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ABSTRACT

The Effects of Exposure to Refugees on Crime: Evidence from the Greek Islands*

Recent political instability in the Middle East has triggered one of the largest influxes of refugees into Europe. The different departure points along the Turkish coast generate exogenous variation in refugee arrivals across Greek islands. We construct a new dataset on the number and nature of crime incidents and arrested offenders at island level using official police records and newspaper reports. Instrumental variables and difference-in-differences are employed to study the causal relationship between immigration and crime. We find that a 1-percentage-point increase in the share of refugees on destination islands increases crime incidents by 1.7-2.5 percentage points compared with neighboring unexposed islands. This is driven by crime incidents committed by refugees; there is no change in crimes committed by natives on those islands. We find a significant rise in property crime, knife attacks, and rape, but no increase in drug crimes. Results based on reported crimes exhibit a similar pattern. Our findings highlight the need for government provision in terms of infrastructure, social benefits, quicker evaluation for asylum, and social security.

JEL Classification: F61, F22, K42, J15

Keywords: crime, migration, natural experiment, Greek islands, difference-in-differences, shiftshare instrumental variable

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1 Introduction

Recent political instability in the Middle East has prompted an unprecedented surge of refugees to Europe. The number of forcibly displaced people around the globe had reached 59.5 million in 2015 (UNHCR, 2015).[1] This constitutes the largest movement of refugees since WWII. Recent turmoil in North Africa and the Middle East, along with continuing violence in Afghanistan, has sparked a massive increase in displacements to the European Union, with the number of refugees applying for asylum reaching a record 1.26 million in 2015 (Eurostat, 2016). This large immigration flow has triggered a debate across European countries about the impact of refugees on the local economy and society. The debate is often characterized by accusations that higher levels of immigration lead to higher crime rates; however, scientific evidence on this point yields mixed results.

This paper investigates the effect of a large influx of refugees on crime activity in Greece, which is arguably the European country most affected by the current refugee crisis.[2,3] The situation in the Middle East acts as a source of exogenous variation for refugee arrivals across Greek islands over time: As a result of political instability in their home countries, refugees fled in boats that departed from various locations along the Turkish coast and headed to the closest Greek island. In this natural experiment, refugees had no impact on which destination island they landed; this depended entirely on the route and distance from the Turkish coast. Whereas some islands are close to the Turkish coast and thus refugees landed on them, others are unexposed to refugees because they are a bit farther from Turkey.

The southern Greek islands, due to their geographic proximity to Turkey, became the first reception point for refugees who sought to move to countries in Central or Northern Europe.[4] However, in 2015, all countries that neighbored Greece decided to close their borders and not accept refugees, and thus all refugees who had reached Greece were sent to refugee camps in the country. At the same time, the European Union and Turkey reached an agreement by which refugees arriving in Greece must apply for asylum; otherwise, they would be sent back to Turkey. In 2015, ten Greek islands near the border with

[1]Specifically, the number of people forcibly displaced was 51.2 million in 2013 and 37.5 million in 2010. The same report states that one in every 122 individuals is now a refugee who is either internally displaced or seeking asylum.

[2]According to the United Nations High Commissioner for Refugees (UNHCR, 2015), 1,000,573 refugees and migrants arrived in Europe from the Middle East and North Africa during 2015. Of these, around 850,000 landed on the Greek islands. Of these, 49% were Syrian, 21% Afghan, and 8% Iraqi. A *Telegraph* article describes why Greece has arguably been the most affected country: `https://www.telegraph.co.uk/travel/destinations/europe/greece/articles/greek-islands-affected-by-refugee-crisis/`.

[3]Figure A1 shows that more than 800,000 of refugees who arrived by sea landed in Greece. Related numbers for Italy and Spain are small and flat over time.

[4]Greece is in the southeasternmost corner of the European Union, which renders the Greek islands the closest destination for refugees from the Turkish coast.

the Turkish coast were required to host refugees until their asylum process was complete.[5] During this time, refugees were not allowed to move to continental Greece or leave the country.

A common concern in studies that examine the relationship between immigration and crime is the self-selection of immigrants in areas with specific characteristics. In particular, an individual's decision to migrate from one location to another is usually affected by characteristics such as employment opportunities, living costs, availability of public services, and pollution in the destination region. In our setting, however since refugees have no control over the destination island, we exploit a setting that avoids this common problem of self-selection of immigrants to specific areas (Chiswick, 1999), and thus enables us to better understand the link between immigration and crime. This is of paramount importance, since this relationship may reveal policy tools that could be used to better accommodate refugees in those islands and other countries in which a similar pattern is observed.

