.823***	-10.954**	4.094
	(2.671)	(4.064)	(4.464)	(4.141)	(4.393)	
Use and Purchase of Drugs	-4.379	0.191	-6.157	-0.148	-7.155	3.400
	(8.842)	(10.052)	(12.140)	(10.354)	(13.016)	
Production and Commerce of Drugs	4.037	-7.073	-23.835	-10.154	-28.352	9.993
	(14.330)	(16.181)	(19.579)	(17.711)	(22.155)	
First-stage regression	2.880***	2.996***	2.837***	2.981***	2.806***	
	(0.668)	(0.701)	(0.701)	(0.719)	(0.751)	
Partial R-squared	0.703	0.700	0.646	0.691	0.634	
F-Stat	18.570	18.271	16.394	17.173	13.977	
Observations	891	891	891	891	891	
Controls for						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	
5-Region Linear Time Trends	No	Yes	Yes	Yes	Yes	
NUTS1 Linear Time Trends	No	No	Yes	Yes	Yes	
5-Region-Year Fixed Effects	No	No	No	Yes	Yes	
NUTS1-Year Fixed Effects	No	No	No	No	Yes	

Notes: The sample includes 81 provinces for each year from 2008 to 2019 (except 2012), therefore the number of observations is 891. The dependent variable is the rate for various types of crimes given above, where the denominator includes both natives and refugees. Each cell shows the estimates for the key variable of interest -- the ratio of migrants to population (migrants+natives) -- in a separate 2SLS regression of the dependent variable on the key variable of interest, a set of province-specific control varibles, a set of geographical-area and year specific control variables as indicated above. The instrument depends on the total number of Syrian refugees in four neighboring countries (Turkey, Lebanon, Jordan, and Iraq) in each year, pre-war population shares of Syrian provinces, the distance of each Syrian province to the closest border entry in each of the neighboring countries, and the distance of each Syrian province to each Turkish province. The province-specific control variables include the logarithm of trade volume, the logarithm of GDP per capita, GDP sector shares, age dependency ratio, average household size, shares of five age categories, and shares of six education categories. The age dependency ratio is the number of people in the "0-14" and "65 and over" age groups per 100 people in the "15-65" age group. GDP sector shares include the shares of agriculture, industry, and services. The age groups are 15-24, 25-34, 35-44, 46-54, and 55-64. The education categories are (i) illiterate, (ii) literate but no diploma, (iii) primary school or primary education graduates, (iv) junior high school and middle school equivalent vocational school graduates, (v) high school and high school equivalent vocational school graduates, and (vi) university and higher educational institution graduates. Each sub-group in the age category indicates the share of that group within the population aged 15-64. Similarly each sub-group in education category shows the share of the specific group over "15 years of age and over". Standard errors, given in parentheses, are clustered at the Nuts2- level. *, **, or *** indicates significance at the 10%, 5% and 1%, respectively.

Table 4: Placebo Regressions on Refugee Effect on Various Types of Crime, 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)	Mean
All	-12.045	4.373	-11.688	11.102	-40.999	104.490
	(22.871)	(31.378)	(35.763)	(32.738)	(42.627)	
Assault	-0.058	1.107	-3.420	2.656	-1.811	11.754
	(4.566)	(5.207)	(4.836)	(5.978)	(5.727)	
Crimes related with firearms and knifes	-3.376	-2.980	-2.021	-2.740	-2.221	3.413
	(2.208)	(2.079)	(2.052)	(1.956)	(2.099)	
Homicide	-2.074	-2.831	-3.408	-2.410	-4.686	4.030
	(2.225)	(2.252)	(2.380)	(2.803)	(3.523)	
Robbery	1.771	4.052*	3.277	4.621**	4.175**	1.654
	(2.669)	(2.155)	(2.048)	(2.056)	(2.001)	
Smuggling	0.193	1.079	0.542	1.120	-0.577	1.416
	(3.598)	(3.468)	(3.678)	(3.839)	(3.933)	
Theft	4.315**	3.517*	1.197	2.036	-0.052	6.796
	(2.138)	(2.079)	(2.162)	(3.089)	(3.720)	
Sexual Crimes	-2.852	-3.685**	-4.011**	-3.583**	-4.324**	1.224
	(1.814)	(1.591)	(1.682)	(1.612)	(1.790)	
Kidnapping	-0.771	0.973	0.603	0.367	-0.310	0.742
	(0.710)	(1.050)	(1.123)	(0.983)	(1.085)	
Defamation	-0.126	-0.589	-2.932**	0.628	-3.220**	1.939
	(1.339)	(1.401)	(1.286)	(1.637)	(1.289)	
Use and Purchase of Drugs	4.026***	3.303***	2.246	3.501***	2.650**	0.738
	(1.442)	(1.267)	(1.423)	(1.013)	(1.185)	
Production and Commerce of Drugs	0.534	-2.183	-2.484	-2.544	-2.135	2.412
	(3.043)	(4.817)	(5.548)	(4.102)	(4.738)	
Observations	324	324	324	324	324	
Controls for						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	
5-Region Linear Time Trends	No	Yes	Yes	Yes	Yes	
NUTS1 Linear Time Trends	No	No	Yes	Yes	Yes	
5-Region-Year Fixed Effects	No	No	No	Yes	Yes	
NUTS1-Year Fixed Effects	No	No	No	No	Yes	

