

Aydemir, Abdurrahman B.; Öztekin, Abdullah Selim

Working Paper

The Impact of Refugees on Crime: Evidence from Syrian Influx in Türkiye by Nativity of Perpetrators and Victims

IZA Discussion Papers, No. 17885

Provided in Cooperation with:

IZA – Institute of Labor Economics

Suggested Citation: Aydemir, Abdurrahman B.; Öztekin, Abdullah Selim (2025) : The Impact of Refugees on Crime: Evidence from Syrian Influx in Türkiye by Nativity of Perpetrators and Victims, IZA Discussion Papers, No. 17885, Institute of Labor Economics (IZA), Bonn

This Version is available at:

<https://hdl.handle.net/10419/320479>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

DISCUSSION PAPER SERIES

IZA DP No. 17885

**The Impact of Refugees on Crime:
Evidence from Syrian Influx in Türkiye by
Nativity of Perpetrators and Victims**

Abdurrahman B. Aydemir
Abdullah Selim Öztekin

MAY 2025

DISCUSSION PAPER SERIES

IZA DP No. 17885

The Impact of Refugees on Crime: Evidence from Syrian Influx in Türkiye by Nativity of Perpetrators and Victims

Abdurrahman B. Aydemir

Sabancı University and IZA

Abdullah Selim Öztekin

Ankara University

MAY 2025

Any opinions expressed in this paper are those of the author(s) and not those of IZA. Research published in this series may include views on policy, but IZA takes no institutional policy positions. The IZA research network is committed to the IZA Guiding Principles of Research Integrity.

The IZA Institute of Labor Economics is an independent economic research institute that conducts research in labor economics and offers evidence-based policy advice on labor market issues. Supported by the Deutsche Post Foundation, IZA runs the world's largest network of economists, whose research aims to provide answers to the global labor market challenges of our time. Our key objective is to build bridges between academic research, policymakers and society.

IZA Discussion Papers often represent preliminary work and are circulated to encourage discussion. Citation of such a paper should account for its provisional character. A revised version may be available directly from the author.

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

The Impact of Refugees on Crime: Evidence from Syrian Influx in Türkiye by Nativity of Perpetrators and Victims*

This paper studies the causal effect of immigration on crime in the context of the massive influx of Syrians to Türkiye, using comprehensive data that spans all stages of the judicial process—from prosecution to incarceration—and includes information on the nativity status of both perpetrators and victims. To isolate causal effects, we employ a two-stage least squares (2SLS) estimation technique, exploiting substantial exogenous variation in the migrant-to-native ratio that arises from the geographical proximity of Turkish provinces to Syrian governorates. The findings reveal a slight increase in total crime at the prosecution stage, while no significant effects are detected for criminal court cases or convictions. Moreover, natives experience increased victimization at the prosecution stage, while their involvement in criminal activities remains unchanged. In contrast, both the likelihood of committing a crime and being a victim of crime increase among immigrants. The analysis further suggests that immigrants may be crowding out natives in specific crime categories, such as smuggling.

JEL Classification: F22, J15, J61, J68, K42

Keywords: immigration, crime, suspects, victimization

Corresponding author:

Abdullah Selim Öztekin
Faculty of Political Sciences
Ankara University
Cad. Ankara
Türkiye
E-mail: asoztek@ankara.edu.tr

* We would like to thank Mevlude Akbulut-Yuksel, Hoyt Bleakley, Iván López Cruz, Yaşar Ersan, Andrew Foster, Tommaso Frattini, Murat Kırdar, Erdal Tekin, participants of the Workshop on the Economics of Refugee Migration, June 22-23, 2023, İstanbul, Türkiye for helpful comments. Usual disclaimers apply.

1 Introduction

Increasing immigration levels lead to concerns among natives due to its potential economic and social consequences. One of the leading concerns widely held in host populations is the propensity of immigration to result in higher crime (Mayda, 2006, Bauer et al., 2000). Potential victimization of natives further heightens these concerns, shaping attitudes toward immigrants, support for immigration policies, and voting behavior (Couttenier et al. 2020). A large and growing literature provides causal estimates of the impact of immigration on overall crime (e.g. Spenkuch, 2014, Alonso-Borrego and Vazquez, 2012, Gehrsitz and Ungerer, 2022). Much less is known, however, about who the perpetrators and victims are of immigration-induced crime - issues that are at the core of immigration related perceptions.¹

In this paper, we study the causal effect of immigration on crime within the context of the massive inflow of Syrians to Türkiye. We first study whether this influx led to an increase in overall crime. Second, using unique data on nativity status, we analyze the propensity of migrants and natives to become victims and perpetrators of crime. Third, with a focus on perpetrators, we investigate how the influx affected various types of crimes committed by migrants and natives. To address these issues, we employ a dataset that captures different stages of the judicial process, including cases handled by prosecutor's offices, cases in criminal courts, court decisions, and incarceration.

The Syrian refugee flow -one of the largest flows in the world- was unexpected and occurred over a relatively short period of time. The conflict in Syria started in 2011 and resulted in large refugee flows to neighboring countries and beyond.² Türkiye, sharing a border of more than 900 km with Syria in the south, started receiving refugees with the onset of the conflict, which resulted in a rapidly growing Syrian population in the country as shown in Figure 1. The number of Syrians officially registered under "Temporary Protection" peaked in 2021, exceeding 3.7 million refugees, which represents 4.4% of the Turkish native population. Until mid-2013 migrants were mostly hosted in refugee camps in South-eastern Türkiye. As the number of refugees increased, they began settling outside of camps and throughout the country. This led to significant geographic variation across provinces in the proportion of refugees relative to the native population, ranging from nearly zero percent to over 20% in border provinces.³ Many of these refugees joined the labor market, predominantly working in the informal sector.⁴

To examine the impact of refugee inflows on crime, we exploit variation in crime rates

¹Megalokonomou and Vasilakis (2023) study crimes committed and reported by immigrants and natives on Greek Islands, Knight and Tribin (2023) study victimization by nationality in Colombia.

²The Syrian flow is part of a substantial surge in the number of forcibly displaced individuals worldwide over the past decade from around 40 million in 2012 to 108 million in 2022 (UNHCR, 2022). This substantial worldwide increase led to a heightened interest in understanding the implications of these flows for host societies.

³In 2019 the mean fraction among 81 provinces was 3.5%. The highest fraction was 81.5% in Kilis province.

⁴According to the 2018 Turkish Demographic Health Survey 61.8 percent of 18-59 year-old Syrian men were in paid employment. The corresponding fraction among natives is 68.9 percent (Demirci and Kırdar, 2021). For refugees under temporary protection working formally in the labor market requires a work permit. The number of work permit holders has been very low among Syrians, about 0.5% of the whole refugee population in 2017.

and refugee populations across provinces and over time. As refugees largely self-selected into their destination provinces, the spatial distribution of refugee populations is unlikely to be random. To address potential endogeneity arising from this non-random settlement pattern, we construct an instrumental variable based on the geographic distance between Syrian and Turkish provinces.

In this context, refugees may exhibit a higher propensity for crime than natives due to demographic factors, including lower educational attainment, a younger age profile, and previous exposure to violence and traumatic events, all of which are typically associated with an increased likelihood of criminal behavior (Freeman 1999, Loeber et al. 2014, Ardino 2012, Couttenier et al. 2019). However, refugees may avoid criminal activity if they intend to seek permanent residency and citizenship in the future, thereby reducing the risk of deportation due to serious criminal charges.⁵ Additionally, the labor market effects of this sudden increase in labor supply may influence the incentives to engage in economically motivated crimes for both refugees and natives. Consequently, the overall impact of the refugee influx on crime rates is theoretically ambiguous *ex ante*.

While understanding the effect of immigration on overall crime is important, distinguishing between immigration-induced changes in criminal behavior among natives and immigrants offers further valuable insights. For example, a positive effect on total crime could be driven by higher crime engagement of immigrants or natives or both. A null effect on total crime, on the other hand, could mask opposing trends in criminal engagement between these groups, with criminal activity increasing in one group while decreasing in the other. Using information on the nativity status of both suspects and convicted offenders available in our data, we directly examine the relative crime propensity of Turkish and foreign nationals, as well as the crime-inducing effects of immigration for each group. Moreover, the data include information on the nativity status of victims, enabling us to analyze victimization patterns separately for natives and foreigners. These analyses allow us to assess whether immigration increases criminal behavior within each group and to identify which groups are more likely to be targeted by crime. Finally, we examine how immigrant influx affects crime types by perpetrators' nativity, offering insights into its impact on criminal incentives in host societies.

Our study utilizes data that capture multiple stages of the judicial process. Sourced from prosecutors' offices and criminal courts, the dataset includes information on the number of cases, offenses, and convictions, as well as the number of individuals involved at various stages—as suspects, defendants, and victims—and those ultimately sentenced. We use alternative measures of crime rate derived from this rich information, which contrasts with existing studies that typically define crime rates based on a specific stage of the criminal justice system, such as

⁵Moreover, UNODC's "Global Study on homicide" (2011) shows that during the pre-migration period when data on intentional homicide rates was available for both Syria and Türkiye, the crime rate in Syria was lower than that in Türkiye. This suggests that refugees may be a population less prone to crime compared to Turkish natives.

police records, cases at prosecutor’s office, or incarceration.⁶ The roles of perceptions, evidence reliability, and the seriousness of crime vary significantly across stages of the judicial process, and only a subset of cases progresses from one judicial stage to the next due to such factors.⁷ By using alternative measures that reflect various stages of the judicial process, we offer a more comprehensive understanding of the impact of immigration on crime.⁸ The results from these measures complement each other and enable us to assess the robustness of our findings.

The first set of our results pertains to total crime. The instrumental variable (IV) estimates indicate that immigration leads to a small increase in crime cases at the prosecution stage. Specifically, a 1 percentage point increase in the share of immigrants leads to an increase of approximately 21 in the overall crime rate per 100K, according to data on the number of cases at prosecutors’ offices. This corresponds to about 0.4% increase in the number of crimes. We find that this increase is mainly accounted for by an increase in cases where perpetrators are unknown. Unlike the increase at the prosecution stage, we find no effect at the criminal court stage in terms of the total number of cases, the total number of offences, and the total number of convictions. Similarly, we find no effect on the total number of convicts entering prison. The results using the number of victims, suspects/defendants involved in cases at prosecutors’ offices and criminal courts corroborate these findings.

While the analysis of overall crime indicates small or no effects of immigration, the analysis by the nativity of individuals uncovers remarkable differences between Turkish nationals and foreign nationals regarding victimization and propensity to engage in crime. Among Turkish nationals, we find no evidence of increased criminal activity. In particular, the estimates show no effect on the involvement of Turkish nationals in prosecutors’ office cases as suspects or in

⁶Studies using police records typically define crime rate as the number of reported crimes per population. Those using prosecutor’s office data may use either the number of cases or suspects as the numerator. Research based on incarceration data uses the number of imprisonments. Examples of studies defining crime rates using police records include Butcher and Piehl (1998), Bianchi et al. (2012), Bell et al. (2013), Chalfin (2014), Spenkuch (2014), Piopiunik and Ruhose (2017), Masterson and Yassenov (2019), Amuedo-Dorantes et al. (2020), Dehos (2021), Gehrsitz and Ungerer (2022), Maghularia and Uebelmesser (2023), and Knight and Tribin (2023). Alonso-Borrego et al. (2012) and Akbulut-Yüksel et al. (2023) use prosecutor’s office data, while Kayaoğlu (2022) relies on criminal courts data. Studies using incarceration data include Moehling and Piehl (2009), Borjas et al. (2010), and Kırdar et al. (2022). offices.

⁷Cases at prosecutor’s office is the closest measure to police records which are regarded as the most comprehensive measure of reported crimes. Police reports, however, exclude cases of tax fraud and involve minor infractions that are not indictable (Maguire, 2012). Also, in Türkiye various complaints are directly filed at the prosecutor’s office. Although providing a broad measure, victimization claims in reported crimes may be unfounded and influenced by negative biases towards racial and migrant groups, raising concerns about the validity of reported crime data (Gove et al., 1985; O’Brien, 1995). Spenkuch (2014) argues that data on actual victimizations would be preferable to reported crimes on theoretical grounds.

⁸Measures of crime based on different steps of the judicial process may be useful in understanding different aspects of the effect of immigration on crime. For example, perceptions of crime, rather than objective levels of crime, may be more salient for the mental well-being of individuals (Goldman-Mellor et al., 2016) and hence analysis of data based on police records or prosecutor’s office would capture such perceptions. On the other hand, more objective and evidence-based crime rates, such as those based on criminal court rulings, are necessary to correct misperceptions (Choi et al. 2023). Besides these official crime data, crime may also be captured by individual surveys. See for example Jobes et al. (2002) for a discussion of the merits of self-reported and official data sources.

criminal court cases as defendants, a reduction in convictions, and no effect on imprisonment. There is evidence of increased victimization among Turkish nationals at the prosecution stage; however, we find no effect on victimization at the criminal court stage. In contrast, we observe an increase in criminal activity among foreign nationals. They are more likely to be involved as suspects in prosecutors' office cases and defendants in criminal court cases, indicating that foreign national criminal offenses increase with the intensity of immigrants. Parallel to these findings, the number of offenses and the number of convictions in criminal courts, and imprisonment increases among foreign nationals. Both prosecutors' office and criminal court data also reveal an increase in the victimization of foreign nationals with higher immigrant intensity. These results suggest an increase in crime primarily concentrated among foreign nationals, with a rise in both their likelihood of becoming perpetrators and victims.

The above results show how criminal behavior and victimization change with immigrant intensity, but do not allow for an assessment of the relative crime engagement of natives and immigrants. Using data on the nativity status of suspects and criminals, we find that, in fact, both the propensity of immigrants to engage in crime and their likelihood of being victims of crime are lower than that of natives. Thus, while immigrant crime participation rises with immigrant intensity, our findings suggest that, on a per capita basis, immigrants are less likely to engage in criminal activity than natives.

The analysis by crime type provides further insights into the nature of immigration-induced crime. The results from criminal court trials show increases in violent crimes, property crimes, public crimes, and smuggling among foreign nationals. In parallel, both convictions and imprisonment rise among foreign-born for each crime type. Among Turkish nationals, while there are no statistically significant effects on the number of offenses for most crime types, we observe significant declines in convictions. This suggests that the arrival of immigrants may be influencing native behavior, potentially shifting them away from serious offences that result in convictions. This may be driven by the expansion of legitimate work opportunities with the arrival of immigrants, which reduces natives' economic incentives to engage in crime. Another possible explanation is that immigrants crowd out natives in certain crime types due to their comparative advantage and more limited outside options.⁹ Our findings on smuggling support this scenario, as smuggling-related crime rise among immigrants while declining among natives. Immigrant networks in both source and destination regions, along with language abilities that facilitate communication with agents involved in organized crime across borders, may provide immigrants with a comparative advantage, leading to the substitution of natives in these activities.

The causal effect of immigration on crime has been widely studied, with research examining various crime types—such as total crime, violent crimes, and property crimes—mainly in

⁹Smuggling is particularly prevalent in the East and Southeast borders of Türkiye and involves trafficking of illicit drugs, smuggling of fuel oil and other goods, and more recently smuggling unauthorized migrants who aim to reach Türkiye or Europe via Türkiye (KOM, 2021).

developed countries. Findings are mixed, with most studies reporting either zero or positive effects, while a few report negative effects.¹⁰ More recently, several studies have explored this relationship in developing countries, including Türkiye, which has experienced significant refugee inflows. Research on the Syrian refugee influx in Türkiye yields mixed results: Kırdar et al. (2022) find a negative effect using incarceration data, while Mercan et al. (2022) report no effect. Kayaoğlu (2022) analyzes criminal court data and finds both null and negative effects depending on the specification. In contrast, Akbulut-Yüksel et al. (2023) use data prosecutors' offices and court convictions and report positive effects. These studies in the Turkish context focus on different stages of the judicial process but do not estimate crime effects by nativity status.