We employ official police data on crime rates, and construct a hand-collected dataset of annual crime activity in all inhabited Greek islands for the period 2012 to 2016.[6] Based on a comprehensive collection of newspapers on crime. In both datasets, we exploit information on the different types of crime committed by both natives and the foreign-born population in the Greek islands: violent crimes (personal robberies/knife attacks and rape); property crimes (property robberies, common theft, and vehicle theft); and drug-related crimes. We combine the crime data with information on the refugee influx obtained from the United Nations Refugee Agency (UNRA).

We use two complementary identification strategies to investigate the causal relationship between the presence of refugees and crime activity. Our *difference-in-differences* approach relies on the comparison of crime rates between exposed and unexposed islands before and after 2015. We complement this analysis by using each island's distance to the Turkish coast interacted with time dummies as an *instrumental variable* for refugees' intensity. This reflects our hypothesis—that islands closer to the Turkish coast were more likely to receive more refugees than those farther away. We use two additional IV methodologies. In the first, we interact the distance of each island with the overall number of refugee arrivals, and in the second we interact the distance with a shift-share instrument (Docquier, Turati, Valette, and Vasilakis, 2019; Ottaviano and Peri, 2005; Saiz, 2003; Card, 2001).

[5]According to the official Asylum Services webpage, of a total of 58,793 applications pending at the end of 2018, 45.6% had been pending for more than 6 months from the day of full registration (`https://www.asylumineurope.org/reports/country/greece/asylum-procedure/procedures/regular-procedure`). People whose asylum applications are successful are eligible for the following benefits: a residence permit that is valid for 3 years, the right to apply for a travel document, and the right to bring family from their country of origin to Greece. Once the decision regarding the asylum application is made, refugees are still likely to wait for another 3 months or more to get their residence permit.

[6]The use of newspaper data is becoming more and more common in economics (Ewens, Gupta, and Howell, 2022; Freddi, 2021; Wilson, 2021).

Findings based on the two methodologies are similar and point in the same direction. In particular, we find that a 1-percentage-point increase in the share of refugees increases crime incidents based on arrested offenders by 1.7-2.5 percentage points compared with neighboring unexposed islands. We find that this increase in crime can be attributed to crimes committed by refugees because there is no change in the number of crimes committed by natives. We also find that there is no increase in drug-related crimes, while there is an increase in the number of property crimes, personal robberies, and rape. It is important to highlight the fact that refugees had very limited access to formal employment while their asylum applications were being examined and they faced strict mobility restrictions.

Our results are robust to two placebo exercises. The first shows that treatment and control groups did not follow differential trends over time. In particular, we show that pre-2015 trends in crime on exposed and unexposed islands are identical. In other words, before 2015, annual violent behavior was unchanged on islands that later received refugees and islands that did not receive refugees. The second exercise shows that islands comparable to the refugee-hosting ones do not experience any change in criminal activity after 2015. These islands are very close in distance to those that received refugees, but are closer to mainland Greece and have similar characteristics.

Several features of our setting are important. First, there is a large number of inhabitable islands in Greece and their distance from the Turkish coast varies significantly. For instance, one group of islands is 6-30 miles west of the Turkish coast and others are 350 miles from it. This is critical in our setting, since an island's distance from the Turkish border is associated with the number of refugees who arrive on the island. Second, after all neighboring countries closed their borders, refugees had to apply for asylum and remain on the reception islands in Greece until their asylum requests were processed. This allows us to investigate crime incidents on those islands given the presence of refugees. Third, many of these islands belong to the same electoral and administrative district, which ensures that they are identical in terms of a plethora of observable and unobservable characteristics, such as the candidates running for office, regional government, police, judiciary, and access to EU funds. These features enable us to exploit exogenous variation in the number of foreign-born population across relatively comparable islands.

Our study makes several important contributions. First, we exploit a setting that triggered the largest influx of refugees into Europe since WWII. In particular, Greece received an remarkably large flow of almost 400,000 refugees (UNHCR, 2015). There is evidence that crime may increase more substantially in areas that now have large inflows of refugees, but previously only had a limited number of foreigners (Entorf and Lange, 2019); in the case of the Greek islands, the foreign-born population was previously less than 1% percent of the total population. Second, we study the effect of refugees on different types of crime, rather than only the aggregated crime rate. This is important, because we can investigate the impact of refugees' intensity on violent crimes, property crimes (robbery, common theft, vehicle theft), and drug-related crimes. Third, we use data on arrested offenders and reported crime, separately. Fourth, this is the first study that examines the impact of exposure to refugees on different types of criminal offenses committed by refugees and natives, separately. There is evidence in the literature that people's voting behavior in the Greek islands, which consist of relatively small societies, is affected by the presence of foreign-born populations. In particular, there is evidence of increased xenophobia in those islands, where refugees are more prevalent and people tend to vote for extreme right-wing parties (Vasilakis, 2018; Dinas, Matakos, Xefteris, and Hangartner, 2019; Hangartner, Dinas, Marbach, Matakos, and Xefteris, 2019; Moriconi, Peri, and Turati, 2019; Edo, Giesing, Oztunc, and Poutvaara, 2019).[7]