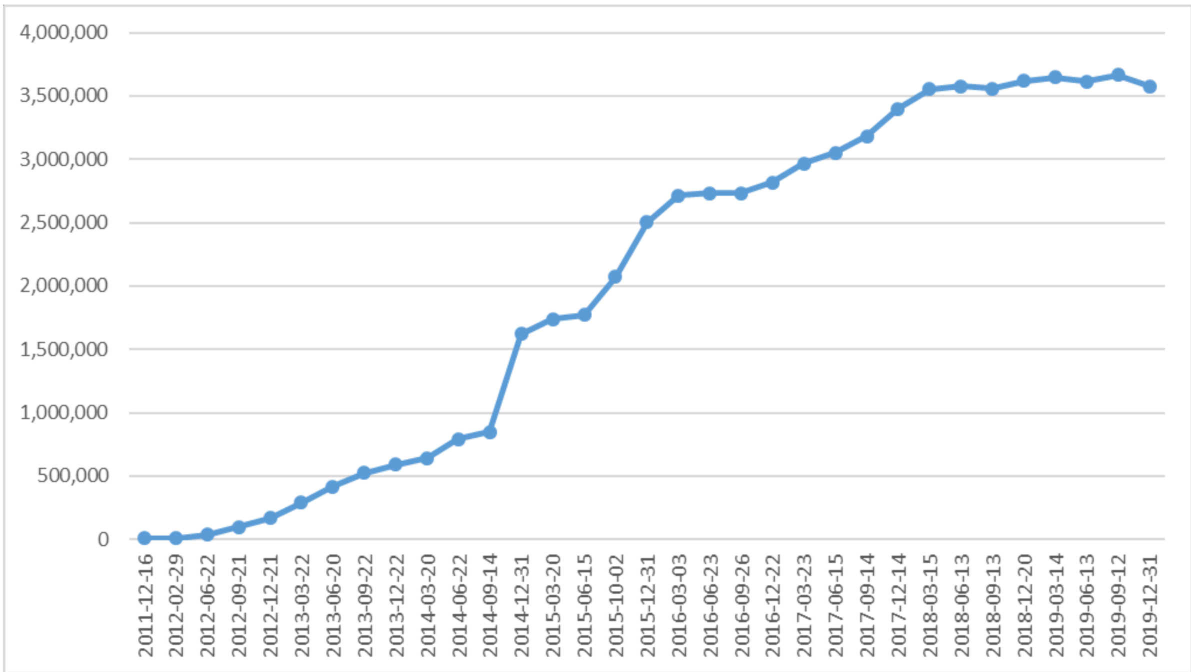
Notes: The sample includes 81 provinces for each year from 2008 to 2011 (pre-shock period), therefore the number of observations is 324. The dependent variable is the rate for various types of crimes given above, where the denominator includes both natives and refugees. For this placebo analysis, the values of the key variable of interest and instrument for 2019 are assigned to the corresponding values for 2011. The key variable of interest and the instrument take the value of zero for 2006-2010. Each cell shows the estimates for the key variable of interest -- the ratio of migrants to population (migrants+natives) -- in a separate 2SLS regression of the dependent variable on the key variable of interest, a set of province-specific control varibles, a set of geographical-area and year specific control variables as indicated above. The instrument depends on the total number of Syrian refugees in four neighboring countries (Turkey, Lebanon, Jordan, and Iraq) in each year, pre-war population shares of Syrian provinces, the distance of each Syrian province to the closest border entry in each of the neighboring countries, and the distance of each Syrian province to each Turkish province. The province-specific control variables include the logarithm of trade volume and the logarithm of GDP per capita. Standard errors, given in parentheses, are clustered at the province level. *, **, or *** indicates significance at the 10%,