Our study contributes to the literature on immigration and crime in several ways. Few studies have been able to analyze crime separately for natives and immigrants (Huang and Kvasnicka 2019, Dehos 2021, Megalokonomou and Vasilakis 2023, Knight and Tribin 2023, Lange and Sommerfeld 2024). These studies typically distinguishing the nativity status of either perpetrators or victims.¹¹ In contrast, our study estimates the effects of immigration on crime based on both perpetrators' and victims' nativity status. Our findings indicate that immigration-induced crime primarily arises among immigrants and does not lead to increased victimization of natives. While numerous studies estimate the effects of immigration on different types of crime, only Megalokonomou and Vasilakis (2023) analyze crime types separately for immigrant and native offenders.¹² To our knowledge, this is the first study in a developing country context to investigate crime by offenders' nativity. Moreover, we examine a broader range of crime types, including public crimes and smuggling, which have received little attention

¹⁰Butcher and Piehl (1998), Chalfin (2014), and Masterson and Yassenov (2019) for the US, Bianchi et al. (2012) for Italy, Maghularia and Uebelmesser (2023) for Germany finds no effect of immigration on crime. Borjas et al. (2010) and Spenkuch (2014) for the US, Gehrsitz and Ungerer (2016) and Piopiunik and Ruhose (2017) for Germany, Alonso-Borrego et al. (2012) for lower educated immigrants in Spain, Knight and Tribin (2023) for Colombia, Bell et al. (2013) for asylum seekers in UK, Megalokonomou and Vasilakis (2023) for Greece find positive effects. Bell et al. (2013) report negative effects for immigrant inflow from EU accession countries in UK while Ozden et al. (2017) find negative effects for on-work visa immigrants in Malaysia. The types of immigrants that are the subject of study differ across these papers some focusing on refugee flows. Those with a refugee focus include Masterson and Yassenov (2019), Maghularia and Uebelmesser (2023), Gehrsitz and Ungerer (2016), Knight and Tribin (2023), Bell et al. (2013), Megalokonomou and Vasilakis (2023).

¹¹Studying the effect of refugees on crime in Germany, Huang and Kvasnicka (2019) finds no evidence of an increase in the victimization of Germans in crimes with refugee suspects. Dehos (2021) finds that Germans do not change their overall criminal engagement in response to immigration while Entorf and Lange (2023) finds evidence on increase in hate crime against refugees in regions with latent anti-refugee sentiment. Lange and Sommerfeld (2024) finds an increase in the number of suspects from refugee countries with the arrival of refugees but insignificant effects for native suspects. Studying the refugee flows to Greek islands, Megalokonomou and Vasilakis (2023) finds that the increase in reported crimes is driven by crimes committed by the foreign-born population, with no change in crimes committed by natives. Knight and Tribin (2023) finds in Colombian context that it was migrants, rather than natives, who faced increased homicides as a result of increased flows from Venezuela. In addition to victims of homicides, Knight and Tribin (2023) study arrests for homicides for which clearance rates are relatively low at around 20 percent, and find little evidence that results are driven by homicides of migrants by other migrants.

¹²For example, Chalfin (2014), Spenkuch (2014) and Masterson and Yassenov (2019) study property and violent crimes, Knight and Tribin (2023) studies homicides, Megalokonomou and Vasilakis (2023) study various crimes types such as robberies and drug crimes.

in the literature. This allows for a more nuanced assessment of immigration-induced crime. Lastly, by analyzing outcomes at different stages of the judicial process—from prosecution to incarceration—our study provides a more comprehensive perspective on the crime effects of immigration.

Our results offer new insights into the mechanisms driving immigration-induced crime. A key argument in the literature is that immigration-driven worsening in labor market outcomes may increase natives’ criminal involvement. However, our results show no rise in natives’ propensity to commit crimes, suggesting that this mechanism is not a major factor in our context. This conclusion aligns with existing evidence on the labor market effects of the Syrian refugee influx in Türkiye, which finds no impact on natives’ overall employment.¹³ Research suggests that immigrants primarily compete with other migrants in the labor market (Manacorda et al. 2006; Warren and Warren 2013; Massey and Gentsch 2014), making them more vulnerable to the negative effects of increased migration (Cortes 2008). Consequently, deteriorating labor market opportunities for immigrants may be driving their higher engagement in crime.¹⁴

The rest of the paper is organized as follows. In the next section, we discuss the massive Syrian refugee flow to Türkiye. Section 3 discusses our data, while Section 4 discusses the judicial system in Türkiye and measures of crime used in the study. Econometric methods are discussed in Section 5. Section 6 reports our main results. Section 7 reports results from robustness analysis regarding the specification and sample years used in our empirical model, and results from several identification checks. Section 8 concludes with a discussion of our main findings.

2 Background Information on Syrian Refugee Flow

After the Syrian uprising erupted in 2011 and escalated into a prolonged civil war, Türkiye began receiving a large influx of refugees fleeing the conflict. These individuals have been registered under the “Temporary Protection” status. Figure 1 presents the annual number of Syrians under Temporary Protection in Türkiye from 2012 onward. The number of Syrians residing in Türkiye was negligible prior to 2012. As of January 2012, only 9,500 Syrians were living in the country. However, as the conflict in Syria intensified, the number of Syrian refugees increased sharply, reaching approximately 170,000 by the end of 2012. This figure rose to 560,000 by the end of 2013 and surged to 1.5 million by the end of 2014. The refugee population continued to grow, reaching 2.5 million in 2015, 3 million in 2016, and 3.5 million in 2017. Since early 2018, the number of Syrians living in Türkiye was around 3.6 million.

¹³While refugees took up jobs in the informal sector and displaced natives, formal employment prospects improved which countered the documented displacement from the informal sector (Aksu et al., 2018).

¹⁴Available labor market data in Türkiye does not cover refugees. Therefore, we cannot test the effects of new flows of immigration on labor market outcomes of existing immigrants.

[Figure 1 to here]

In addition to those under “Temporary Protection” status, a considerable number of Syrians reside in Türkiye with a "Residence Permit".¹⁵ The first year in which provincial distribution of residence permit holders by nationality became available is 2012. According to the Address-Based Population Registration System (ABPRS) data there were 10,067 Syrians with a residence permit in Türkiye by the end of 2012. This number reached 115,000 in 2019. To enhance the robustness and reliability of our results, we include the number of Syrians with residence permits in the total count of count of Syrians residing in each province across Türkiye.

In response to the humanitarian crisis, the Turkish government initially accommodated the refugees in temporary facilities such as schools and public buildings. As the number of refugees escalated, the government established refugee camps in provinces near the border. During the year 2012, almost all Syrians resided in these camps. By mid-2013, however, the Syrian population reached 300,000 and exceeded the capacity of the camps. As a result, immigrants began to settle in the South-Eastern provinces of Türkiye and later spread to other regions in the country. By the end of 2019, only a small fraction (2%) of the total Syrian refugee population was residing within designated refugee camps. The remaining refugees were dispersed across various regions of the country. Although most of them settled in urban areas near the Syrian border, some of them migrated to larger metropolitan areas such as İstanbul, Ankara, İzmir and Bursa. However, the proportion of refugees to the local population is in general very low for the provinces that are far from the border. Figure 2 illustrates the distribution of Syrian refugees in Türkiye across the 81 provinces. Refugees are predominantly located in provinces bordering Syria. The highest proportion (81%) is observed in Kilis, followed by other provinces close to the border.

[Figure 2 to here]

3 Data

This study utilizes several province-level datasets, with two primary sources related to the judicial system. First, administrative data from the Ministry of Justice are used to obtain information from public prosecutors’ offices and criminal courts. While some components of this dataset—such as aggregate statistics—are publicly available, detailed information on nationality and crime types is confidential. Second, incarceration data are drawn from the Convicts Received Into Prison Statistics, published by the Turkish Statistical Institute (TurkStat).

¹⁵Residence Permit holders include both individuals who were initially under Temporary Protection and later adjusted their legal status, as well as Syrians who were admitted directly under residence permit categories. There are several types of residence permits. For instance, foreign spouses may be granted a Family Residence Permit, while individuals intending to establish business or commercial ties in Türkiye may receive a Short-Term Residence Permit.

The Ministry of Justice data covers the years from 2006 to 2019. However, since nationality and type of crime information are available only after 2009, we restrict our study to the 2009-2019 period. We conducted robustness checks by extending the study period to 2006-2019 for outcomes with available data and found that this restriction has a negligible effect.

For the size of the refugee shock, we combine the number of Syrians—comprising both individuals under Temporary Protection status and those holding Residence Permits—with census data to calculate the provincial share of Syrians at the end of each year. At the onset of the crisis, most Syrians sought refuge in camps established and maintained by the Disaster and Emergency Management Authority (DEMA). For the years 2012 and 2013, provincial-level refugee allocations were obtained from DEMA reports. Following the establishment of the Directorate General of Migration Management (DGM) under the Ministry of Interior, provincial refugee statistics have been reported by DGM, and we rely on these data from 2014 onward. Data on Syrians holding residence permits are drawn from TurkStat’s annual population statistics by country of origin.

In our analysis, we incorporate economic and demographic control variables that may potentially affect crime rates. The economic control variables include total trade volume, GDP per capita, unemployment rate, and male labor force participation rate. In addition, we consider several demographic variables, such as the percentage of low-educated individuals, the share of men aged 15-39, the percentage of the province population residing in towns with a population of over 100,000, and the average household size. These control variables were obtained from TurkStat at the province level. Finally, we utilized Google Maps to calculate travel distances between each province in Türkiye and the provinces in Syria, which we use in the construction of our instrumental variable.

4 The Judicial System and Measurement of Crime

Criminal investigations in the judicial system in Türkiye originate from cases filed either to the prosecutor’s offices or the police. The police cases that require judicial investigation are transferred to the prosecutor’s offices. The economics of crime literature primarily focuses on the number of offenses reported to the police (Machin; 2013, Spenkuch, 2013) for constructing crime rates. In the absence of data from police records, the analysis in this paper starts with cases at prosecutor’s offices. In addition to the prosecution stage, we analyze indicators of crime from all consecutive stages in the judicial process, including cases at criminal courts, sentences at criminal courts, and incarceration.

The judicial process can extend beyond a year, but cases carried over from previous years can be distinguished from those initiated in the current year. Throughout the study, we use the number of new cases filed each year, which provides us a flow measure consistently defined across years.¹⁶

¹⁶The data does not permit tracking an individual case through judicial stages.

Figure 3 offers a snapshot of the data used in the study for the year 2015. The first column reports the number of cases at prosecutor’s office. At the prosecution stage, the prosecutor’s office considers each complaint as a case file. It is possible that a file involves multiple offences, e.g. a complaint of property crime may involve two separate offences of “break in” and “theft”. A case may involve multiple perpetrators and multiple victims. In our analysis, we focus on natural person suspects/victims that exclude juridical persons in trials. Perpetrators in cases handled by the prosecutor’s office may either be known or unknown. In 2015, 76% of the files received by the prosecutor’s office were cases with identified perpetrators, while 24% had unknown perpetrators.

[Figure 3 to here]

Column 2 of Figure 3 provides statistics from the criminal court stage. If deemed necessary for trial, the prosecutor’s office forwards files to the criminal court for trial provided that perpetrators can be identified. The criminal court also considers each complaint as a single case. Depending on the nature of crime, cases are handled by different types of courts that include high criminal courts, basic criminal courts, and enforcement - the order reflecting the severity of crimes handled by these courts. Since each case may involve multiple offences, suspects, and victims, we also analyze the number of offenses, defendants (perpetrators), and victims in addition to the number of cases. A comparison of the number of cases with known perpetrators in columns 2 and 1 (1,404,458 and 2,691,145) suggests that approximately 52% of the cases get transferred from prosecutor’s offices to criminal courts.

The third stage of the judicial process we examine is given in column 3 of Figure 3 which refers to the criminal court trials that result in convictions. Comparison of the number of offences in criminal court cases in column 2 (3,226,012) with the number of sentences in column 3 (1,531,696) suggest that approximately 47% of offences result in convictions.

The final stage of the criminal justice system in our analysis comprises the number of convicts entering prison. The actual number of individuals entering prison represents a small subset of those sentenced to imprisonment. For instance, in 2015, while 1,531,696 people were convicted in criminal courts, only 431,081 individuals received prison sentences. Column 4 of Figure 3 shows that in the same year, 168,726 individuals ended up in prison which corresponds to 39% of those sentenced to prison. Due to deferrals, not all individuals receiving prison sentences serve time in prison. In Türkiye, for example, sentences under 2 years may be postponed, leading to conditional releases for offenders. In general, imprisonment results from severe crimes which are relatively uncommon occurrences. Additionally, procedural aspects such as appeals that are common for prison convictions can complicate the timing of imprisonment.

In our context, the crime measure at the prosecution stage most closely resembles the crime rate based on police records. However, significant selection takes place as cases advance through judicial stages, from prosecution to incarceration. With each stage, both the likelihood that the defendants committed the charges and the severity of the offenses increase. As a result, each

stage represents a distinct measure of crime. Consequently, analyzing data from a specific stage reflects the unique characteristics of that stage. Using crime measures from different stages, therefore, offers a more comprehensive analysis of crime.

In addition to total crime, we study specific types of crime within the criminal court stage and incarceration. Previous literature has studied violent and property crimes for the total population. Beyond these two categories, we also investigate public crimes and smuggling. Unlike violent crimes, which target specific individuals and result in physical, psychological, or other types of harm, public crimes involve offences against public health, environment, public security, public peace, or public morality. Public crimes are particularly significant because they can affect large groups of citizens without targeting any specific individual. Smuggling—which encompasses the trafficking of illicit drugs, fuel, various goods, and unauthorized migrants—is of particular relevance in our context due to its prevalence in border regions, where many refugees reside. Similar to natives, immigrants may also become involved in such activities through their networks. These four crime types represent a subset of all criminal offences. Other crimes, not included in these categories, fall under specialized legal areas such as cadastral, commercial, consumer, enforcement, and intellectual and industrial property courts.

5 Econometric Analysis

In our empirical analysis of the impact of refugee flow on crime, we estimate the following baseline equation,

$$\frac{Y_{ct}}{Natives_{c2011}} = \beta \frac{Refugees_{ct}}{Natives_{c2011}} + \gamma X_{ct} + \theta_c + \tau_t + \varepsilon_{ct} \quad (1)$$

where c and t index provinces and years respectively, Y_{ct} denotes various outcomes of interest, $Refugees_{ct}$ is the total number of Syrians in province c in year t , $Natives_{c2011}$ is the native population in province c in 2011. On the left-hand side of equation (1), we use several crime ratios for 100K as outcome variables. On the right-hand side, our key independent variable is the refugee share (in percentage terms) which is defined as the ratio of the number of refugees relative to the native population in 2011.

The key parameter of interest β represents the gradient of crime rate with respect to the refugee share. X is a vector of province characteristics which includes the log of total trade volume, per-capita GDP, unemployment rate, male labor force participation rate, the percentage of low-educated individuals (less than high school) among individuals older than 18, the share of men aged 15-39, the average household size, and the percentage of the province population residing in towns with a population over 100,000. The X vector aims to control province characteristics that may change over time for reasons unrelated to immigration. If these changes are correlated with both migration intensity and the outcome, controlling them allows unbiased estimates. However, some of these characteristics may be endogenous to mi-

grant shock and hence may be bad controls. Our robustness section shows that our results are not sensitive to these X characteristics. Table 1 presents the descriptive statistics of the main outcome variables for the pre-and post-crisis years, along with the control variables utilized in the study.

In equation (1), θ_c and τ_t stand for province and year fixed effects, respectively. Province fixed effects capture province characteristics that are constant over time while year fixed effects capture year specific shocks to crime rates that are common across provinces. In our main specification, we account for pre-trends in the outcome of interest by including controls for region-specific year fixed effects (regions broadly defined at 12 NUTS-1 level) and baseline outcome variable interacted with year dummies. The interaction of baseline outcome with year dummies allows the trends to differ between regions with high and low values of the outcome (Akbulut-Yuksel et al.(2023)). Finally, ε_{ct} is the error term. All regressions are weighted by the province’s population in 2011. To allow for correlation in error terms over time within provinces, we cluster standard errors at the province level.

We scale the number of crimes and the size of the refugee influx in equation (1) by the pre-shock (i.e. year 2011) population size of the province. Other studies that adopt ratio specifications similarly use pre-shock populations for scaling, both in the context of the analysis of crime (Huang and Kvasnicka (2019), Entorf and Lange (2023), and Lange and Sommerfeld (2024)), as well as, in other contexts (e.g. Bleakley (2007, 2010), Ersan et al.(2023)). An alternative approach is to use the current population size, i.e. total population (natives and refugees) in province p at year t , as the denominator (e.g. Jaitman and Machin 2013, Bell and Machin 2011). However, this latter approach is prone to common divisor bias discussed by Kronmal (1993), leading to biased estimates of the refugee effects on the outcome.¹⁷ Therefore, from a methodological standpoint we prefer to use the pre-shock population in our ratio specifications.

The use of the pre-shock population is also important for the interpretation of the key parameter of interest β . Our specification examines changes in crime from the perspective of pre-shock residents of an area who are later exposed to immigrant inflows. Specifically, we analyze how per capita crime experienced by the original population shifts as immigrant intensity rises. This differs from an approach that includes the total current population in the denominator, which estimates the change in per capita crime by considering the entire population in that area, including both the pre-shock residents and migration-driven inflows and outflows.