The literature leans more toward a null association between immigration and crime. Hines and Peri (2019) exploit an increase in the deportation rate due to the introduction of an immigration enforcement program and examine whether immigration enforcement affects local crime. They find that an increase in deportation rates does not reduce crime rates for violent offenses or property offenses, and that the program did not increase police effectiveness in solving crimes or local police resources. Masterson and Yasenov (2019) exploit a resettlement refugee ban in the U.S. and find no effect on crime rates when there was a 66% drop in the resettlement of refugees in the U.S. from 2016 to 2017. In their case, these null effects are consistent across all types of crime. Also, Light and Miller (2018) find no association between the presence of undocumented immigrants and crime.[8] In contrast to these studies, and in line with a smaller body of literature, we find a positive association between the presence of refugees in exposed islands and crime.[9] The literature proposes several reasons to expect such a positive relationship. First, immigrants and natives may have different propensities to commit crime (Bianchi, Buonanno, and Pinotti,

[7] Vasilakis (2018) uses data from Greece and finds that a 1% increase in the share of refugees is associated with an increase in the share of votes for Golden Dawn—the right-wing party of Greece—by 5%.

[8] Lee, Martinez, and Rosenfeld (2001) focus on the impact of immigration on Latino and black homicide rates at census tract level in three cities: Miami, El Paso, and San Diego. With the exception of Black homicides in San Diego, the relative size of the new immigrant population has either a negative or insignificant effect on the murder rate for both groups. Chalfin (2013) also finds that Mexican immigration is not associated with a change in the rates of either violent or property crimes in U.S. cities.

[9] Piopiunik and Ruhose (2017) exploit the collapse of the Soviet Union and the exogenous assignment of immigrants across regions upon arrival in Germany. They find that immigration increases almost all types of crime, including property crime and drug-related crime. Bianchi, Buonanno, and Pinotti (2012) use data from Italian provinces over the period 1990-2003 and find that immigration increases the incidence of property crimes, while it leaves unaffected all other types of crime. In particular, the authors find that a 1% increase in the total number of migrants is associated with a 0.1% increase in property crimes (i.e., robberies and thefts); no such effect is revealed for violent crimes (i.e., rape and aggravated assault). Spenkuch (2013) finds a positive association between immigration and all type of property crime using data from the U.S. from 1980 to 2000. Nevertheless, he finds no impact of immigration on rape.

2012; Ousey and Kubrin, 2009). According to the economic theory of crime, individuals with lower outside options commit more crime (Becker, 1968). This may be because immigrants and natives face different legitimate labor market opportunities, different probabilities of being convicted, and different costs of conviction (Borjas, 1998). Also, Butcher and Piehl (2007) stress that the punishment immigrants face includes the risk of deportation, which may be a powerful deterrent to criminal activities. Another channel through which immigration may affect crime is spillover effects: Immigration may affect crime rates as a result of natives' response to the inflows of immigrants. Borjas, Grogger, and Hanson (2010) show that U.S. natives, and black males in particular, increase their criminal activities in response to labor market competition with immigrants. Third, immigrants who have committed an offense in a destination country experience a significantly higher cost of crime than natives because of a greater probability of incarceration (Butcher and Piehl, 2007). In line with these theories, we find that refugees are more prone to engage in crime compared with natives in destination islands.[10]

Refugees are a special category of immigrants, since they are forced to migrate and differ markedly from other migrants (Dustmann, Fasani, Frattini, Minale, and Schönberg, 2017). Thus, studying the relationship between exposure to refugees and crime is of particular interest. Bell, Machin, and Fasani (2013) examine the effect of refugee arrivals on crime using data for England and Wales for the period 2002-2009 and find that asylum seekers were more likely to engage in economic crime in the destination country (UK).[12] This may be explained by the fact that labor market opportunities available to asylum seekers are much worse than for natives. In our study, refugees had no legal status in Greece; This could, in theory, cause them to engage in even more criminal activities since they had no or very limited labor market opportunities. Akbulut-Yuksel, Mocan, Tumen, and Turan (2022) and Dehos (2017) examine the impact of refugees on crime using the same refugee crisis we do. Both studies find a positive association between the influx of refugees and crime incidents. Akbulut-Yuksel, Mocan, Tumen, and Turan (2022) focus on the impact of refugees on crime in Turkey, which shares land borders with Syria; 3.7 million refugees entered and stayed in Turkey as a result of the civil war in Syria. They find that the influx of refugees between 2012 and 2016 generated an additional 75,000 to 150,000 crimes per year, but they are