Table 5: Investment in Armed Forces and Change in per-capita Armed Forces in Migrant Receiving Regions

	(1)	(2)	(3)	(4)	(5)	Mean
A) Effect of the Migrant Shock on the Number of Security Personnel (Controlling for the Native Population)						
A1) OLS Results	0.099	0.141	-1.870	0.234	-1.639	10.756
	(0.921)	(0.858)	(1.512)	(1.375)	(1.931)	
A2) 2SLS Results	0.470	0.698	-0.720	0.808	-0.703	10.756
	(0.825)	(0.797)	(1.316)	(1.157)	(1.336)	
First-stage regression	1.857***	1.946***	1.724***	1.883***	1.660***	
	(0.123)	(0.199)	(0.118)	(0.246)	(0.190)	
Partial R-squared	0.717	0.731	0.720	0.719	0.749	
F-Stat	229.509	95.710	211.798	58.846	76.604	
Observations	286	286	286	286	286	
B) Effect of the Migrant Shock on the Number of Security Personnel per Person (Native and Refugee)						
B1) OLS Results	-0.145	-0.152	-0.221**	-0.154	-0.186*	0.029
	(0.089)	(0.090)	(0.099)	(0.095)	(0.105)	
B2) 2SLS Results	-0.062	-0.105	-0.192*	-0.107	-0.108	0.029
	(0.058)	(0.086)	(0.116)	(0.081)	(0.070)	
First-stage regression	1.853***	1.945***	1.716***	1.878***	1.574***	
	(0.125)	(0.197)	(0.144)	(0.242)	(0.247)	
Partial R-squared	0.715	0.731	0.695	0.719	0.694	
F-Stat	221.396	97.229	141.929	60.247	40.464	
Observations	286	286	286	286	286	
Controls for						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	
NUTS2 Fixed Effects	Yes	Yes	Yes	Yes	Yes	
5-Region Linear Time Trends	No	Yes	Yes	Yes	Yes	
NUTS1 Linear Time Trends	No	No	Yes	Yes	Yes	
5-Region-Year Fixed Effects	No	No	No	Yes	Yes	
NUTS1-Year Fixed Effects	No	No	No	No	Yes	