The host population’s sense of security is likely influenced more by how often they experience crime firsthand or hear about it through their networks and the media—rather than overall

¹⁷In our context the bias arises primarily because any change in the number of residents in a province, such as that due to the changing number of refugees over time, builds in a spurious correlation between the dependent and key explanatory variables that share the common denominator (the number of residents in province c in year t). The common divisor problem was first recognized by Pearson (1896); an example of common divisor bias was later provided by Neyman (1952: 143). This problem is highlighted in the context of the analysis of crime by Tarling (2018) and in the accounting literature by Chan et al. (2016).

crime rates per capita in the entire population. While the latter measure is also valuable, it addresses a different question. For instance, average crime per capita in an area may inform police staffing decisions, whereas our approach better captures the host population’s assessment of immigration-induced crime.^{18, 19}

Equation (1) uses a continuous intensity parameter, specifically the ratio of refugees, at the provincial level for each of the 81 provinces in Türkiye over the sample period. The conflict in Syria started in mid-2011, but Türkiye received the first Syrians at the end of 2011. Therefore, 2012 marks the onset of refugee flow and hence the time of treatment. Since there is a negligible number of Syrians prior to 2012²⁰, we have a Difference-in-Differences (DiD) setting. DiD analysis assumes parallel trends for the treatment and control regions prior to treatment and violation of this assumption leads to biased estimation of β . Thus, we assess pre-treatment trends through placebo exercises in the robustness checks section.

OLS estimation of equation (1) assumes that the refugee shares are exogenous. While the Turkish government constructed refugee camps and placed early immigrants in these camps, after June 2013 refugee camps were no longer capable of hosting all Syrians, and refugees spread all over the country.²¹ Hence, the location choice of refugees after 2013 is likely to be endogenous. If refugees choose provinces based on observable and unobservable characteristics that influence crime, then the correlation between the refugee share and the error term will result in biased estimates. The non-random location choice of refugees is thus a major threat to the validity of estimates. In fact, we test endogeneity and reject the null hypothesis that the

¹⁸Our analysis is akin to estimating the changes in job prospects of natives in an area as a result of immigrant inflows in the context of the labor market effects of immigrants flows. The alternative approach that estimates effects on average crime, using the total current population in the denominator, is similar to estimating how job prospects in area change as a result of immigration, averaging over both natives and immigrants.

¹⁹Several studies (e.g., Lange and Sommerfeld, 2024; Bell et al., 2013) incorporate current population size (including both natives and immigrants) as a control variable, due to concerns about a potential mechanical effect. Specifically, a larger immigrant population in a given area increases the number of individuals who could potentially engage in criminal activity, which may lead to a higher crime rate when crime rates are computed relative to baseline population size. This concern is relevant in our context, when we examine the crime rate of a region over time. However, we opt not to include current population size as a control for two primary reasons. First, the immigrant population in a province may be correlated with unobserved factors that also influence crime, while native populations may respond to migrant influxes by relocating to other regions, thus rendering current population size -the sum of immigrant and native populations- an endogenous variable. Second, the hypothesized mechanical effect may not materialize if a higher number of immigrants in a region results in a reduction in crime rates among this group. This reduction could occur, for instance, through the creation of job opportunities within immigrant communities, which could mitigate crime intensity. Additionally, when comparing two regions, a higher share of immigrants in one region does not necessarily imply a higher absolute number of immigrants in that region, thereby ruling out a mechanical effect. For instance, although the number of refugees in Osmaniye is less than half that in Kayseri, Osmaniye has a larger proportion of refugees in its population, owing to its smaller population size.

²⁰The number of Syrians in Türkiye was 6,883 and 8,747 in 2010 and 2011, respectively. Syrian ratio in the total population was around 0.01%.

²¹Refugee camps are generally located in border provinces, and several of them are very close to the border. However, there are some refugee camps in non-border provinces (Kahramanmaraş, Malatya, Adana, and Adıyaman) as well. One could consider using the location of these refugee camps to construct an IV assuming the locations were chosen independent of factors related to crime. However, if the government built these camps due to the location choice of the refugees, that would point out a potential endogeneity problem.

refugee population is exogenous at conventional significance levels.

To address endogeneity concerns, in a two-stage least squares (2SLS) strategy, we instrument the ratio of refugees with a distance-based instrument leveraging the variation in total migrant stock in Türkiye over time and the geographical proximity of provinces to the source Syrian governorates. This strategy follows the distance-based instrumental variable suggested in the existing literature (Del Carpio and Wagner (2016)). We have 81 provinces in Türkiye and there are 13 different governorates in Syria. By using Google Maps, we calculate the travel distance from each province in Türkiye to each governorate in Syria. Then, using refugee numbers and travel distances, we construct our instrument as follows:

$$IV_{ct} = \sum_{s=1}^{13} \frac{\pi_s T_t}{d_{cs}} \quad (2)$$

where T_t is the total number of refugees living in Türkiye in year t . Distance parameter d_{cs} is the travel distance from province c in Türkiye to region s in Syria. The share of Syrians living in region s in Syria (in 2011) is denoted by π_s . Pre-war distribution of Syrians is taken from Syrian population records distributed by the Syria Central Bureau of Statistics. The instrument deflates the total number of Syrians by the distance between each province in Türkiye and each governorate in Syria.

Our identifying assumption is that, conditional on the set of covariates, the distance-based instrument influences the outcomes only through its effect on the share of refugees. This implies that the instrument is uncorrelated with pre-shock trends in the outcomes. To check the validity of this identification assumption, we adopt an event study design, with the results presented in the robustness section.

6 Results

We start by examining the impact of refugee flow on overall crime rates. Table 2 provides 2SLS estimates and Table 3 provides the corresponding OLS estimates from five different specifications that vary in the set of controls. The independent variable is the percent of the total number of Syrians in a province to the pre-shock province population in 2011. The dependent variable is the number of crimes in a given year per 100k inhabitants, considering the 2011 population of the province. In column (1) we control for year and province fixed effects. Column (2) adds controls for changes in province level characteristics that may be correlated with crime. Columns (3) to (5) introduce controls for pre-existing trends. Time trends are controlled with 12 NUTS-1 regions specific linear time trends in Column (3) and with 12 NUTS-1 region-year interactions in Column (4). Column (5) adds a further control to Column (4) specification that interacts crime volume in a province in the baseline year 2011 with a linear time trend, allowing trends in crime to differ between low and high crime regions. Allowing trends to differ by baseline crime is important because NUTS-1 regions cover wide geographic areas and there are

significant differences in baseline crime rates across provinces within a NUTS-1 region.²² Thus, our richest and preferred specification (5) allows time trends in crime to differ both by region and pre-shock crime level. In these and the following tables, we present the coefficients for the key parameter of interest, the ratio of immigrants, which identifies the change in crime intensity in a province due to immigrant influx. For the 2SLS estimates, the first stage F-statistics are reported in the bottom panel of the table and exceed the recommended levels in the literature in all specifications, including those that allow for more flexible pre-existing time trends.

We present results from successive stages of the judicial process across multiple panels. The top panel of Table 2 presents results for the number of cases at prosecutors' offices. In the first row, coefficient estimates are positive for the first two columns where we do not control for time trends. In the following columns where we add controls for pre-existing trends, only the last specification in column (5) yields a significant and positive coefficient estimate. The estimate of 20.6 is significant at 5 % level. This coefficient implies that a 1 percentage point increase in the ratio of immigrants is estimated to lead to an increase of 20.6 in overall crime rate per 100k. This corresponds to about 0.4% increase in the number of crimes per 100k.

Some of the cases handled by prosecutors' offices involve unknown perpetrators. For example, about a quarter of the cases were of this nature in 2015. The next two rows of the top panel reports results for the cases where perpetrators are unknown and where they are known. The results in column (5) show positive and significant effects for cases with unknown perpetrators but no effect for the cases with known perpetrators. This suggests that as immigrant intensity increases, identifying perpetrators becomes more difficult, potentially due to shifts in the types of crimes committed or changes in the identities of the criminals involved. This finding, novel to the literature, is significant because crimes with unknown perpetrators that go unpunished can undermine individuals' sense of security and erode trust in the legal system.

The next panel studies the number of cases in criminal courts. The estimates in the first row of this panel indicate null effects for the total number of cases similar to the result for the number of cases at prosecutors' offices where perpetrators are known. This result is not surprising, as only cases with identified perpetrators proceed to courts. We can also estimate the effects by distinguishing between types of criminal courts. We find no increase in the number of cases at high criminal court and the basic criminal court indicating that immigration does not lead to an increase in more serious crimes. The only positive effects are observed for cases at court of criminal enforcement, however, these effects disappear in the most flexible specification. In sum, results indicate an increase in crime cases at prosecutors' offices, primarily involving cases with unknown perpetrators, but no effects at criminal court stage.

A criminal case may involve multiple crimes, such as a break-in and theft during a property crime. The third panel of Table 2 estimates effects at criminal courts in terms of the number

²²For instance, although Antalya and Kahramanmaraş belong to the same NUTS-1 region, the number of cases per 100,000 at prosecutors' offices is significantly different in 2011—Antalya reports 6,666 cases, whereas Kahramanmaraş has fewer than 3,000, less than half of Antalya's figure.

of crimes committed by natural persons and similarly finds no significant effects. The fourth panel for the natural person convictions and the last panel for the number of convicts in prison (i.e. imprisonment) also show null effects. These results from various judicial stages offer a more comprehensive understanding of the impact of immigration on crime and demonstrate that conclusions can be sensitive to the specific stage of the judicial process under investigation. Notably, while the first panel indicates an increase in the number of cases handled by prosecutors' offices—the closest measure to crime measures based on police records—, no significant effects are observed in the subsequent stages of the judicial process—namely, court cases, convictions, and imprisonment.²³

Table 3 presents the OLS estimates that correspond to the 2SLS estimates of Table 2. Almost all OLS estimates indicate null effects. OLS coefficient estimates in Table 3 that correspond to the significant 2SLS coefficient estimates in column (5) of Table 2 are smaller in absolute value. This downward bias in OLS estimates may arise from the endogenous location choice of refugees and suggests that refugees choose locations that have lower crime rates. Although refugee numbers are based on various official sources, inaccuracies in the reported figures may exist, particularly during the initial years of the Syrian refugee influx when tracking mechanisms were less robust. Such measurement errors in refugee counts could also contribute to the observed downward bias in the OLS estimates.

The estimates in the literature for the effect of immigration on total crime vary across studies. Bianchi et al. (2012) estimates an elasticity of 0.03 for total crime with respect to the share of immigrants in Italy. Bell et al. (2013) report an elasticity of approximately 0.16 for total crime related to asylum seekers in England. Piopiunik and Ruhose (2017) find an elasticity of 0.4 in the context of ethnic Germans immigrants for the number of reported crimes. Studies in the Turkish context report mixed results regarding the effect of immigration on total crime including positive, null, and negative effects. Akbulut-Yüksel et al. (2023) in the Turkish context report elasticities in the order of 0.049-0.054, for the number of cases handled by prosecutors' offices. Kayaoglu (2022) finds that total criminal court cases per capita (including refugees) decrease by 1.6 percentage points for a one percentage point increase in refugee share but finds null effects when crime rates are defined per native population. Kırdar et al. (2022) find that a 10-point increase in the percentage of refugees in the population leads to a 8.1 percent drop in the crime rate per capita (including refugees) using data on incarcerations. While our estimates are not directly comparable to other Turkish studies due to differences in econometric specifications and crime measures, the small positive effect we observe for total crime at the prosecution stage, along with the null effects in the subsequent stages of the judicial process, are broadly inline with earlier estimates per native population

²³We get qualitatively very similar results if we replace 2011 population with year t native population size as the denominator in the ratio specifications in equation (1). This result, consistent with Kırdar et al. (2022) who find no significant immigration-induced change in the internal migration of natives, suggests that our time trends capture the remaining secular changes in native population size. We discuss this issue in the Robustness section along with other alternative measures of crime.

from Türkiye.²⁴

The cases handled by prosecutors' offices and criminal courts may involve multiple victims and multiple suspects/defendants. Table 4 uses the information on the number of victims, suspects/defendants involved in these cases. Consider for example the top panel for prosecutors' offices. The first row now defines crime rate as the number of suspects per population rather than the number of cases per population. The results in the top panel for the number of suspects at prosecutors' offices yield parameter estimates similar to the parameter estimates for the number of cases in Table 2. The total number of suspects increases, which is accompanied by an increase in the number of unknown suspects but no change in the number of natural person suspects – i.e. suspects whose identity is known. With increased crime, there is also an increase in the number of victims. The results in the second panel for the number of defendants and victims in criminal courts, on the other hand, indicate no significant effect similar to the results for the number of cases in courts in Table 2.

6.1 Crime by Nationality

An increase in crime driven by immigration, such as the rise observed in cases handled by prosecutors' offices, can manifest under various scenarios that differ in the nativity status of perpetrators and victims. For instance, the increase in the overall crime rate may stem from higher criminality among immigrants, and result in the victimization of natives. Conversely, a rise in criminality among natives could specifically target immigrants. It is also possible that increases in both criminality and victimization are predominantly confined to a particular group, such as immigrants. Additionally, null effects on the total crime rate at the population level may mask significant effects within smaller subgroups. Distinguishing between these scenarios provides valuable insights into the nature of immigration-induced crime and the mechanisms at play.

Table 5 leverages information on the nationality of victims and suspects/defendants to estimate the effects separately for natives and foreign-born individuals.²⁵ The data for victims includes all cases targeting natural persons even if the perpetrators cannot be identified. However, since nationality information is unavailable for cases where perpetrators are unknown, the analysis for suspects/defendants is limited to cases where the perpetrators are identified. The results presented in column (5) of the top panel for prosecutors' offices show statistically significant increases in both foreign national suspects and victims. Specifically, the parameter estimates suggest that a 1 percentage point increase in the share of immigrants corresponds to

²⁴Focusing on specific crime types, Spenkuch (2014) finds elasticity estimates of 0.123 and 0.065 respectively for property crime rates and violent crime rates with respect to the share of immigrants. Elasticity estimate of property crime rates with respect to the prison population is -0.321 in Levitt (1996).

²⁵The available data provides a breakdown by foreign-born status but not by national origin within the foreign-born category. As a result, the effect of the Syrian influx is estimated for the outcomes of natives and the foreign-born population, with the latter group primarily consisting of Syrians, although it also includes individuals from other nationalities. It is important to note, however, that the variation in the foreign-born population during our sample period is predominantly driven by the Syrian influx.

an increase of approximately 12.6 and 20.2 per 100K in the rates of foreign national suspects and victims, respectively.²⁶ In the subsequent panel for criminal courts, we similarly find increases for foreign national defendants and victims. Consistent with these findings, the following three panels show increases in the number of offenses, convictions, and instances of imprisonment among foreign nationals. These results indicate that both criminal activity and victimization rise among the foreign-born population.

The results in Table 5 for Turkish nationals present a contrasting picture. In the top panel for prosecutors' offices, while an increase is observed in the number of native victims, no significant effect is found for the number of native suspects. Moving to the next panel for criminal courts, we observe no significant effects for either native defendants or native victims. Similarly, the last three panels—examining the number of offenses, convictions, and instances of imprisonment—show no increase for natives. In fact, the estimates for native suspects and defendants are negative but statistically insignificant, while the negative effect on the number of convictions is marginally significant. Thus, these findings provide no evidence of heightened criminal activity among natives.

Although there is an indication of increased victimization among natives at the prosecution stage, we do not observe a similar effect at criminal court cases. This could be because the reported offenses are not severe enough to warrant a court hearing or because the perpetrators remain unidentified. Overall, our results do not support that higher immigration leads to increased criminal involvement among natives, nor do they provide evidence of a rise in native victimization that would necessitate court proceedings. However, the findings suggest that in regions with higher immigrant intensity, both criminal behavior and victimization increase among immigrants.

While above results in Table 5 inform how criminal behavior and victimization among natives and foreign-born respond to rising immigrant intensity, an important question of interest in both the public and policy discussions of immigration is whether the rate at which immigrants engage in crime is more or less than natives. In particular, there is public concern that immigrants may have a higher propensity to engage in criminal activity compared to natives. A related issue is whether the rate at which immigrants are victimized is higher than natives which may lead to their marginalization, reducing their economic and social prospects in the host country.

To examine the relative crime propensity of immigrants, we adopt the approach of Knight and Tribin (2023) by comparing the variation in the share of immigrants —across provinces and within each province over time— to the variation in the share of crimes involving immigrant perpetrators. To the extent that immigrants engage in crime at the same rate as natives, the shares of crimes involving immigrants should increase proportionally. Conversely, if immigrants

²⁶Note that while we find significant positive effects for foreign-born suspects in Table 5, we find no significant effect for the total number of suspects in Table 4. This is likely due to the fact that foreign-born are a small fraction of the total population.

engage in crime at a lower rate than natives, we would expect the share of crimes involving immigrant perpetrators to rise more slowly than the share of immigrants residing in these areas. A similar approach is applied when examining the victimization of immigrants relative to natives. More formally, using information on population shares of refugees and the share of foreign-born among perpetrators and victims we estimate the following model:

$$\frac{Y_{f,ct}}{(Y_{f,ct} + Y_{n,ct})} = \beta \frac{Refugees_{ct}}{(Refugees_{ct} + Natives_{ct})} + \gamma X_{ct} + \theta_c + \tau_t + \varepsilon_{ct} \quad (3)$$

where c and t index provinces and years respectively, $Y_{f,ct}$ and $Y_{n,ct}$ denote outcomes of interest among foreign-born and natives respectively, $Refugees_{ct}$ is the total number of Syrians in province c in year t , $Natives_{ct}$ is the native population in province c in year t . When examining engagement in crime, the dependent variable in equation (1) captures the share of crimes committed by the foreign-born population relative to total crime in province c in year t , while the main variable of interest on the right hand side referring to coefficient β is the share of refugees in the population of province c in year t . The dependent variable is similarly defined for victimization, measuring victimization share of foreign-born. The remaining variables in equation (3) are defined similar to equation (2).