[10]Other studies find a negative relationship between immigration and crime. Butcher, Piehl, and Liao (2008) were the first to show that immigrants are less likely to commit criminal offenses than natives. In particular, U.S.-born men are 10 times more likely than foreign-born men to be in jail or prison. Zhang (2014) shows that a 10% increase in the recent-immigrant or established-immigrant share decreases the property crime rate by 2% to 3% in Canada. He also provides suggestive evidence that immigration has spillover effects, such as changing neighborhood characteristics, which reduces crime rates in the long run. These findings depend crucially on the research design, the county, and the types of migration.[11]

[12]Bell, Machin, and Fasani (2013) studied a second migrant flow due to the expansion of the European Union in 2004. These migrants had a strong attachment to the labor market: An increase by 1% in the share of the second type of migrants reduced crime by 0.39%.

not able to distinguish between crimes committed by refugees and natives. Dehos (2017) examines the effects of refugees on crime in Germany, which welcomed a large number of refugees. He finds a positive association between the share of recognized refugees and the overall crime rate, which is driven by non-violent property crimes and frauds. Similar to these studies, we find a positive association between refugees and crime activity. Similar to Spenkuch (2013); Bell, Machin, and Fasani (2013); and Dehos (2017), we find a positive association between immigration and property crime. However, different from Bianchi, Buonanno, and Pinotti (2012); Spenkuch (2013); and Dehos (2017), we find that rape also increased significantly in response to the migration wave, but not the number of drug-related crimes.[13] Also, different from Akbulut-Yuksel, Mocan, Tumen, and Turan (2022), we have information on whether each crime was committed by natives or refugees and analyze for each separately.

The rest of the paper is organized as follows. Section 2 presents the background of the refugee crisis and Section 3 describes the data. Section 4 presents the empirical method, Section 5 presents the results, and Section 6 concludes.

2 Background

Political instability in the Middle East since 2015 has caused the largest flow of refugees[14] into Europe since WWII. This unprecedented wave of refugees to Europe must be viewed in the context of civil war and terror in Syria, Iraq, and Afghanistan, which resulted in around 250,000 casualties and 12 million displaced persons according to UN estimates (UNHCR, 2015). This caused people to leave their homes and first reach Turkey[15] by land due to its proximity. Their ultimate goal was to reach Northern Europe and apply for asylum (IOM, 2015). From Turkey, there are two ways to enter Europe. First, by land since Turkey shares borders with Greece (and Bulgaria). However, most of these people are civil war fugitives, and thus are not allowed to legally enter the country. The Greek government also constructed a 4-meter fence along the Greek-Turkish land border to restrict illegal migration. The only other option for refugees seeking to enter Europe is via the Aegean Sea, which is how most refugees entered Europe via Greece and sought asylum.[16]

[13] A drug-related crime involves possessing, manufacturing, or distributing drugs such as cocaine, heroin, morphine, and amphetamines. A drug-related crime involves drug trafficking and production.

[14] We cannot exclude the possibility that some of those migrants were economic migrants.

[15] In April 2016, Turkey alone hosted close to 3 million registered refugees `https://data2.unhcr.org/en/situations/syria`, most of whom seek to reach Northern Europe.

[16] Smugglers rely on informants to avoid patrols from coast guards and the navy, and if a boat loaded with migrants is detected, some of the passengers are instructed to fall overboard to compel the Greek authorities to initiate a search and rescue operation instead of forcing the illegal boat to return to Turkish waters. Turkish, Greek, Kurdish, and Balkan

Registered arrivals of refugees in 2015 reached almost 1 million, with the bulk of migrants entered the Greek islands bordering Turkey by sea (UNHCR, 2015; IOM, 2015). In particular, refugees used boats that departed from various locations along the Turkish coast and headed for the closest Greek island. Weather conditions could affect the route, and which island refugees ended up on depended entirely on their route from the Turkish coast. Figure 2 shows annual arrival rates of refugees at a disaggregated geographic level (i.e., county) in Greece for each year in the period 2012-2016. Of the 107 inhabited islands of Greece, a small group is 6-30 miles west of the Turkish mainland; others are as much as 350 miles distant. Islands close to Turkey are mostly exposed to refugees, as shown by the darker color that indicates refugee arrival intensity. The Greek islands close to Turkey are Chios, Lesvos, Kastelorizo, Kos, Leros, Kalymnos, Agathonisi, and Samos and are the 7 exposed islands we use in our analysis.