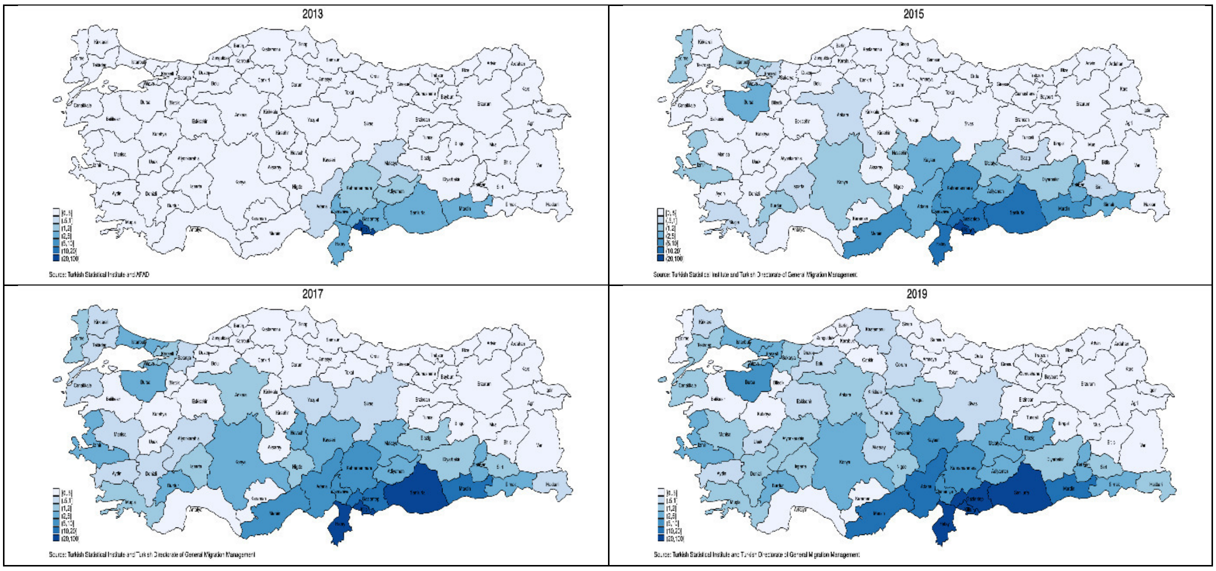
Notes: The sample includes 26 NUTS-2 level regions for each year from 2008 to 2019 (except 2012). Therefore, the number of observations is 286. The dependent variable in panel (A) is the logarithm of the number of security personnel (working in the field of defense and compulsory social security), whereas it is the number of security personnel per capita (natives+migrants) in panel (B). The regression in panel (A) controls for the logarithm of native population. Each cell shows the estimates for the key variable of interest -- the ratio of migrants to population (migrants+natives) -- in a regression of the dependent variable on the key variable of interest, a set of NUTS2-region specific control variables, a set of geographical-area and year specific control variables as indicated above. In the 2SLS regresssions, the instrument depends on the total number of Syrian refugees in four neighboring countries (Turkey, Lebanon, Jordan, and Iraq) in each year, pre-war population shares of Syrian provinces, the distance of each Syrian province to the closest border entry in each of the neighboring countries, and the distance of each Syrian province to each Turkish province. The Nuts2-specific control variables include the logarithm of trade volume, the logarithm of GDP per capita, GDP sector shares, age dependency ratio, average household size, shares of five age categories, and shares of six education categories. The age dependency ratio is the number of people in the ”0-14” and ”65 and over” age groups per 100 people in the ”15-65” age group. GDP sector shares include the shares of agriculture, industry, and services. The age groups are 15-24, 25-34, 35-44, 46-54, and 55-64. The education categories are (i) illiterate, (ii) literate but no diploma, (iii) primary school or primary education graduates, (iv) junior high school and middle school equivalent vocational school graduates, (v) high school and high school equivalent vocational school graduates, and (vi) university and higher educational institution graduates. Each sub-group in the age category indicates the share of that group within the population aged 15-64. Similarly each sub-group in education category shows the share of the specific group over “15 years of age and over”. Standard errors, given in parentheses, are clustered at the Nuts2- level. *, **, or *** indicates significance at the 10%, 5% and 1%, respectively.

Figure 1: Number of Syrian Refugees in Turkey over Time



Notes: The data come from the UNHCR.

Figure 2: Density of Syrian Refugees in Turkey across Provinces: 2013, 2015, 2017, and 2019



Notes: The provincial data on the number of Syrians for 2013 comes from the Disaster and Emergency Management Presidency of Turkey (AFAD). The Ministry of Interior Directorate General of Migration Management provides information on the number of Syrian refugees across provinces for 2015 to 2019. Using these numbers and the province populations obtained from TurkStat, we generate the percentage of Syrian refugees in each province over time.