We estimate equation (3) through 2SLS utilizing the same instrument in equation (2). For the interpretation of the coefficient β consider the case where the dependent variable is the foreign-born share of perpetrators. In this case, a 2SLS coefficient equal to one is inconsistent with foreign-born engaging in crime disproportionately, since it implies that the share of foreign-born in crimes rise in proportion to their share in the population. In contrast, when the 2SLS coefficient is less than one, this is consistent with the propensity of foreign-born engaging in crime being lower than natives, since the share of foreign-born perpetrators in crime rise more slowly than their share in the population.

The results of estimation from this analysis is presented Table 6. The coefficient estimates of β in column 5 of the top panel are 0.348 for the suspect share and 0.519 for the victim share, both statistically different from 1 at the 95 percent confidence level. These results suggest that a 10 percentage point increase in the share of refugees residing in a province leads to a 3.48 percentage point increase in the share of foreign-born suspects and a 5.19 percentage point increase in the share of foreign-born victims of crimes in those areas. The coefficient estimates are lower than 1 for all panels involving criminal court defendants and victims, offenses, convictions, and incarcerations.²⁷ In sum, these results consistently indicate that both the propensity of immigrants to engage in crime and their likelihood of being victims of crime are lower than that of natives.

This result aligns with Panel A of Figure 4, which depicts per capita crime rates in the total

²⁷In an alternative specification we replace the refugee share in right hand side of equation (3) with foreign-born share. The results remain both qualitatively and quantitatively similar, all β coefficients below 1, which is expected since the variation in this right hand side variable is primarily driven by changes in the refugee population.

population for high- and low-immigrant-intensity regions.²⁸ While per capita crime, initially slightly higher in high-intensity regions, follows a similar trend to low-intensity regions before the migration shock, the crime rate in high-intensity regions declines relative to low-intensity regions after 2013. Panel B of Figure 4, by contrast, illustrates per capita crime experienced by the pre-shock population. Consistent with the findings in Table 2, which suggest minimal impact of immigration on crime experienced by natives, crime rates in high- and low-intensity regions exhibit similar trends both before and after the migration shock.²⁹

[Figure 4 to here]

6.2 Types of Crime by Nationality

Table 7 extends the analysis by nativity status to different types of crime by estimating the effect of immigrant intensity separately for violent crimes, property crimes, public crimes, and smuggling. The table presents 2SLS estimates across three panels: the top panel reports the number of offenses, the middle panel examines the number of convictions, and the bottom panel addresses imprisonment, as measured by the number of individuals incarcerated. Each panel presents results for the total population, natives, and foreign nationals, reporting results from the most flexible specification (5) for brevity.

The results for the foreign-born population show a consistent pattern across all panels. In the top panel, which examines offenses in criminal courts, there is an increase across all crime types as immigrant intensity rises, with the effect being particularly pronounced for smuggling. In the middle panel, which looks at convictions, the foreign-born exhibit statistically significant increases across all crime types. Similarly, the final panel on imprisonment indicates an increase in imprisonment for immigrants.

Considering the results for natives across the three panels, most crime types show no statistically significant effects in terms of the number of offenses. However, there are significant declines in both convictions and the number of individuals incarcerated. This suggests that the arrival of immigrants may influence the behavior of natives, potentially steering them away from serious offenses that result in convictions and imprisonment. One possible explanation for this shift is the increase in legitimate work opportunities associated with the arrival of immigrants, which could reduce the incentives for natives to engage in economically motivated crimes, such as property crime.³⁰

Another potential explanation could be the displacement of natives from certain types of criminal activities. For instance, the results show an increase in smuggling activities among the

²⁸For the purposes of this figure, a region is classified as high-intensity if the immigrant ratio exceeds 2%, and low-intensity otherwise. Note that in our econometric analysis, we use a continuous measure of immigrant intensity.

²⁹In the robustness section, we also report results from a specification replacing the denominator with the total population in year t .

³⁰Previous work in the Turkish context documents an increase in formal jobs among natives due to the immigrant shock (Aksu et al., 2022).

foreign-born population, accompanied by a decline among natives. This shift may be attributed to the specific nature of smuggling, which often require well-established networks in both source and destination regions, as well as along transit routes. Immigrants with access to networks and relevant language skills may possess a comparative advantage in engaging in such organized criminal activities. Furthermore, immigrants with fewer opportunities in the host country’s labor market may be more willing to take on the higher risks associated with activities that carry severe legal penalties, similar to the phenomenon of immigrants accepting less desirable jobs in the labor market (e.g. Martin 1993, Zavodny 2015). These dynamics could result in the substitution of natives by immigrants in criminal activities.

7 Robustness Analysis

We perform a series of tests to evaluate the robustness of our results, focusing primarily on the number of cases at prosecutors’ offices, as this measure captures the broadest definition of crime and forms the basis for our baseline results. Also, data on cases from prosecutors’ offices is available starting from 2006, allowing us to perform robustness analyses for sample years and conduct various placebo tests.

7.1 Checks for specification, sample years, outliers, and weighting

We begin by conducting robustness tests concerning the set of controls in our specifications and the sample years used in the analysis. The results of these tests are presented in Table 8. The first row of Table 8 replicates our baseline results from the first row of Table 2 for ease of comparison. In the first robustness exercise, we restrict the set of time-varying province characteristics —intended to control for province-level confounders— to demographic variables only, excluding other potentially endogenous factors, such as the unemployment rate and trade volume. The results in the second row of Table 8, reflecting this restriction, show coefficient estimates that remain very similar to the baseline results.

The next two robustness tests pertain to the sample years. While for most of our outcome variables data is available from 2009 to 2019, forming our main estimation sample, data for the total number of cases at prosecutors’ offices is available starting from 2006. In the third row of Table 8, we incorporate these pre-immigration shock years, extending the sample period to 2006-2019. Additionally, we consider the impact of the the failed coup attempt in July 2016, which led to the arrest and prosecution of individuals suspected of involvement in the subsequent years. Although we expect these effects to be captured by the year-region fixed effects, we conduct further analysis using data from 2006 to 2016 to isolate the period before these events and present the results in the fourth row. The findings from both the third and fourth rows of Table 8 are qualitatively similar to the baseline results, further reinforcing the robustness of our analysis.

All our estimates use province populations as weights. To test the sensitivity of our results to an alternative weighting strategy, we use province populations aged 15-40 as weights. This choice is motivated by the fact that criminal activity is particularly prevalent among younger individuals (Loeber et al., 2014). Under this weighting strategy, provinces with younger populations are given greater influence in the results. As shown in row 5 of Table 8, our findings remain robust when using the 15-40 age group is used as the weight.

Next, we examine the sensitivity of our results to the set of provinces included in the analysis. First, we exclude Kilis province, an outlier in terms of refugee share, where the population nearly doubled due to the influx of refugees. In a second sensitivity analysis, we exclude the largest five metropolitan areas—Istanbul, Ankara, İzmir, Bursa, Antalya—from the sample. The estimates corresponding to these adjustments, presented in rows 6 and 7 of Table 8, are consistent with our baseline results, further confirming the robustness of our findings.

7.2 Pre-trend analysis: Placebo tests and event-study

The validity of our instrument relies on the assumption that crime trends in provinces with high and low instrument values would have been the same, conditional on the set of covariates, in the absence of the refugee shock. To test this assumption, we conduct a placebo test similar to those by Dustmann et al. (2017) and Jaeger et al. (2020), with the results presented in Table 9. For this test, we restrict our sample to the pre-shock period, covering the years 2006 to 2011, during which we do not expect any effects from immigration.

In this placebo test, we assign the refugee numbers from 2017-2019 to the years 2009-2011, as if immigration had occurred during these earlier years, and run 2SLS regressions. According to our identification assumption—that the instrument is not correlated with unobserved pre-existing trends in crime outcomes—this regression should yield a statistically insignificant effect for our key instrumented variable. The first row of Table 9 presents the baseline estimates for comparison, while the second row shows the results from this placebo test. In our preferred specification, column (5), the effect disappears in the placebo test, indicating no evidence of a correlation between the instrument and pre-existing time trends, conditional on the included covariates.

Using the same pre-shock years, we conduct a second placebo regression (similar to Aksu et al., 2022) using residual trends. To compute residual trends, we first regress the dependent variable on the set of controls from our specification, and then regress the resulting residuals on the instrument’s value in 2019. The results, presented in the third row, show coefficients that are very close to zero and statistically insignificant, providing further support for the assumption that the instrument is uncorrelated with residual trends.

We next extend the above tests of instrument validity by conducting an event study, similar to earlier work (e.g. Erten and Keskin (2021)). The event study framework allows for dynamic lags and leads to examine whether there are any pre-existing trends in the outcome variables

that could potentially bias our results.

We estimate the following specification:

$$\frac{Y_{ct}}{Natives_{c2011}} = \sum_{t=2006}^{2019} \beta_t(Year_t * IV_c) + \gamma X_{ct} + \theta_c + \tau_t + \varepsilon_{ct} \quad (4)$$

where IV_c is the cross-section component of our instrument in 2019 and β_t is the coefficient for different years.³¹ The omitted year is 2011, the last year before the Syrian crisis escalated. The rest of the equation is identical to equation (1). Figure 5 plots the coefficients for pre- and post-influx years. Figure 5 shows no evidence of any pre-trends in crime, which indicates that, conditional on controls, the trends in crime across provinces with varying levels of refugee influx would have been similar in the absence of the refugee shock, reinforcing the validity of our instrument.

[Figure 5 to here]

Figure 5 also shows that the effects appear in the first year following the refugee flow and peak around 2015. The effects decline in the following period and, while remaining positive, lose statistical significance. The marked increase in the first few years and the fall in effects in the remaining period could be driven by several factors. The initial increase in crime may stem from the trauma associated with the ethnic conflict in Syria and the forced displacement of refugees, which could lead to higher crime rates. Over time, however, the effects of this trauma may decline as refugees settle into their host regions. The refugee shock and its scale were also unexpected and unprecedented for both local and central governments in Turkey, meaning that settlement services and income support programs were not immediately available. The subsequent decline in crime effects may therefore be influenced by the increased availability of these support programs over time.³²

7.3 Randomization inference

We also perform a randomization inference exercise to demonstrate that the estimated impacts, though small, represent the true effects of refugees on crime. In this exercise, we randomly assign the distance instrument 1,000 times, creating a placebo distance instrument in each sample. Specifically, for each outcome where we report statistically significant coefficients, we generate 1,000 samples with randomly assigned distance instruments across provinces and years. We then estimate the refugee effects using our main specification within each simulated sample,

³¹We also conducted event study analysis utilizing instruments from alternative years, including the average of instruments post-crisis. We get similar event study results using alternative instrument values.

³²The decline in crime could also be attributed to the increased allocation of security forces over time to regions where immigrants reside. However, Kirdar et al. (2022) find no evidence of an increase in the number of armed forces in regions with higher immigrant density. As a result, they conclude that it is unlikely the government responded to the refugee shock by adjusting the allocation of armed forces across regions.

using the placebo distance instrument. This allows us to test the null hypothesis that there is no reduced form refugee effect, also known as the Fisher null hypothesis. To carry out this randomization inference, we derive the distribution of the estimated beta coefficients from the placebo distance instruments and examine how often our estimated coefficient from the true distance instrument falls within this distribution.

In Figure 6, we present the distribution of the estimated coefficients from the placebo distance instruments for the refugee ratio, which also serves as our first stage specification in the IV analysis. Notably, our estimated coefficient from the true distance instrument does not fall within the distribution of coefficients generated from the placebo distance instruments. This implies that the relationship between the distance instrument and the refugee ratio is not due to random chance.

[Figure 6 to here]

Similarly, Figure 7 presents the results of the randomization inference exercise using placebo distance instruments for the three crime measures analyzed in the top panel of Table 2: all cases, unknown perpetrator cases, and known perpetrator cases at the prosecutor’s office. The randomization inference indicates that, at conventional significance levels with zero p-values, we can reject the null hypothesis of no refugee effect. This supports that our point estimates of the effects of refugees on crime are not driven by random chance. In sum, it is difficult to argue that our significant point estimates for the relationship between the refugee population ratio and crime are coincidental; rather, they likely represent genuine causal effects of refugee presence.

[Figure 7 to here]

7.4 Robustness to alternative instruments

In this section, we evaluate the robustness of our results with respect to the instrument employed for identification. We consider two alternative instruments to test the robustness of our findings.

The first alternative instrument leverages the fact that some refugees were initially placed in camps by government authorities, particularly during the early years of the refugee influx. This enables us to create a two-part distance-based instrument that separately accounts for the distribution of in-camp and out-of-camp refugee populations, allowing us to more precisely capture the geographic distribution of refugees. Specifically, the first component of our instrument is based on the total population residing in camps, while the second component pertains to the total refugee population living outside of camps. We construct our instrument by incorporating refugee numbers and travel distances, formulated as follows:

$$IV_{ct} = \mathbf{1}_{ct} \sum_{s=1}^{13} \frac{\pi_s C_t}{d_{cs}} + \sum_{s=1}^{13} \frac{\pi_s T_t}{d_{cs}} \quad (5)$$

where C_t and T_t are the total numbers of refugees living in camps and out of camps in year t , respectively. Distance parameter d_{cs} is the travel distance from province c in Türkiye to region s in Syria. Parameter π_s denotes the fraction of Syrians living in each governorate s in Syria in 2011. The indicator function in the first part of the instrument using the camp population is equal to 1 if province c has a refugee camp in year t . The instrument deflates the total number of Syrians by the distance between each province in Türkiye and each governorate in Syria.

Prior research in the Turkish context has used an instrument based on historical settlement patterns of Arabs (e.g., Altındağ et al. 2020). This approach aligns with the use of instruments based on immigrants' past settlement patterns, a method commonly employed in migration literature (e.g., Altonji and Card, 1991; Card, 2001). Building on this precedent, we develop a second alternative instrument using the share of the Arabic-speaking population from the 1965 Census to predict the refugee share. The 1965 population census provides data on the mother tongue of the resident population, enabling us to use the distribution of Arabic speakers from that period to estimate the settlement patterns of Syrian refugees in present-day Türkiye. Specifically, we construct this alternative instrument as follows:

$$IV_{ct}^{Alternative} = \frac{Arabic_{c1965}}{Total\ Arabic_{1965}} T_t \quad (6)$$

where $Arabic_{c1965}$ is the number of Arabic speaking population in province c and $Total\ Arabic_{1965}$ is the total number of Arabic speakers in Türkiye in 1965, and T_t is the total number of Syrian refugees living in year t .

Table 10 presents results for the baseline specification using our original instrument in the first row, followed by results using the two alternative instruments in the subsequent rows. The instrument incorporating camp information yields results very similar to those from the baseline specification. When employing the IV based on the Arabic-speaking population, we observe qualitatively similar results; however, the coefficient estimate from our preferred specification in column (5) is smaller in magnitude and is less precisely estimated.

7.5 Robustness to alternative specifications

In further robustness analysis, we explore alternative econometric specifications and present the results in Table 11. The key dependent variable in our baseline specification is defined as the percentage of the total number of Syrians in a province in a given year relative to the pre-shock province population in 2011. In the first alternative specification, we replace the denominator in this ratio with the size of the native population in year t . The results in the second row of Table 11 are similar to the baseline results in row 1, which is expected given that provincial native populations are highly correlated with pre-shock population levels.³³

In the second alternative specification, we replace the denominator with the total population

³³The previous studies in the Turkish context find no evidence of refugee-induced native sorting at the province level (Kayaoglu, 2022; Aksu et al. 2022).

in year t , including both natives and refugees.³⁴ The results in row 3 differ from the baseline, with negative coefficient estimates that are statistically significant across all specifications, indicating a reduction in crime. As discussed in Econometric Analysis section, this result is susceptible to common divisor bias, leading to underestimation, as discussed by Kronmal (1993), Clemens and Hunt (2019), and Bartlett and Partnoy (2020).³⁵ The reduction in crime in the total population implied by this specification, however, is consistent with our earlier results in Table 6, which show lower crime engagement among immigrants compared to natives.