When the migration influx started to peak in 2015, most refugees made their way to Western and Northern Europe; Germany, Hungary, and Austria had the most asylum applications in that year. In an attempt to restrict illegal migration, all countries neighboring Greece closed their borders. As a result, more than 70,000 refugees were stuck in Greece, and the government built more than 50 refugee camps across the country to house them. In response, the European Union, Greece, and Turkey reached an agreement that required asylum seekers to remain in a group of Greek islands—e.g., Chios, Lesvos, Leros, Tilos, Samos, Kastelorizo, Kalymnos, Kos, Agathonisi, and Rhodes—until their asylum application is complete. Unfortunately, the Greek islands did not have the infrastructure or buildings necessary to accommodate such a large number of refugees.

In general islands are mainly populated by natives and may have lower crime rates.[17] Unlike the mainland, in which refugees would have fewer mobility constraints, the fact that refugees landed on reception islands renders them less likely to move to other islands or the mainland, especially given their lack of legal documents.[18] From the mainland, refugees could attempt to go to the north, since Greece shares land borders with Albania, Bulgaria, the former Yugoslav Republic of Macedonia, and Turkey.

smugglers organize the crossing from the Turkish coast to the Greek islands for amounts that usually cost between 2,500 and 3,500 euro (Papadopoulou, 2004).

[17]The crime rate in the mainland is generally higher than the crime rate in the affected islands. In particular, in 2012, 2013, and 2014 the crime rate in the mainland was 1.59%, 1.09%, and 1.04% (excluding Athens and Thessaloniki), while it was 0.16%, 0.04% and 0.02% in the affected islands, respectively.

[18]We later investigate whether some types of crime are more typical in islands close to an international border (i.e. smuggling and drug trafficking).

3 Data and Descriptive Statistics

3.1 Data

This study draws on a new panel data set that covers all habitable Greek islands. The data provide information on crime rates based on arrests at island level for natives and refugees, separately. We use official police annual data per type of crime in our main analysis. This enables us to examine the effect of immigration on different types of crimes, such as knife attacks, vehicle and property theft, selling or buying drugs, rape and other types of crime, such as protests and damage to property. Additionally, we gathered information on crime records based on arrested offenders from local newspapers[19] on Greek islands over the period 2012 to 2016,[20] and aggregated the data on an annual basis. We acknowledge that our arrest data represent a subset of crime data reported to the police (i.e., crimes for which a potential offender has been identified). We also obtained data on reported crime by type, island, and year for all years in our sample period. We use these additional data on reported crime as a robustness check.

We provide a list of the local newspapers we included in our data collection in Figure A2.[21] In general, newspapers in Greece usually provide fairly comprehensive coverage for the entire country. We acknowledge that our data refer to reported crime and not the actual level of crime.[22]

Below, we report some examples of how crime incidents were reported in newspapers:

Example 1: Three people were arrested yesterday in Chios (a Syrian, a Moroccan, and an Algerian, aged 23, 26, and 27, respectively) charged with theft and aggravated assault. According to the investigation, the aforementioned people broke into a cafeteria in Chios and removed various alcoholic beverages and instant drinks. They also caused material damage.

Example 2: On Monday (02/01) evening, a 46-year-old migrant was arrested by a police officer from Samos Security Office, in Vathi, Samos, for charges of cabin robbery. In particular, as revealed by police investigation data, the 46-year-old, yesterday at noon, entered the 57-year-old's cabin in the area and

[19]Each crime incident reported in the newspaper usually provides information about the ethnicity of the individual who was charged with (suspected of) the crime, the specific crime committed, and where the incident occurred. The name of the person who committed the crime and information about the victim are not usually reported.

[20]Krueger and Pischke (1996) also collect county-level data on crime incidents against foreigners in Germany derived from magazine reports and newspapers. They find different patterns of violence in the eastern and western parts of the country.

[21]These are print or online newspapers that are issued in both exposed and unexposed islands. Newspapers issued in big cities do not report island-specific crime incidents.

[22]Survey data could provide total incidents and reported and unreported incidents, but we do not have access to such data.

removed various products of worth 2,000 euro. The theft was found and seized. The theft will be taken to the Samos Public Prosecutor's Office.

In our main analysis we rely on official police data, while we also use the dataset that relies on newspaper records in robustness exercises.[23]

Data on refugee arrivals per island are provided by the UNHCR. We obtained geographic data on each island's distance from the Turkish coast from Google Maps, which provides satellite imagery and geospatial data visualizations and measurements. Population data are collected from the National Greek statistical service. Information on island economic indicators, such as the unemployment rate and income, is provided by the National Statistical Authority.

Table 1 presents summary statistics for the main variables of interest. There are on average 241 refugees (sd=1,801) across all Greek islands in the sample, but exposure to refugees varies significantly across islands. In particular, some islands are not exposed to refugees at all, and others have almost 29,000 refugees. This is a substantial number, given that some islands are very small. The average refugee share across all Greek islands is 1.1%, but this varies dramatically between islands that are exposed and unexposed to refugees: between 0% and 98%.[25] We also report summary statistics for different types of crimes committed by natives and refugees, separately. We collect those statistics from police reports, but also statistics for the crime measures reported by newspapers.