APPENDIX

Table A1: Refugee Effect on Various Types of Crimes, Controlling for the Number of Armed Forces per capita – 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)	Mean
All	-157.237*	-147.596	-115.089	-175.053	-140.343	195.918
	(87.194)	(120.948)	(145.566)	(128.352)	(156.880)	
Assault	-46.168**	-55.181**	-41.548	-59.974**	-44.400*	28.307
	(21.001)	(23.936)	(26.694)	(25.029)	(26.494)	
Crimes related with firearms and knifes	0.484	2.459	3.617	3.221	3.533	5.496
	(6.175)	(4.456)	(5.814)	(4.579)	(6.015)	
Homicide	-12.545***	-14.514***	-7.377	-14.636**	-7.362	8.058
	(4.508)	(4.901)	-5,632	(5.711)	(6.517)	
Robbery	-7.796	-4.704	-4.235	-5.416	-4.783	6.625
	(9.896)	(11.352)	(13.342)	(12.152)	(14.489)	
Smuggling	20.644***	22.128**	23.398	17.435	21.902	5.310
	(5.496)	(10.156)	(14.480)	(10.616)	(15.796)	
Theft	-36.566*	-40.875	-55.807	-46.703	-60.723	25.342
	(18.886)	(31.999)	(35.567)	(34.746)	(38.994)	
Sexual Crimes	-14.624***	-13.284***	-11.514**	-14.032***	-12.237**	5.021
	(2.578)	(3.569)	(4.601)	(4.101)	(4.827)	
Kidnapping	-9.386***	-10.216**	-6.406*	-11.801***	-7.747*	3.009
	(2.488)	(4.031)	(3.834)	(4.497)	(4.229)	
Defamation	-9.088***	-9.369*	-9.552*	-10.905**	-10.986**	4.094
	(2.810)	(4.939)	(5.596)	(4.997)	(5.351)	
Use and Purchase of Drugs	-4.333	0.344	-6.086	-0.026	-7.173	3.400
	(7.157)	(9.504)	(10.176)	(9.585)	(10.495)	
Production and Commerce of Drugs	4.139	-6.881	-23.637	-9.923	-28.100	9.993
	(15.171)	(18.601)	(22.283)	(20.352)	(25.080)	
First-stage regression	2.880***	2.996***	2.836***	2.980***	2.805***	
	(0.540)	(0.541)	(0.599)	(0.553)	(0.643)	
Partial R-squared	0.703	0.699	0.645	0.690	0.634	
F-Stat	28.420	30.69	22.394	29.066	19.025	
Observations	891	891	891	891	891	
Controls for						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	
5-Region Linear Time Trends	No	Yes	Yes	Yes	Yes	
NUTS1 Linear Time Trends	No	No	Yes	Yes	Yes	
5-Region-Year Fixed Effects	No	No	No	Yes	Yes	
NUTS1-Year Fixed Effects	No	No	No	No	Yes	

Notes: The sample includes 81 provinces for each year from 2008 to 2019 (except 2012), therefore the number of observations is 891. The dependent variable is the rate for various types of crimes given above, where the denominator includes both natives and refugees. Each cell shows the estimates for the key variable of interest -- the ratio of migrants to population (migrants+natives) -- in a separate 2SLS regression of the dependent variable on the key variable of interest, per capita number of individuals working in the field of defense and compulsory social security at the NUTS2-region level, a set of province-specific control variables, a set of geographical-area and year specific control variables as indicated above. The instrument depends on the total number of Syrian refugees in four neighboring countries (Turkey, Lebanon, Jordan, and Iraq) in each year, pre-war population shares of Syrian provinces, the distance of each Syrian province to the closest border entry in each of the neighboring countries, and the distance of each Syrian province to each Turkish province. The province-specific control variables include the logarithm of trade volume, the logarithm of GDP per capita, GDP sector shares, age dependency ratio, average household size, shares of five age categories, and shares of six education categories. The age dependency ratio is the number of people in the "0-14" and "65 and over" age groups per 100 people in the "15-65" age group. GDP sector shares include the shares of agriculture, industry, and services. The age groups are 15-24, 25-34, 35-44, 46-54, and 55-64. The education categories are (i) illiterate, (ii) literate but no diploma, (iii) primary school or primary education graduates, (iv) junior high school and middle school equivalent vocational school graduates, (v) high school and high school equivalent vocational school graduates, and (vi) university and higher educational institution graduates. Each sub-group in the age category indicates the share of that group within the population aged 15-64. Similarly each sub-group in education category shows the share of the specific group over "15 years of age and over". Standard errors, given in parentheses, are clustered at the Nuts2- level. *, **, or *** indicates significance at the 10%, 5% and 1%, respectively.