The final two specifications estimate logarithmic equations where the dependent variable is the logarithm of the number of crimes, and the key independent variable is the logarithm of the total number of Syrians. Similar logarithmic models were used by Spenkuch (2013) in the US context and Akbulut-Yüksel et al. (2023) in the Turkish context. In line with Spenkuch (2013), these specifications also control for the logarithm of the contemporaneous native population and total population, respectively. A potential issue with these specifications is that the logarithmic transformation of the shock alters the scale of treatment, possibly leading to specification error.³⁶ Nevertheless, for comparative purposes, we present estimates from these models. Using the log of the distance-based IV as our instrument for the key independent variable, the results in the last two columns of Table 11 yield elasticity estimates that are qualitatively similar to but larger in magnitude than our baseline estimates.³⁷

8 Conclusion

This paper examines the causal effect of immigration on crime, focusing on the large influx of Syrians into Türkiye. Using unique administrative data that covers various stages of the judicial process—ranging from cases at prosecutor’s offices to criminal courts, court decisions, and incarceration—we apply an instrumental variable (IV) methodology to estimate the impact of immigration on crime. In addition to studying overall crime rates, we analyze effects by nativity status and investigate the likelihood of migrants and natives becoming victims or perpetrators of crime with rising immigrant intensity. The nativity information also enables us to estimate the propensity of migrants to engage in criminal activity and to become victims of crime, relative to natives. Furthermore, we assess the impact of immigration on different types

³⁴In the Turkish context Kırdar et al., (2022) uses a ratio specification where the denominator is the total population in year t , including both natives and refugees. Kayaoğlu (2022) also uses a similar ratio equation using a log transformation of the dependent variable.

³⁵We also estimated a model that extends the specification in row 3 by adding $1/(\text{Total population})$ as an additional control, as suggested by Kronmal (1993). The results remain very similar to those presented in row 3. Note, however, that adding $1/(\text{Total Population})$ to the equation does not solve the "ratio problem" (Bartlett and Partnoy, 2020). Moreover, this additional term complicates the analysis as it includes the number of refugees which is an endogenous variable.

³⁶Additionally, logarithmic transformation can produce variables that are less intuitively appealing, making it more challenging to interpret the meaning of the associated parameter estimates. (Shaver, 2007 and Wiseman, 2009).

³⁷If we use a distance-based instrument without taking logs, the resulting first stage F-values are close to zero whereas they are above conventional levels using the log transformation.

of crime, including violent crimes, property crimes, public crimes, and smuggling, with a focus on nativity of offenders.

We find that the influx of immigrants leads to a small increase in crime in terms of cases at the prosecution stage, primarily driven by an increase in cases with unknown perpetrators. However, this increase at the prosecution stage does not translate into a corresponding rise in criminal court outcomes, as measured by the number of cases, offenses, convictions, or imprisonments.

The analysis of crime by nativity status for victims and suspects/defendants reveals significant differences between Turkish nationals and foreign nationals. We find no evidence of increased criminal activity among Turkish nationals as immigrant intensity rises. While there is evidence of increased victimization among Turkish nationals at the prosecution stage, these effects do not persist at the criminal court stage. In contrast, the propensity for foreign nationals to become both perpetrators and victims of crime increases with immigrant intensity. When we study the propensity of migrants to commit crime or become a victim of crime, we find that both propensities are in fact lower relative to natives. Thus, the concern that immigrants may be more likely to engage in criminal behavior is not supported in our context.

The analysis of crime types by nativity reveals no significant effects for Turkish nationals regarding the number of offenses across most crime categories. However, there are significant declines in convictions across all types of crime, suggesting that natives are becoming less likely to engage in serious offenses that result in convictions. Conversely, among foreign nationals, there is an increase in all crime types with rising immigrant intensity.

These findings contribute new insights to the literature on immigration-induced crime. The increase in cases at prosecutors' offices with unknown perpetrators suggests that the identification of offenders may become more challenging following an influx of immigrants, potentially leading to a lower sense of security among citizens as these crimes often go unpunished. Our estimates from different stages of the judicial process also underscore that conclusions about the effects of immigration-induced crime can be sensitive to the type of data used. For instance, in our study, evidence of an immigration-induced increase in crime is observed at the prosecution stage, but not when examining data from the court stage or convictions.

In terms of criminal engagement, immigration could theoretically lead to increased crime among groups whose labor market opportunities are adversely affected by the inflow of immigrants. Our findings reveal no increase in crime among natives and, in fact, a reduction in convictions. In contrast, crime rates rise among foreign nationals. The results for natives are consistent with prior research in the Turkish context, which suggests that the arrival of immigrants may improve natives' access to legitimate employment opportunities, thereby reducing their incentives to engage in economically motivated crimes (Aksu et al., 2022). Immigrants, on the other hand, may face heightened competition from other immigrants in the labor market (Manacorda et al., 2006; Warren and Warren, 2013; Massey and Gentsch, 2014), and increases in immigration are most likely to adversely affect the employment prospects of other immig-

rants (Cortés, 2008). The observed rise in crime among foreign nationals may be driven by this intensified intra-group competition. An alternative explanation for the increase in convictions among foreign nationals—alongside a decline in convictions among natives across various crime types, such as smuggling—is the possibility of displacement in criminal activity. Such displacement may result from immigrants’ greater willingness to take risks due to limited alternative opportunities, or from specific advantages, such as transnational networks, that are particularly relevant for crimes like smuggling and less accessible to natives.

Regarding victimization, our analysis investigates whether natives’ involvement in judicial processes as victims increases and finds no significant effects, suggesting no direct impact of immigration-induced crime on the native population. It is important, however, to note that the natives may be affected indirectly through immigration-induced crime. For example, even when not directly targeted, natives’ sense of security and overall life satisfaction may be adversely affected by exposure to immigration-induced crime. Additionally, increased crime may raise the cost of policing and public safety, potentially resulting in a greater tax burden on natives. These indirect effects, however, are beyond the scope of our analysis.

Our results also highlight the importance of focusing on regions with higher concentrations of immigrants. While these areas may offer social and economic support through migrant networks, our findings indicate that immigrants in such regions are more likely to engage in criminal activities and to experience victimization. This emphasizes the potential value of targeted services for immigrants in high-density areas. Enhancing labor market opportunities and reinforcing social support systems—especially for those affected by forced displacement—could be critical in reducing crime.

References

- [1] Akbulut-Yuksel, M., N. Mocan, B. Turan, and S. Tümen (2023). The crime effect of refugees Journal of Policy Analysis and Management, forthcoming
- [2] Akgündüz, Y. E., Bağır, Y. K., Cilasun, S.M., & Kırdar, M. G. (2023). Consequences of a massive refugee influx on firm performance and market structure. Journal of Development Economics, 162, 103081.
- [3] Aksu, E., R. Erzan, and M. G. Kırdar (2022). The Impact of Mass Migration of Syrians on the Turkish Labor Market, Labour Economics 76, 102183.
- [4] Alonso-Borrego, C., Garoupa, N., & Vazquez, P. (2012). Does Immigration Cause Crime? Evidence from Spain. American Law and Economics Review, 14(1), 165–191. <http://www.jstor.org/stable/42705611>
- [5] Altındağ, O., Bakış, O. and Rozo, S., (2020) Blessing or burden? The impact of refugees on businesses and the informal economy J. Dev. Econ., 146 (2020), Article 102490
- [6] Amuedo-Dorantes, C., Bansak, C., & Pozo, S. (2021). Refugee Admissions and Public Safety: Are Refugee Settlement Areas More Prone to Crime? International Migration Review, 55(1), 135–165. <https://doi.org/10.1177/0197918320920192>
- [7] Ardino, Vittoria. 2012. “Offending Behaviour: The Role of Trauma and PTSD.” European Journal of Psychotraumatology 3 (1): Article 18968. <https://doi.org/10.3402/ejpt.v3i0.18968>.
- [8] Bauer, T. , M. Lofstrom, , K.F. Zimmermann (2000). Immigration policy, assimilation of immigrants, and natives’ sentiments towards immigrants: evidence from 12 OECD countries. Swedish Econ. Policy Rev. 7, 11–53 .
- [9] Bartlett, Robert P. and Partnoy, Frank, The Ratio Problem (May 1, 2020). Available at SSRN: <https://ssrn.com/abstract=3605606> or <http://dx.doi.org/10.2139/ssrn.3605606>
- [10] Bell, B., Fasani, F., & Machin, S. (2013). Crime and immigration: evidence from large immigrant waves. The Review of Economics and Statistics, 95(4), 1278–1290. <http://www.jstor.org/stable/43554827>
- [11] Bell, B. and Machin, S. (2011). The impact of migration on crime and victimisation: A report for the migration advisory committee. Centre for Economic Performance, LSE, London.
- [12] Bianchi, M., Buonanno, P., & Pinotti, P. (2012). Do immigrants cause crime? Journal of the European Economic Association, 10(6), 1318–1347. <http://www.jstor.org/stable/23354009>

- [13] Bleakley H. (2007). Disease and Development: Evidence from Hookworm Eradication in the American South. *Q J Econ.* 122(1):73-117. doi: 10.1162/qjec.121.1.73. PMID: 24146438; PMCID: PMC3800113.
- [14] Bleakley H. (2010). Malaria Eradication in the Americas: A Retrospective Analysis of Childhood Exposure. *American Economic Journal: Applied Economics*, 2(2), 1–45.
- [15] Borjas, G. J., J. Grogger and G. H. Hanson (2010). Immigration and the Economic Status of African-American Men. *Economica*, 77(306), 255–282. <http://www.jstor.org/stable/27764418>
- [16] Butcher, K. F. and A. M. Piehl (1998). Cross-City Evidence on the Relationship between Immigration and Crime. *Journal of Policy Analysis and Management*, 17(3), 457–493. <http://www.jstor.org/stable/3325557>
- [17] Chalfin, A. (2014). What is the Contribution of Mexican Immigration to U.S. Crime Rates? Evidence from Rainfall Shocks in Mexico. *American Law and Economics Review*, 16(1), 220–268. <http://www.jstor.org/stable/24735702>
- [18] Chan, K. F., Powell, J. G., Shi, J., and Smith, T. (2018). Dividend persistence and dividend behaviour. *Accounting and Finance*, 58(1), 127-147. <https://doi.org/10.1111/acfi.12208>
- [19] Choi, S., CY Choi and S. Kim (2023). Tackling misperceptions about immigrants with fact-checking interventions: A randomized survey experiment, *Labour Economics*, Volume 84, 102428, <https://doi.org/10.1016/j.labeco.2023.102428>.
- [20] Clemens, M. A. and J. Hunt (2019). The labor market effects of refugee waves: reconciling conflicting results. *ILR Review*, 72(4), 818–857. <https://www.jstor.org/stable/26957133>
- [21] Cortes, P. (2008). The effect of low-skilled immigration on U.S. prices: Evidence from CPI data. *Journal of Political Economy*, 116(3), pp. 381-422.
- [22] Couttenier, M., V. Petrencu, D. Rohner, and M. Thoenig (2019). “The Violent Legacy of Conflict: Evidence on Asylum Seekers, Crime, and Public Policy in Switzerland.” *American Economic Review* 109 (12): 4378–425.
- [23] Couttenier M. s. Hatte, M. Thoenig, and S. Viachos (2020). The Logic of Fear: Populism and Media Coverage of Immigrant Crimes. Working Paper, CEPR Discussion Papers 13496.
- [24] Dehos, F. T. (2021). The refugee wave to Germany and its impact on crime, *Regional Science and Urban Economics*, Volume 88, 103640, ISSN 0166-0462, <https://doi.org/10.1016/j.regsciurbeco.2020.103640>.

- [25] Demirci, M. and M. G. Kirdar (2023). The labor market integration of Syrian refugees in Turkey, *World Development* 162, 106138.
- [26] Dustmann, C., Schönberg, U., and Stuhler, J. (2017). Labor supply shocks, native wages, and the adjustment of local employment. *The Quarterly Journal of Economics*, 132(1), 435-483.
- [27] Entorf, H., and M. Lange (2023). Refugees welcome? Understanding the regional heterogeneity of anti-refugee hate crime. *Reg. Sci. Urban Econ.* 101, 103913.
- [28] Ersan, Y., G. Gülay, and A.S. Öztekin (2023). Immigrants and natives' financial decision making: Evidence from Türkiye. *Borsa Istanbul Review* 23: S29-S37.
- [29] Erten, B., and Keskin, P. (2021). Female employment and intimate partner violence: Evidence from Syrian refugee inflows to Türkiye. *Journal of Development Economics*, 150, Article 102607.
- [30] Freeman, R. B. (1999). The Economics of Crime (pp. 3529–71) in Orley C. Ashenfelter and David Card, eds., *Handbook of Labor Economics*, Vol. 3. Amsterdam: Elsevier.
- [31] Gehrsitz, M. and Ungerer, M. (2022). Jobs, crime and votes: a short-run evaluation of the refugee crisis in germany. *Economica*, 89(355), 592-626. <https://doi.org/10.1111/ecca.12420>
- [32] Goldman-Mellor, S., Margerison-Zilko, C., Allen, K. et al. Perceived and Objectively-Measured Neighborhood Violence and Adolescent Psychological Distress. *J Urban Health* 93, 758–769 (2016). <https://doi.org/10.1007/s11524-016-0079-0>
- [33] Gove, Walter, Michael Hughes, and Michael Geerken. (1985). Are Uniform Crime Reports a Valid Indicator of the Index Crimes? An Affirmative Answer with Minor Qualifications, *23 Criminology* 451–501.
- [34] Huang, Y., Kvasnicka, M., 2019. Immigration and Crimes against Natives: the 2015 Refugee Crisis in Germany. *IZA Discussion Paper* 12469.
- [35] Jaeger, D. A., Joyce, T. J., & Kaestner, R. (2018). A Cautionary Tale of Evaluating Identifying Assumptions: Did Reality TV Really Cause a Decline in Teenage Childbearing? *Journal of Business & Economic Statistics*, 38(2), 317–326. <https://doi.org/10.1080/07350015.2018.1497510>
- [36] Jobes, P. C., & Donnermeyer, J. F. (2002). Preaching to the Choir: A Comparison of the Use of Integrated Data Sets in Criminology Journals in Australia, England and the United States. *Australian & New Zealand Journal of Criminology*, 35(1), 79–98. <https://doi.org/10.1375/acri.35.1.79>

- [37] Kayaoglu, A. (2022). Do refugees cause crime?, *World Development*, Volume 154, 105858, ISSN 0305-750X, <https://doi.org/10.1016/j.worlddev.2022.105858>.
- [38] Kırdar, M.G., I. Lopez Cruz and B. Türküm (2022). The Effect of 3.6 Million Refugees on Crime, *Journal of Economic Behavior and Organization* 194, 568-582.
- [39] Knight, B. and A. Tribin (2023). Immigration and violent crime: Evidence from the Colombia-Venezuela Border, *Journal of Development Economics*, Volume 162, 103039.
- [40] KOM (2021). KOM Daire Başkanlığı Kaçakçılık ve Organize Suçlarla Mücadele 2021 Raporu KOM Yayınları: Ankara.
- [41] Kronmal, R. A. (1993). Spurious Correlation and the Fallacy of the Ratio Standard Revisited. *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, 156(3), 379–392. <https://doi.org/10.2307/2983064>
- [42] Lange, M. and K. Sommerfeld, (2024). Do refugees impact crime? Causal evidence from large-scale refugee immigration to Germany, *Labour Economics*, Elsevier, vol. 86(C)
- [43] Loeber, R., Farrington, D., Bruinsma, G., Weisburd, D., 2014. Age-Crime Curve. *Encyclopedia of Criminology and Criminal Justice*. Springer doi: 10.1007/ 978-1-4614-5690-2_474
- [44] Maguire, M. (2012). Criminal statistics and the construction of crime. In *The Oxford Handbook of Criminology* (pp. 206–244). Oxford: Oxford University Press.
- [45] Maghularia, R. and S. Uebelmesser (2023), Do immigrants affect crime? Evidence for Germany, *Journal of Economic Behavior & Organization*, Volume 211, Pages 486-512, ISSN 0167-2681, <https://doi.org/10.1016/j.jebo.2023.05.018>.
- [46] Manacorda, M., Manning, A., and Wadsworth, J. (2006), The Impact of Immigration on the Structure of Male Wages: Theory and Evidence from Britain, CReAM Discussion Paper No. 08/06.
- [47] Martin, P.L. (1993). The missing bridge: How immigrant networks keep Americans out of dirty jobs. *Population and Environment*. 14, 539–565. <https://doi.org/10.1007/BF01276572>
- [48] Massey, D.S., and Gentsch, K. (2014). Undocumented migration to the United States and the wages of Mexican immigrants. *International Migration Review*, 48(2), pp. 482-499.
- [49] Masterson, D. and V. Yassenov. (2021). Does Halting Refugee Resettlement Reduce Crime? Evidence from the US Refugee Ban. *American Political Science Review*, 115(3), 1066-1073. doi:10.1017/S0003055421000150