Crime rates are computed by deriving the total number of crime incidents per type by the island's total population (natives and refugees). Across the different types of crime, we show summary statistics

[23]One may argue that newspaper incidents are likely to cover only the "tip of the iceberg", meaning that newspapers usually focus on more severe crime incidents that may spark public interest. If this is the case, low-profile crime may not be included in the newspaper data and therefore lead to underestimation of criminal activity. We provide more details on how we obtained newspaper crime incidence in Appendix B. The official police data we use in the main analysis and the data we obtained from local newspapers only report arrests. A potential disadvantage of using data on arrests is that changes in crime incidents may be a result of changes in the treatment of refugees by the police rather than changes in their actual criminal behavior (Fasani, 2018). Thus, we also complement official police data on arrests with official police data on reported crime (not only arrests). These official police records on reported crime cover all crime incidents independent of whether the suspect is arrested. Thus, while using the data on reported crime we cannot conduct an analysis in which we examine how the results change when perpetrators are refugees or natives. Given that there may be media bias in crime reporting by newspapers (Couttenier, Hatte, Thoenig, and Vlachos, 2019), we use this data in a robustness exercise. In other words, by using official police crime records in the main analysis, we alleviate concern that newspapers might be more likely to report a crime if it is committed by refugees.[24] We use data on all reported crime incidents obtained from official police records in a robustness exercise, but we prefer to use arrest data in the main analysis in order to be able to separate crime incidents based on whether the perpetrator is a native or refugee. We find it reassuring that we use several data sources that capture different types of crime activity or crime reporting.

[25]For example, Agathonisi is the northernmost Dodecanese island in Greece, is very small (only 13 square kilometers), and is only 5 miles from the Turkish coast. The island's registered total native population in the 2011 census was 185 inhabitants. Hundreds of refugees have landed on Agathonisi. This means that at several points in time the refugees might outnumber natives. On islands such as Agathonisi, the share of refugees reported by the United Nations is up to 98% of the total island population. Some reported stories about refugees' arrivals to this island can be found here: https://www.theguardian.com/world/2016/jan/12/refugee-rescues-continue-winter-greece-agathonisi.

using the crime rate computed by newspapers and the one reported by the police. We also show different statistics for whether the crime was committed by natives or refugees. Of all possible types of crime, robberies and personal crimes (or knife attacks) have the highest rates. In particular, the personal robberies rate (based on police data) is 0.074 cases committed by natives per 100,000 total population and 0.097 cases committed by refugees per 100,000 total population. Also, the vehicle theft rate (based on police data) is 0.017 cases are committed by natives and 0.019 cases are committed by refugees per 100,000 total population. These crime rates correspond to the islands' crime rates in the sample period only.

We rely on the tests presented in Table 2 to show that exposed and unexposed islands are statistically indistinguishable on important economic indicators, such as size and native population. Columns (1) and (2) show the mean and standard deviation for the exposed and unexposed islands for each variable, respectively. Column (3) presents the difference (1) - (2) and the standard error of the difference. The economic indicators we include are the unemployment rate and log income at island-year configuration. In particular, the differences in terms of island-specific unemployment rates and log income are small and statistically insignificant. The same applies to differences in terms of native population and island size; there are no statistically significant differences between the two types of islands. However, we notice that there are considerable differences between exposed and unexposed islands with respect to refugee inflow and log-distance from the Turkish coast. In particular, exposed islands are much closer to the Turkish coast than unexposed islands. Also, the share of refugees is around 26% in exposed islands and 0.1% in unexposed islands. This is the variation we exploit in the following section.

4 Identification

We exploit exogenous variation in the number of refugees across different islands to identify the effect of the refugee influx on crime patterns in the Greek islands. We employ two empirical strategies—a difference-in-differences approach and instrumental variables—to identify the causal effect of exposure to refugees on different types of crime incidents. We provide details on those identification methods in this section.

4.1 Difference-in-differences Methodology

The first empirical strategy compares crime intensity before and after the arrival of refugees between a treatment and a control group of islands. This relies on a difference-in-differences (DiD) methodology. The underlying logic behind this design is that inhabited islands that received and hosted refugees after 2015 are the treatment group and the remaining inhabited islands, which did not receive or host refugees, are the control group. In other words, we will investigate how the exogenous change in refugee presence, as well as the intensity of this presence, affects crime activity in exposed compared with unexposed islands. Thus, we define a dummy $Treat_i$, which is equal to 1 for islands that received refugees (treatment group/exposed islands) and 0 for islands that did not receive and host refugees (control group/unexposed islands). Also, we define a dummy $Post_t$ that takes the value 1 for years later than 2015 and 0 otherwise. To investigate the relationship between exposure to immigrants and crime incidents, we estimate the following DiD specification:

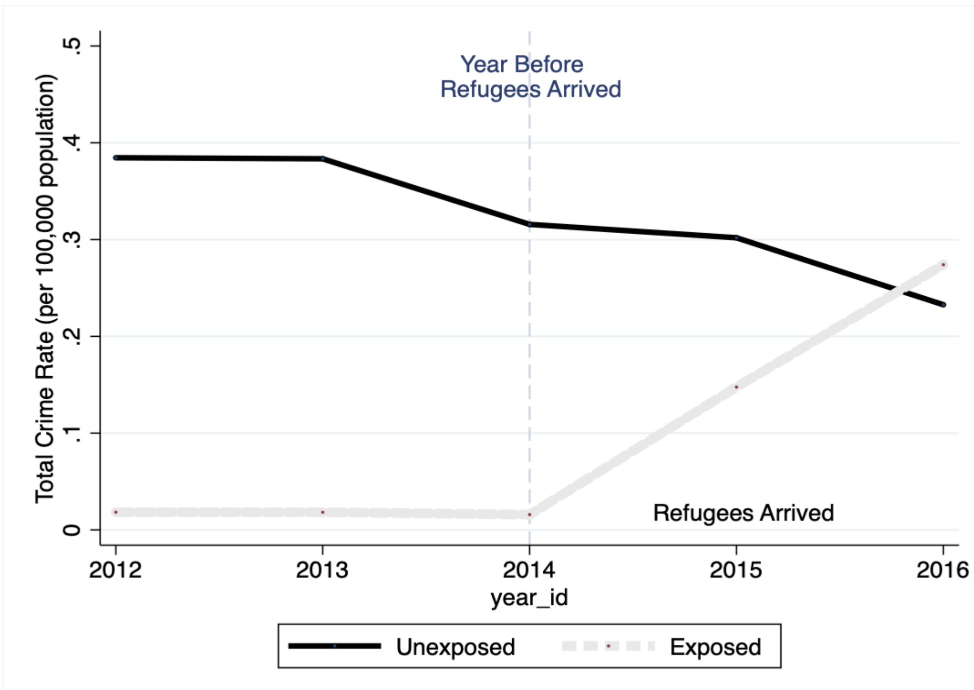
$$Y_{it} = \alpha + \beta Treatment_i \times Post_t + \gamma_i + \gamma_t + \epsilon_{it}, \tag{1}$$

where Y_{it} is the outcome of interest in Greek island i at time t; $Treatment_i$ is a dummy variable equal to 1 if the island is in the treatment group (i.e., the 7 islands that are close to Turkey as explained in Section 2) and 0 otherwise; $Post_t$ is a dummy variable equal to 1 after the year 2015 and 0 in 2014, 2013, or 2012. Identification of the effect of the foreign-born population on crime incidents relies on within- and across-island changes in both of these variables, controlling for year- and island-specific unobserved shocks. Given that treatment and control groups are not evenly distributed across the Aegean, we need to weight our interaction of interest with the share of refugees to capture the different levels of exposure to refugees across islands. We assign different weights proportional to the share of refugees in each island-year configuration using a weighted least square estimation. We also include γ_i and γ_t, which represent island and year fixed effects, respectively, to control for island- and year-specific unobserved heterogeneity that could affect violent behavior. ϵ_{it} is the error term. As an outcome variable, we use the different types of crime incidents committed by refugees and locals based on police and newspaper data, together and separately. We cluster standard errors at island level.

4.1.1 Parallel Time Trends

To enhance the credibility of our DiD estimation, we examine the existence of parallel trends, which is required for identification of the effects of interest. To do so, we compare mean crime rates between exposed and unexposed islands before the arrival of refugees in 2015. If the parallel trends assumption is violated, the difference in crime rates between exposed and unexposed islands after 2015 may not be fully attributable to the arrival of refugees.

Figure 1:
Time Trends of Total Crime



Note: Crime rates are shown for exposed islands (dashed line) and unexposed islands (solid line) separately. Total crime rate is measured per 100,000 total population.

Figure 1 provides evidence of the parallel trends assumption for total crime rates. We show that the pre-treatment trajectories of crime rates between exposed and unexposed islands before 2015 are similar, as indicated by the slopes of the time trends before 2015.

4.2 Instrumental Variable Methodology

The second empirical strategy also exploits the different intensity of refugees across islands depending on geographic proximity to the Turkish coast, but now uses a non-binary measure of treatment.