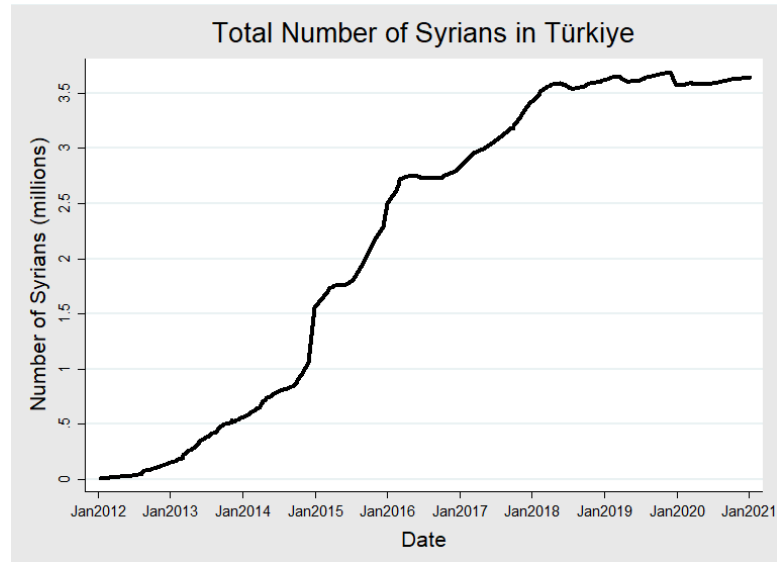
- [50] Mayda, A.M. (2006). Who is against immigration? A cross-country investigation of individual attitudes toward immigrants. *Rev. Econ. Stat.* 88 (3), 510–530.
- [51] Mercan, M. A., H. Barlin and N. Begen (2022) Is there a link between immigration and incarceration rate?: Evidence from the Syrian refugee influx to Turkey, *Global Crime*, 23:3, 306-333, DOI: 10.1080/17440572.2022.2077331
- [52] Megalokonomou, R. and C. Vasilakis (2023), The Effects of Exposure to Refugees on Crime: Evidence from the Greek Islands, *European Economic Review* 160, 104605.
- [53] Moehling, C. and A.M. Piehl (2009). Immigration, crime, and incarceration in early twentieth-century America. *Demography* 46, 739–763. <https://doi.org/10.1353/dem.0.0076>
- [54] Neyman, Jerzy. 1952. Lectures and Conferences on Mathematical Statistics and Probability. 2nd edition. Washington, DC: Graduate School, U.S. Department of Agriculture.
- [55] O’Brien, Robert. 1995. Crime and Victimization Data. Beverly Hills, CA: Sage.
- [56] Ozden, C., Testaverde, M., Wagner, M., 2017. How and why does immigration affect crime? Evidence from Malaysia. *World Bank Econ. Rev.* 32 (1), 183–202. doi: 10.1093/wber/lhx010 .
- [57] Pearson, K. 1897. On a Form of Spurious Correlation Which May Arise When Indices are Used in the Measurement of Organs. *Proceedings of the Royal Society of London* 60:489-98.
- [58] Piopiunik, M and J. Ruhose (2017), Immigration, regional conditions, and crime: Evidence from an allocation policy in Germany, *European Economic Review*, Volume 92, Pages 258-282, ISSN 0014-2921, <https://doi.org/10.1016/j.euroecorev.2016.12.004>.
- [59] Shaver, J.M.(2007). Interpreting empirical results in strategy and management research. In: D.J.Ketchen and D.D.Bergh(Eds), *Research methodology in strategy and management* (Vol. 4,pp. 273–294). Oxford, UK:Elsevier.
- [60] Spenkuch, J. L. (2014). Understanding the Impact of Immigration on Crime. *American Law and Economics Review*, 16(1), 177–219. <http://www.jstor.org/stable/24735701>
- [61] Tarling, Roger (2018). Editorial: The Effect of Imprisonment on Crime, *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 10.1111/j.1467-985X.1994.tb00562.x, 157, 2, (173-176).
- [62] UNHCR (2022). Global Trends, Forced Displacements in 2022, United Nations High Commissioner for Refugees, Statistics and Demographics Section, Denmark.
- [63] NODC (2011). Global study on homicide. United Nations Office on Drugs and Crime. Statistics and survey section, United Nations Office on Drugs and Crime, Vienna.

- [64] Warren, R., and Warren, J.R (2013). Unauthorized immigration to the United States: Annual estimates and components of change, by state, 1990 to 2010. *International Migration Review*, 47(2), pp. 296-329.
- [65] Wiseman, R. M. (2009). On the use and misuse of ratios in strategic management research. *Research methodology in strategy and management*, Volume 5, 75–110. Emerald Group Publishing Limited.
- [66] Zavodny, M. (2015). Do Immigrants Work in Worse Jobs than U.S. Natives? Evidence from California. *Industrial Relations*. Volume54, Issue2, P. 276-293.

Figures and Tables

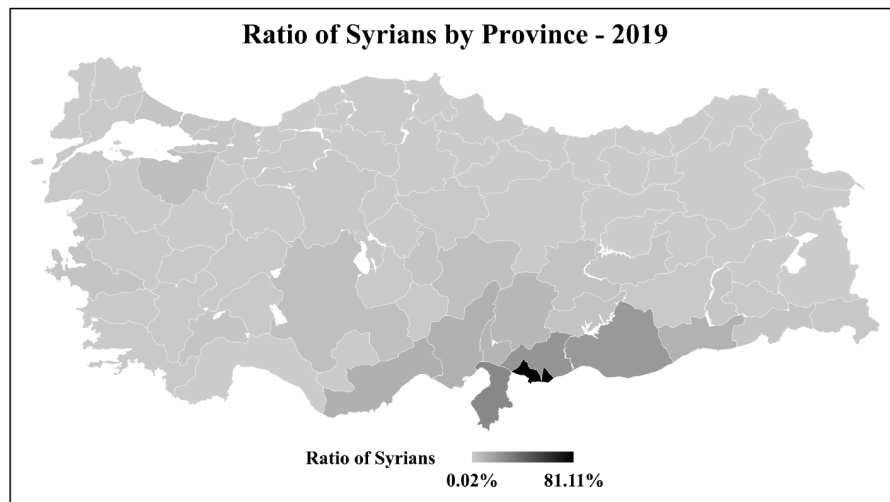
Figures

Figure 1: Total Number of Syrians in Türkiye



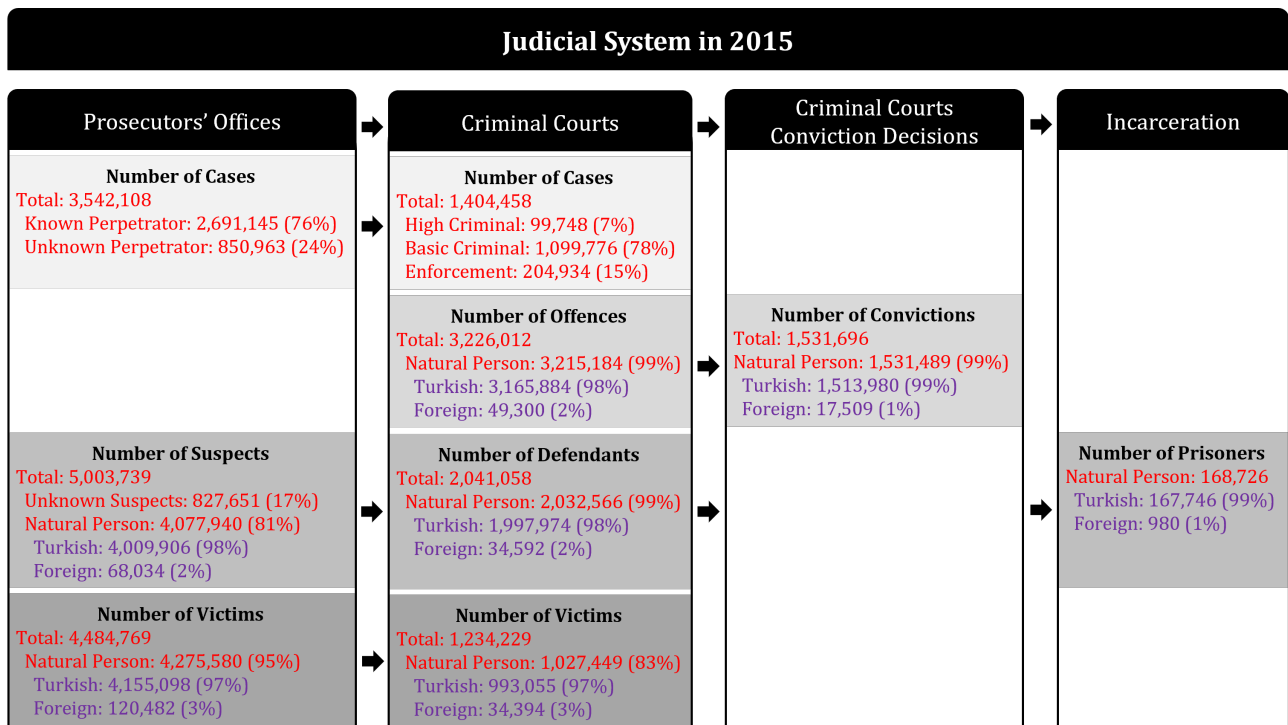
Source: UNHCR

Figure 2: The Ratio of Syrians to the Province Population



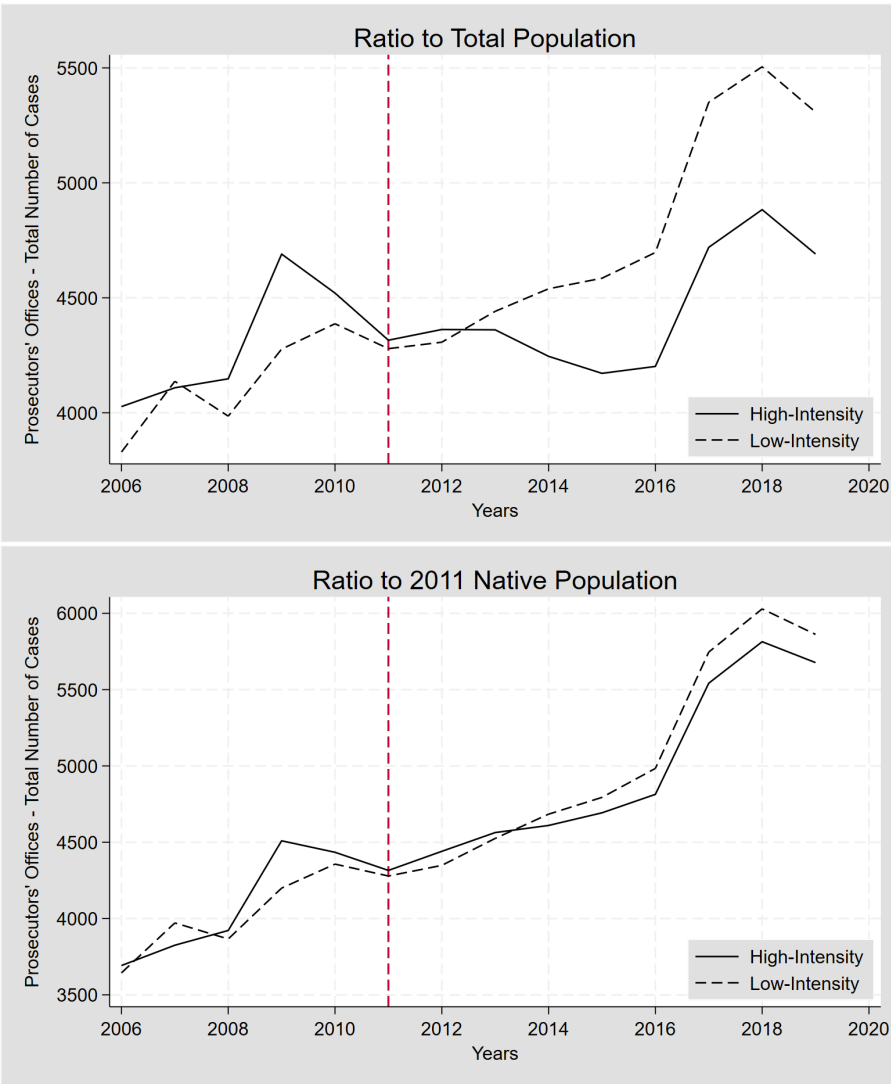
Source: Directorate General of Migration Management

Figure 3: Judicial System in 2015



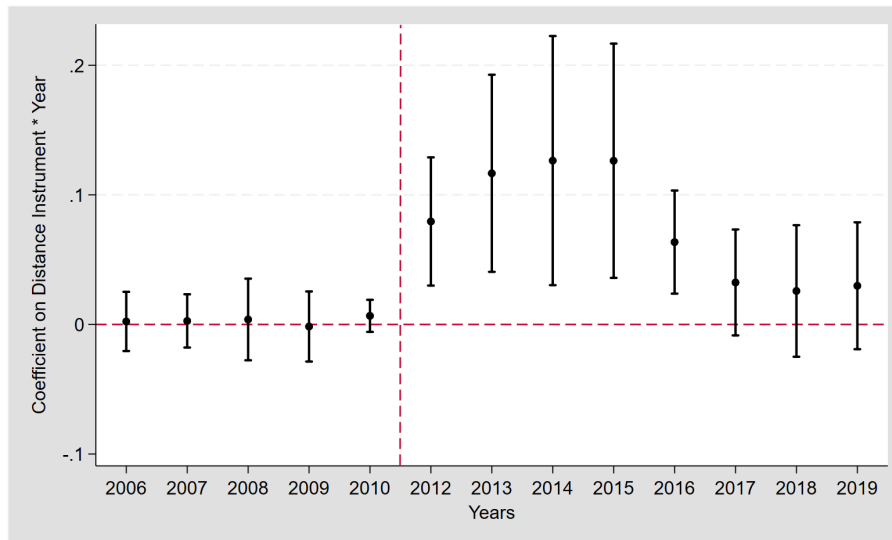
Source: Author's calculations based on Ministry of Justice administrative data

Figure 4: Crime Ratio by Year



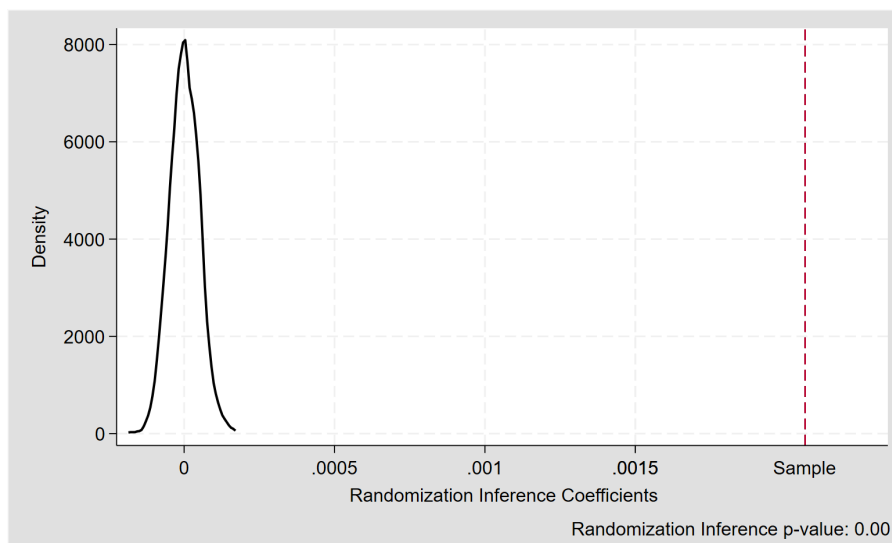
Notes: Author's calculations based on Ministry of Justice administrative data. Panel A depicts per capita crime rates in the total population for high (the immigrant ratio exceeds 2%.) and low-immigrant-intensity regions. Panel B shows per capita crime experienced by the pre-shock population.

Figure 5: Event Study



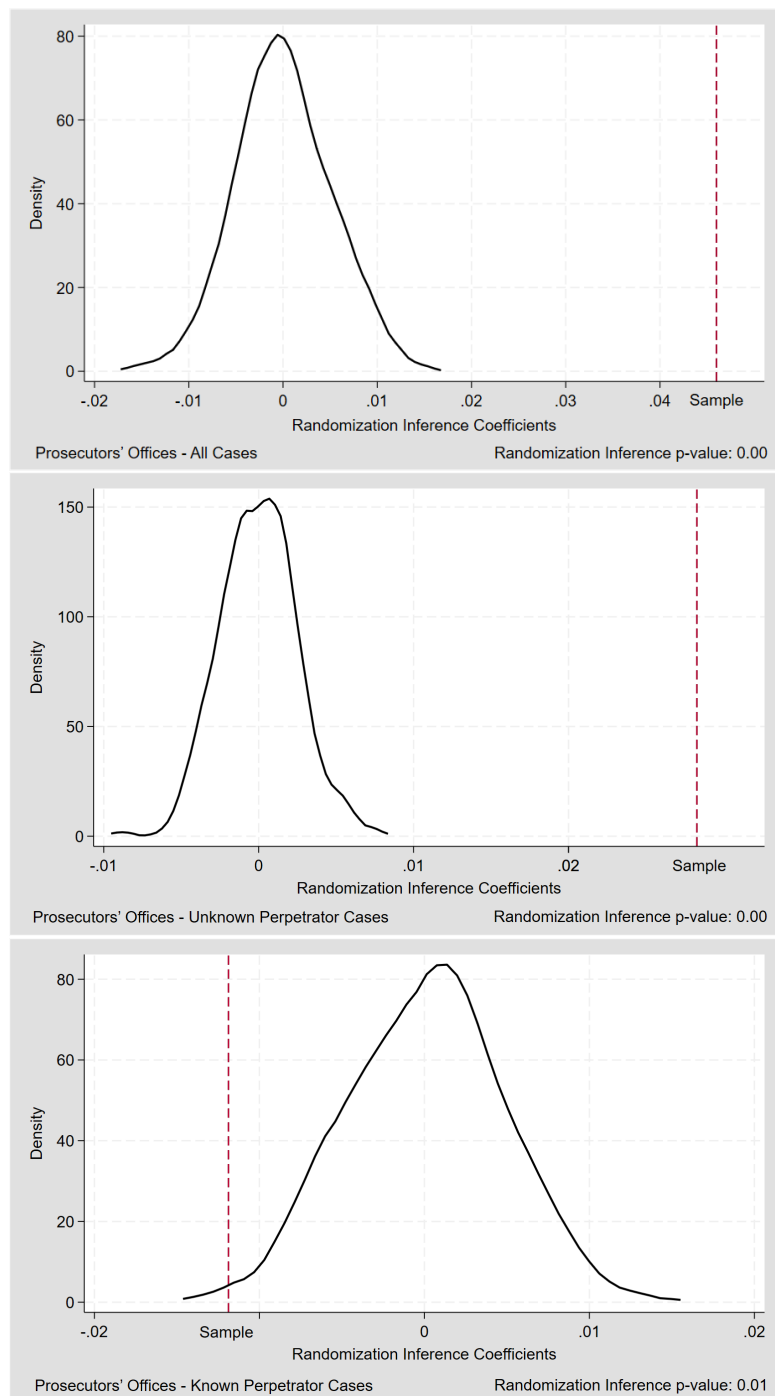
Notes: The figure plots the coefficients for pre- and post-influx and 95% confidence intervals from the event-study regression equation (4) that compares crime ratios in provinces that are more exposed to the refugee inflow shock to those that are less exposed in each year before and after the Syrian refugee inflows. The cross-section component of the instrument in 2019 is used. The year 2011 is omitted as it is the last year before the Syrian crisis.

Figure 6: Randomization Inference for the First Stage - Placebo Distance Instrument.



Notes: The figure presents the distribution function for the estimated coefficients for the randomization inference exercise. Particularly, we conduct 1000 simulations where we randomly assign the distance instrument and estimate our first stage specification, and subsequently plot the distribution function for the estimated coefficients. The dependent variable is the ratio of Syrian refugees. Regressions include all controls, province and year fixed effects, and region (12-NUTS1) specific year fixed effects. Observations are provinces. Moreover, the figure displays the estimated coefficient with the red dashed line for our sample and reports the randomization inference p-value on the bottom right of the figure.

Figure 7: Randomization Inference for Reduced Form - Placebo Distance Instrument.



Notes: The figure presents the distribution function for the estimated coefficients for the randomization inference exercise. Particularly, we conduct 1000 simulations where we randomly assign the distance instrument and estimate reduced form specification, and subsequently plot the distribution function for the estimated coefficients. The dependent variable is crime measures per 100K for the total number cases, unknown perpetrator cases and known perpetrator cases in prosecutors' offices. Regressions include all controls, province and year fixed effects, region (12-NUTS1) specific year effects, and the province trend interacted with the pre-refugee level (in the year 2011) of the concerning outcome variable. Observations are provinces. Moreover, the figures in each panel display the estimated coefficient with the red dashed line for our sample with the corresponding crime outcome and reports the randomization inference p-value on the bottom right of each figure.

Tables

Table 1: Descriptive Statistics

	Pre-Crisis	Post-Crisis	Mean
Ratio of Syrians	0 (0.000)	3.142 (6.319)	2.285 (5.567)
Dependent Variables (Rate per 100K people)			
Prosecutors' Offices - Total Cases	4353.545 (906.161)	5067.266 (1117.769)	4872.614 (1110.271)
Criminal Courts - Total Cases	2174.409 (664.520)	1970.359 (542.090)	2026.009 (584.780)
Criminal Courts - Crimes by Natural Person	4265.425 (1106.270)	4293.367 (1034.785)	4285.746 (1054.206)
Criminal Courts - Natural Person Convictions	1666.226 (651.850)	2171.037 (713.908)	2033.361 (732.563)
Incarceration - Convicts in Prison	108.363 (48.606)	262.386 (109.645)	220.379 (118.712)
Control Variables			
Log Trade Volume	14.736 (2.784)	15.010 (2.729)	14.935 (2.745)
Log GDP Per-capita	9.144 (0.463)	9.201 (0.459)	9.186 (0.461)
Unemployment Rate	0.121 (0.037)	0.109 (0.044)	0.112 (0.042)
Male Labor Force Participation Rate	0.709 (0.037)	0.716 (0.036)	0.714 (0.036)
Ratio of Low-educated	0.682 (0.073)	0.606 (0.078)	0.627 (0.084)
Ratio of men aged 15-39	0.212 (0.014)	0.204 (0.015)	0.206 (0.015)
Average Household Size	4.035 (1.035)	3.639 (0.808)	3.747 (0.893)
Proportion of High-density Urban Centers	0.714 (0.229)	0.737 (0.217)	0.731 (0.220)
Observation	243	648	891

Notes: The entries are the means and standard deviations. The unit of observation is province-year.

Table 2: Overall Crime Effect

	(1)	(2)	(3)	(4)	(5)	
Prosecutors' Offices - Number of Cases						Mean Y
Total Number of Cases	29.519 (18.592)	23.336* (12.548)	-5.684 (10.408)	-2.544 (10.827)	20.599** (9.826)	4872.614 (1110.271)
Unknown Perpetrator	4.823 (9.232)	6.069 (7.079)	2.794 (5.747)	5.174 (5.299)	12.595*** (4.670)	987.365 (528.064)
Known Perpetrator	24.696 (18.669)	17.267* (9.747)	-8.478 (6.792)	-7.718 (7.824)	-5.600 (9.731)	3885.250 (876.841)
Criminal Courts - Number of Cases						
Total Number of Cases	19.538* (10.724)	13.742** (6.141)	2.625 (5.099)	3.733 (4.917)	-4.263 (5.842)	2026.009 (584.779)
High Criminal Court	0.884 (1.235)	0.239 (0.947)	-1.522** (0.719)	-2.228*** (0.829)	-2.892*** (1.064)	156.042 (87.092)
Basic Criminal Court	13.488 (12.831)	9.839 (7.280)	-2.010 (4.772)	-0.621 (4.973)	-4.188 (5.107)	1537.177 (428.744)
Court of Criminal Enforcement	5.165 (4.101)	3.664 (2.617)	6.156*** (1.564)	6.582*** (1.449)	-2.379 (2.530)	332.790 (247.334)
Criminal Courts - Number of Offences						
Crimes by Natural Person	27.345** (11.634)	18.635*** (6.658)	10.295 (11.051)	11.625 (11.100)	-2.742 (11.956)	4285.746 (1054.206)
Criminal Courts - Number of Convictions						
Natural Person Convictions	10.056 (9.849)	4.476 (6.145)	-7.714 (7.913)	-6.594 (8.472)	-13.074 (10.011)	2033.361 (732.563)
Incarceration - Number of Convicts in Prison						
Number of Convicts in Prison	0.013 (0.964)	0.757 (0.820)	-1.785 (1.355)	-1.909 (1.337)	-0.111 (0.875)	220.379 (118.712)
First Stage F-Stat	51.254	85.478	71.332	57.891	48.983	
Observation	891	891	891	891	891	
Year and Province FE	Yes	Yes	Yes	Yes	Yes	
X Controls All	No	Yes	Yes	Yes	Yes	
12 Region Trend	No	No	Yes	No	No	
12 Region-Year FE	No	No	No	Yes	Yes	
Baseline - Year Interaction	No	No	No	No	Yes	

Notes: The dependent variable is crime measures per 100K. Each cell shows the 2SLS estimates for the ratio of Syrians to the 2011 native population. Control variables include log trade volume, per-capita GDP, unemployment rate, male LFP rate, the ratio of low-educated individuals, the share of men aged 15-39, the average household size, and the percentage of the province population residing in city centers. All regressions include province and year-fixed effects. In column 2, we add control variables. Column 3 regressions include region (12-NUTS1) specific linear time trends, whereas column 4 controls for region (12-NUTS1) specific year effects. Column 5 regressions also control for province trend interacted with the pre-refugee level (in year 2011) of the concerning outcome variable. The last column reports the mean dependent variables. F-stat reports the first stage F-stat for each specification. All regressions are weighted by province 2011 population. Standard errors are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Overall Crime Effect - OLS

	(1)	(2)	(3)	(4)	(5)	
Prosecutors' Offices - Number of Cases						Mean Y
Total Number of Cases	16.209*	13.369*	-1.072	4.015	14.054*	4872.614
	(8.537)	(7.844)	(10.085)	(10.139)	(8.430)	(1110.271)
Unknown Perpetrator	9.084	8.957*	4.865	5.167	7.489**	987.365
	(6.050)	(4.693)	(3.359)	(3.361)	(2.949)	(528.064)
Known Perpetrator	7.125	4.413	-5.937	-1.152	0.661	3885.250
	(5.829)	(5.540)	(8.537)	(8.220)	(8.914)	(876.841)
Criminal Courts - Number of Cases						
Total Number of Cases	7.025*	5.509	3.088	5.482	3.096	2026.009
	(3.820)	(3.772)	(4.569)	(4.280)	(4.748)	(584.779)
High Criminal Court	0.586	0.642	0.036	0.006	-0.239	156.042
	(0.786)	(0.697)	(0.827)	(0.995)	(1.129)	(87.092)
Basic Criminal Court	0.516	0.012	-2.892	-0.932	-1.569	1537.177
	(4.126)	(3.829)	(4.789)	(4.645)	(4.638)	(428.744)
Court of Criminal Enforcement	5.923***	4.855**	5.943***	6.409***	2.257	332.790
	(2.104)	(1.909)	(1.443)	(1.379)	(2.076)	(247.334)
Criminal Courts - Number of Offences						
Crimes by Natural Person	16.343**	13.413*	11.613	16.772*	12.325	4285.746
	(7.023)	(6.742)	(9.681)	(8.820)	(9.453)	(1054.206)
Criminal Courts - Number of Convictions						
Natural Person Convictions	7.530	5.575	5.928	7.412	5.469	2033.361
	(6.342)	(5.419)	(6.751)	(6.726)	(7.968)	(732.563)
Incarceration - Number of Convicts in Prison						
Number of Convicts in Prison	0.968	1.384**	0.409	0.426	1.549**	220.379
	(0.773)	(0.647)	(1.202)	(1.332)	(0.727)	(118.712)
Observation	891	891	891	891	891	
Year and Province FE	Yes	Yes	Yes	Yes	Yes	
X Controls All	No	Yes	Yes	Yes	Yes	
12 Region Trend	No	No	Yes	No	No	
12 Region-Year FE	No	No	No	Yes	Yes	
Baseline - Year Interaction	No	No	No	No	Yes	

Notes: The dependent variable is crime measures per 100K. Each cell shows the OLS estimates for the ratio of Syrians to the 2011 native population. Control variables include log trade volume, per-capita GDP, unemployment rate, male LFP rate, the ratio of low-educated individuals, the share of men aged 15-39, the average household size, and the percentage of the province population residing in city centers. All regressions include province and year-fixed effects. In column 2, we add control variables. Column 3 regressions include region (12-NUTS1) specific linear time trends, whereas column 4 controls for the region (12-NUTS1) specific year effects. Column 5 regressions also control for province trend interacted with the pre-refugee level (in year 2011) of the concerning outcome variable. The last column reports the mean dependent variables. All regressions are weighted by province 2011 population. Standard errors are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Overall Crime Effect - Number of Suspects and Victims

	(1)	(2)	(3)	(4)	(5)	
Prosecutors' Offices - Number of Suspects and Victims						Mean Y
Total Number of Suspects	32.336 (21.771)	30.440* (15.650)	-10.430 (19.218)	-4.928 (20.256)	27.059** (11.677)	6637.362 (1511.415)
Unknown Suspects	4.322 (9.540)	5.469 (7.257)	1.867 (5.875)	4.437 (5.310)	11.336** (4.698)	966.414 (526.683)
Natural Person Suspects	27.906 (20.677)	25.121** (12.518)	-11.721 (16.400)	-10.340 (17.294)	1.559 (13.231)	5549.649 (1199.685)
Total Number of Victims	38.155*** (14.077)	30.657*** (8.430)	17.093 (13.957)	25.629** (12.729)	43.857*** (14.922)	5682.257 (1298.189)
Natural Person Victims	28.071** (14.208)	26.539** (11.228)	26.170* (15.004)	28.026* (15.354)	47.651*** (15.724)	5333.083 (1306.160)
Criminal Courts - Number of Defendants and Victims						
Total Number of Defendants	22.713* (11.844)	16.883** (6.852)	5.274 (7.649)	7.432 (6.653)	-3.710 (7.657)	2862.783 (734.219)
Natural Person Defendants	23.183* (12.364)	17.290** (7.195)	5.540 (7.778)	7.672 (6.887)	-4.191 (7.858)	2835.151 (728.028)
Total Number of Victims	17.616** (6.957)	9.954* (5.152)	5.531 (7.866)	10.369* (6.266)	-0.987 (5.907)	1691.552 (503.736)
Natural Person Victims	12.969*** (3.632)	8.837** (3.545)	7.691 (5.408)	9.054* (5.369)	1.254 (5.175)	1305.861 (347.319)
First Stage F-Stat	51.254	85.478	71.332	57.891	48.983	
Observation	891	891	891	891	891	
Year and Province FE	Yes	Yes	Yes	Yes	Yes	
X Controls All	No	Yes	Yes	Yes	Yes	
12 Region Trend	No	No	Yes	No	No	
12 Region-Year FE	No	No	No	Yes	Yes	
Baseline - Year Interaction	No	No	No	No	Yes	

Notes: The dependent variable is crime measures per 100K. Each cell shows the 2SLS estimates for the ratio of Syrians to the 2011 native population. Control variables include log trade volume, per-capita GDP, unemployment rate, male LFP rate, the ratio of low-educated individuals, the share of men aged 15-39, the average household size, and the percentage of the province population residing in city centers. All regressions include province and year-fixed effects. In column 2, we add control variables. Column 3 regressions include region (12-NUTS1) specific linear time trends, whereas column 4 controls for region (12-NUTS1) specific year effects. Column 5 regressions also control for province trend interacted with the pre-refugee level (in year 2011) of the concerning outcome variable. The last column reports the mean dependent variables. F-stat reports the first stage F-stat for each specification. All regressions are weighted by province 2011 population. Standard errors are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Number of Suspects and Victims by Nationality

	(1)	(2)	(3)	(4)	(5)	
Prosecutors' Offices - Number of Suspects and Victims by Nationality						Mean Y
Turkish National Suspects	15.618 (21.473)	11.886 (12.949)	-24.859 (15.289)	-22.953 (16.002)	-11.655 (12.793)	5456.398 (1164.248)
Foreign National Suspects	12.288*** (1.835)	13.235*** (1.225)	13.139*** (1.600)	12.612*** (1.799)	12.611*** (1.805)	93.251 (113.055)
Turkish National Victims	17.328 (11.538)	16.595* (8.623)	10.042 (12.544)	10.339 (12.555)	27.332** (13.512)	5206.113 (1241.475)
Foreign National Victims	10.743** (4.282)	9.944** (4.253)	16.127*** (3.289)	17.687*** (3.278)	20.210*** (2.716)	126.970 (183.819)
Criminal Courts - Number of Defendants and Victims by Nationality						
Turkish National Defendants	19.694 (12.672)	13.156* (7.236)	1.989 (7.728)	4.346 (6.749)	-8.049 (7.678)	2792.097 (725.553)
Foreign National Defendants	3.489*** (0.426)	4.134*** (0.406)	3.551*** (0.391)	3.326*** (0.366)	3.264*** (0.468)	43.054 (49.579)
Turkish National Victims	10.230*** (3.075)	6.995*** (1.937)	1.738 (4.474)	2.126 (4.642)	-5.760 (4.783)	1267.342 (335.987)
Foreign National Victims	2.738 (2.073)	1.842 (2.387)	5.953*** (1.288)	6.928*** (1.139)	7.114*** (1.188)	38.519 (68.337)
Criminal Courts - Number of Offences by Nationality						
Crimes by Turkish National	22.583* (12.014)	13.116* (6.751)	5.423 (10.919)	6.983 (10.882)	-8.476 (11.656)	4224.821 (1047.872)
Crimes by Foreign National	4.750*** (0.686)	5.528*** (0.619)	4.997*** (0.758)	4.743*** (0.696)	4.692*** (0.761)	57.860 (65.716)
Criminal Courts - Number of Convictions by Nationality						
Turkish National Conviction	7.643 (10.027)	1.988 (6.127)	-10.936 (7.737)	-9.962 (8.316)	-16.834* (9.771)	2012.376 (725.019)
Foreign National Conviction	2.413*** (0.527)	2.488*** (0.485)	3.222*** (0.390)	3.368*** (0.381)	3.382*** (0.384)	20.985 (33.771)
Incarceration - Number of Convicts in Prison by Nationality						
Turkish National Convicts	-0.178 (0.961)	0.552 (0.820)	-2.048 (1.336)	-2.174* (1.319)	-0.422 (0.869)	219.020 (117.902)
Foreign National Convicts	0.191*** (0.048)	0.205*** (0.039)	0.262*** (0.034)	0.265*** (0.030)	0.271*** (0.028)	1.358 (2.183)
Year and Province FE	Yes	Yes	Yes	Yes	Yes	
X Controls All	No	Yes	Yes	Yes	Yes	
12 Region Trend	No	No	Yes	No	No	
12 Region-Year FE	No	No	No	Yes	Yes	
Baseline - Year Interaction	No	No	No	No	Yes	

Notes: The dependent variable is crime measures per 100K. Each cell shows the 2SLS estimates for the ratio of Syrians to the 2011 native population. Control variables include log trade volume, per-capita GDP, unemployment rate, male LFP rate, the ratio of low-educated individuals, the share of men aged 15-39, the average household size, and the percentage of the province population residing in city centers. All regressions include province and year-fixed effects. In column 2, we add control variables. Column 3 regressions include region (12-NUTS1) specific linear time trends, whereas column 4 controls for the region (12-NUTS1) specific year effects. Column 5 regressions also control for province trend interacted with the pre-refugee level (in year 2011) of the concerning outcome variable. The last column reports the mean dependent variables. All regressions are weighted by province 2011 population. Standard errors are clustered at the province level. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 6: Share of Foreign National in Crime

	(1)	(2)	(3)	(4)	(5)	
Prosecutors' Offices - Share of Foreign National Suspects and Victims						Mean Y
Foreign National Suspects Share	0.290*** (0.046)	0.324*** (0.032)	0.354*** (0.036)	0.338*** (0.043)	0.348*** (0.049)	1.718 (1.983)
Foreign National Victims Share	0.293*** (0.088)	0.250** (0.105)	0.452*** (0.070)	0.498*** (0.071)	0.519*** (0.061)	2.348 (3.068)
Criminal Courts - Share of Foreign National Defendants and Victims						
Foreign National Defendants Share	0.207*** (0.033)	0.251*** (0.024)	0.254*** (0.018)	0.241*** (0.018)	0.253*** (0.022)	1.670 (1.907)
Foreign National Victims Share	0.384* (0.226)	0.296 (0.262)	0.790*** (0.142)	0.890*** (0.123)	0.890*** (0.125)	2.935 (4.597)
Criminal Courts - Share of Foreign National Offences						
Crimes by Foreign National Share	0.195*** (0.023)	0.232*** (0.022)	0.226*** (0.018)	0.217*** (0.013)	0.226*** (0.016)	1.471 (1.661)
Criminal Courts - Share of Foreign National Convictions						
Foreign National Conviction Share	0.158*** (0.027)	0.180*** (0.025)	0.206*** (0.014)	0.216*** (0.014)	0.236*** (0.016)	1.079 (1.583)
Incarceration - Share of Foreign National Convicts in Prison						
Foreign National Convicts Share	0.117*** (0.010)	0.121*** (0.010)	0.156*** (0.020)	0.144*** (0.009)	0.144*** (0.009)	0.617 (0.827)
Year and Province FE	Yes	Yes	Yes	Yes	Yes	
X Controls All	No	Yes	Yes	Yes	Yes	
12 Region Trend	No	No	Yes	No	No	
12 Region-Year FE	No	No	No	Yes	Yes	
Baseline - Year Interaction	No	No	No	No	Yes	

Notes: The dependent variable is the share of foreign national suspects at time t . Each cell shows the 2SLS estimates for the ratio of Syrians to the total population. Control variables include log trade volume, per-capita GDP, unemployment rate, male LFP rate, the ratio of low-educated individuals, the share of men aged 15-39, the average household size, and the percentage of the province population residing in city centers. All regressions include province and year-fixed effects. In column 2, we add control variables. Column 3 regressions include region (12-NUTS1) specific linear time trends, whereas column 4 controls for the region (12-NUTS1) specific year effects. Column 5 regressions also control for province trend interacted with the pre-refugee level (in year 2011) of the concerning outcome variable. The last column reports the mean dependent variables. All regressions are weighted by province total population. Standard errors are clustered at the province level. All other notes are the same as in Table 1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Type of Crime

	Natural Person Total		Turkish National		Foreign National	
	(5)		(5)		(5)	
Criminal Courts - Number of Offences		Mean Y		Mean Y		Mean Y
Violent	-7.147 (6.647)	1694.755 (556.142)	-8.348 (6.532)	1680.372 (554.402)	1.077*** (0.289)	13.669 (15.825)
Property	-0.690 (2.135)	763.408 (248.026)	-1.684 (2.076)	751.051 (243.410)	0.954*** (0.136)	11.563 (13.340)
Public Crimes	-0.419 (2.892)	580.941 (183.239)	-1.318 (2.809)	563.927 (177.526)	0.661*** (0.229)	16.397 (23.120)
Smuggling	-4.902*** (1.047)	96.093 (119.650)	-6.240*** (0.919)	85.746 (104.128)	1.650*** (0.177)	10.142 (26.927)
Criminal Courts - Number of Convictions						
Violent	-4.329* (2.312)	549.627 (266.725)	-4.593** (2.292)	547.344 (265.728)	0.219** (0.086)	2.283 (3.446)
Property	-3.288 (2.019)	451.541 (194.410)	-3.684* (2.027)	446.867 (191.761)	0.334*** (0.113)	4.674 (7.087)
Public Crimes	-3.372 (2.525)	275.942 (149.108)	-3.899* (2.352)	273.308 (148.312)	0.469** (0.185)	2.634 (7.145)
Smuggling	-4.290 (2.758)	86.694 (124.506)	-5.746** (2.739)	79.170 (111.406)	2.058*** (0.296)	7.524 (21.777)
Incarceration - Number of Convicts in Prison						
Violent	-0.397** (0.198)	61.346 (40.860)	-0.427** (0.197)	61.196 (40.768)	0.017* (0.009)	0.150 (0.292)
Property	-0.225* (0.127)	45.392 (32.527)	-0.257** (0.121)	45.023 (32.197)	0.022 (0.014)	0.370 (0.745)
Public Crimes	-0.101 (0.135)	14.323 (10.659)	-0.108 (0.135)	14.301 (10.648)	0.007*** (0.001)	0.022 (0.082)
Smuggling	-0.290 (0.334)	18.909 (16.786)	-0.402 (0.319)	18.286 (16.323)	0.111*** (0.022)	0.624 (1.105)
First Stage F-Stat	48.983		48.983		48.983	
Observation	891		891		891	
Year and Province FE	Yes	Yes	Yes	Yes	Yes	Yes
X Controls All	Yes	Yes	Yes	Yes	Yes	Yes
12 Region Trend	No	No	No	No	No	No
12 Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Baseline-Year Interaction	No	Yes	No	Yes	No	Yes

Notes: The dependent variable is crime measures per 100K. The table presents the 2SLS estimates for specification (5). Control variables include log trade volume, per-capita GDP, unemployment rate, male LFP rate, the ratio of low-educated individuals, the share of men aged 15-39, the average household size, and the percentage of the province population residing in city centers. Specification (5) include province and year-fixed effects, all control variables, the region (12-NUTS1) specific year effects, and province trend interacted with the pre-refugee level (in year 2011) of the concerning outcome variable. F-stat reports the first stage F-stat for specification (5). All regressions are weighted by province 2011 population. Standard errors are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Total Number of Cases in Prosecutors' Offices - Robustness Tests

	(1)	(2)	(3)	(4)	(5)
Baseline					
Total Number of Cases	29.519 (18.592)	23.336* (12.548)	-5.684 (10.408)	-2.544 (10.827)	20.599** (9.826)
Only Demographic Controls					
Total Number of Cases	29.519 (18.592)	25.271* (14.174)	-2.808 (10.511)	-0.085 (11.056)	22.811** (10.684)
Years 2006-2019					
Total Number of Cases	39.335** (19.855)	32.189*** (12.236)	-2.643 (8.787)	-0.051 (12.201)	26.614*** (10.318)
Years 2006-2016					
Total Number of Cases	59.454*** (22.930)	47.052*** (10.729)	15.598** (7.128)	18.474* (10.380)	39.088*** (9.219)
Weighted by Resident Population Aged 15-40					
Total Number of Cases	31.281 (19.795)	23.971* (13.051)	-6.493 (10.738)	-2.967 (11.056)	20.683** (9.884)
Outlier Drop: Kilis Province					
Total Number of Cases	32.325 (21.218)	26.736* (14.939)	-9.612 (12.372)	-6.815 (12.977)	23.826* (13.185)
Dropping the largest metropolitans: İstanbul, Ankara, İzmir, Bursa, Antalya					
Total Number of Cases	15.877 (10.871)	14.846 (9.288)	13.344** (6.096)	12.781* (6.949)	26.232*** (9.319)
Observation	891	891	891	891	891
Year and Province FE	Yes	Yes	Yes	Yes	Yes
X Controls All	No	Yes	Yes	Yes	Yes
12 Region Trend	No	No	Yes	No	No
12 Region-Year FE	No	No	No	Yes	Yes
Baseline - Year Interaction	No	No	No	No	Yes

Notes: The dependent variable is the total number of cases in prosecutors' offices per 100K. Each cell shows the 2SLS estimates for the ratio of Syrians to the 2011 native population. Control variables include log trade volume, per-capita GDP, unemployment rate, male LFP rate, the ratio of low-educated individuals, the share of men aged 15-39, the average household size, and the percentage of the province population residing in city centers. All regressions include province and year-fixed effects. In column 2, we add control variables. Column 3 regressions include region (12-NUTS1) specific linear time trends, whereas column 4 controls for region (12-NUTS1) specific year effects. Column 5 regressions also control for province trend interacted with the pre-refugee level (in year 2011) of the concerning outcome variable. The last column reports the mean dependent variables. All regressions are weighted by province 2011 population. Standard errors are clustered at the province level. *** p< 0.01, ** p<0.05, * p<0.1.

Table 9: Total Number of Cases in Prosecutors' Offices - Placebo Tests

	(1)	(2)	(3)	(4)	(5)
Baseline					
Total Number of Cases	29.519 (18.592)	23.336* (12.548)	-5.684 (10.408)	-2.544 (10.827)	20.599** (9.826)
Placebo test for 2006-2011 - (2017-2018-2019 IVs for 2009-2010-2011)					
Total Number of Cases	11.325* (6.458)	12.113 (7.970)	-4.506 (5.731)	-2.072 (4.364)	8.659 (5.729)
Residual test for 2006-2011 using 2019 IV					
Total Number of Cases	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Observation	486	486	486	486	486
Year and Province FE	Yes	Yes	Yes	Yes	Yes
X Controls All	No	Yes	Yes	Yes	Yes
12 Region Trend	No	No	Yes	No	No
12 Region-Year FE	No	No	No	Yes	Yes
Baseline - Year Interaction	No	No	No	No	Yes

Notes: The dependent variable is the total number of cases in prosecutors' offices per 100K. Each cell shows the 2SLS estimates for the ratio of Syrians to the 2011 native population. Control variables include log trade volume, per-capita GDP, unemployment rate, male LFP rate, the ratio of low-educated individuals, the share of men aged 15-39, the average household size, and the percentage of the province population residing in city centers. All regressions include province and year fixed effects. In column 2, we add control variables. Column 3 regressions include region (12-NUTS1) specific linear time trends, whereas column 4 controls for region (12-NUTS1) specific year effects. Column 5 regressions also control for province trend interacted with the pre-refugee level (in year 2011) of the concerning outcome variable. The last column reports the mean dependent variables. All regressions are weighted by province 2011 population. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Total Number of Cases in Prosecutors' Offices - IV Test

	(1)	(2)	(3)	(4)	(5)
Baseline					
Total Number of Cases	29.519 (18.592)	23.336* (12.548)	-5.684 (10.408)	-2.544 (10.827)	20.599** (9.826)
First Stage F-Stat	51.254	85.478	71.332	57.891	48.983
Camps are Seperate					
Total Number of Cases	28.992 (18.227)	22.879* (12.368)	-5.775 (10.583)	-2.345 (10.758)	20.931** (9.923)
First Stage F-Stat	51.554	85.444	70.126	56.843	37.881
Alternative Arabic IV					
Total Number of Cases	12.920* (7.553)	9.485 (5.867)	-8.598 (12.431)	-5.670 (12.761)	11.024 (13.647)
First Stage F-Stat	41.554	46.618	64.240	54.257	44.762
Observation	891	891	891	891	891
Year and Province FE	Yes	Yes	Yes	Yes	Yes
X Controls All	No	Yes	Yes	Yes	Yes
12 Region Trend	No	No	Yes	No	No
12 Region-Year FE	No	No	No	Yes	Yes
Baseline - Year Interaction	No	No	No	No	Yes

Notes: The dependent variable is the total number of cases in prosecutors' offices per 100K. Each cell shows the 2SLS estimates for the ratio of Syrians to the 2011 native population. Control variables include log trade volume, per-capita GDP, unemployment rate, male LFP rate, the ratio of low-educated individuals, the share of men aged 15-39, the average household size, and the percentage of the province population residing in city centers. All regressions include province and year-fixed effects. In column 2, we add control variables. Column 3 regressions include region (12-NUTS1) specific linear time trends, whereas column 4 controls for region (12-NUTS1) specific year effects. Column 5 regressions also control for province trend interacted with the pre-refugee level (in year 2011) of the concerning outcome variable. The last column reports the mean dependent variables. All regressions are weighted by province 2011 population. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Total Number of Cases in Prosecutors' Offices - Alternative Specifications

	(1)	(2)	(3)	(4)	(5)
Baseline					
Total Number of Cases	29.519 (18.592)	23.336* (12.548)	-5.684 (10.408)	-2.544 (10.827)	20.599** (9.826)
Ratio: Refugees to Native Population					
Total Number of Cases	36.161* (20.743)	21.057** (10.604)	4.631 (7.647)	9.795* (5.654)	15.413* (8.598)
Ratio: Refugees to Total Population					
Total Number of Cases	-3.855 (25.169)	-23.332* (12.478)	-43.878*** (11.712)	-35.919*** (9.590)	-30.979** (13.994)
Log Equation with Native Population					
Total Number of Cases	0.116 (0.133)	0.055 (0.043)	0.031 (0.021)	0.040*** (0.010)	0.038*** (0.009)
Log Equation with Total Population					
Total Number of Cases	0.356 (1.419)	0.061 (0.079)	0.028 (0.024)	0.027** (0.011)	0.023* (0.009)
Year and Province FE	Yes	Yes	Yes	Yes	Yes
X Controls All	No	Yes	Yes	Yes	Yes
12 Region Trend	No	No	Yes	No	No
12 Region-Year FE	No	No	No	Yes	Yes
Baseline - Year Interaction	No	No	No	No	Yes

Notes: The dependent variable is the total number of cases in prosecutors' offices per 100K. Each cell shows the 2SLS estimates for the ratio of Syrians to the 2011 native population. Control variables include log trade volume, per-capita GDP, unemployment rate, male LFP rate, the ratio of low-educated individuals, the share of men aged 15-39, the average household size, and the percentage of the province population residing in city centers. All regressions include province and year-fixed effects. In column 2, we add control variables. Column 3 regressions include region (12-NUTS1) specific linear time trends, whereas column 4 controls for region (12-NUTS1) specific year effects. Column 5 regressions also control for province trend interacted with the pre-refugee level (in year 2011) of the concerning outcome variable. The last column reports the mean dependent variables. All regressions are weighted by province 2011 population. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.