4.2.1 Naive OLS Specification

We discuss the naive specification first and then explain the underlying logic behind our instrument. To examine the naive relationship between exposure to different shares of refugees and crime incidents, we estimate the following regression specification:

$$Y_{it} = \beta_1 + \beta_2 ShareofRefugees_{it} + \gamma_i + \gamma_t + \epsilon_{it}, \tag{2}$$

where Y_{it} measures the crime incidents in island i and year t. We control for island-specific factors that affect crime and remain constant over time by including a full set of island fixed effects. We also include year fixed effects to control for unobserved heterogeneity at year level. We cluster standard errors at island level to allow for nonzero covariance of the error term within each island. The main coefficient of interest is β_2 and indicates how exposure to refugees affects crime incidents. Estimating this equation with OLS would yield biased estimates, since the share of refugees is an endogenous variable.

In a general setting, the OLS estimates in specification (2) are likely to be biased for several reasons. One potential concern could be the self-selection of migrants in specific areas, which could cause endogeneity in migrants' settlement patterns. For example, migrants may choose to locate on islands that are larger and densely populated—and thus might have a higher crime growth rate—because these islands might offer better employment prospects. This would bias OLS estimates upward. Or they may choose to locate on islands that are small and less urbanized—and might have a low crime growth rate—because housing prices are more affordable on those islands. This would bias OLS estimates downward. Another concern could be omitted variables that are likely to affect both migration and crime, such as a change in unobservable economic factors or the police force on one island. Better economic factors on one island increase job market opportunities for refugees, and thus might render the island more appealing. Better economic factors might also reduce crime, because now there are jobs for everyone. Not being able to fully control for these economic factors will therefore bias conventional OLS estimates of the effects of migration on crime.[26]

Measurement error could bias the estimates and could occur for two reasons: First, there might be measurement error in the calculation of the number of refugees entering the country, since monitoring unofficial migrants entering the country from the sea could be challenging. Second, measurement error

[26] Another possible omitted factor is changes in the police and navy due to cuts or expansions in European funds, which are difficult to observe. Reduced police and navy force presence on an island might render it more accessible to refugees. At the same time, reduced police and navy protection increases crime incidents, and this introduces bias in our estimates.

could come from crime incidents that were never reported. Both threats could bias conventional OLS estimates. Nevertheless, we deal with these by exploiting exogenous variation in refugees' exposure across islands over time, which is caused by political instability in neighboring counties.

4.2.2 Using Each Island's Distance from Turkey as an Instrument

To obtain a clean identification, we rely on an instrumental variable approach and use each island's distance from the Turkish coast interacted with time dummies as an instrument for the number of refugee arrivals.[27] Identification comes from the time-varying effect of geographic distance on migration, which reflects gradual changes in transportation and communication costs. The exclusion restriction requires that distance from the Turkish coast only affects the number of refugees who arrive to a given Greek island, but does not affect other variables that are likely to influence crime behavior on those islands.[28] To test whether the first-stage regression is sufficiently strong (Stock and Motohiro, 2005), we need to examine whether islands closer to the coast were indeed more likely to have received more refugees than those farther away. It is important to note that any factor that affects all refugees in a similar way, such as the outbreak of the civil war in Syria or expansion of the wars in Lebanon or Egypt, is captured by time fixed effects, and thus would not invalidate the identification strategy. Since the foreign-born population in unexposed islands acts as a control group, only factors that change at the same time as the number of refugees and exclusively affect the foreign-born population on exposed islands may be potential threats to the identification strategy.

We also use two instrumental variables that follow a logic similar to the IV methodology we explain above. Our first instrument for the share of refugees in each island uses the distance from the Turkish coast interacted with the stock of refugees in each year. Then, we follow the existing "shift-share" literature (Docquier, Turati, Valette, and Vasilakis, 2019; Ottaviano and Peri, 2005; Saiz, 2003; Card, 2001) and use the share of refugees in 2012 (the first year for which we observe data) in each island to attribute to each island the growth rate of its share in later years. Then we interact the distance from the Turkish coast with the predicted stock of refugees based on 2012. In particular, the instrument is the interaction

[27] This way, our instrument varies by island and year. A similar identification strategy was also used in Vasilakis (2018).

[28] In Appendix Table A.2 we show that there is no correlation between proximity from the Turkish coast and smuggling presence at island level. The outcome variable here is the share of smugglers out of the total population, and to derive this we divide the number of smugglers by the total population (natives and migrants). The variable of interest is distance from the Turkish coast. In column (1) we show that the estimated effect is small and statistically insignificant (estimated effect=-0,001, se=0.001) when no controls are added. The relationship between smuggling activity and distance from the Turkish coast remains very weak and statistically indistinguishable from zero when we add controls for island-specific income and island-specific unemployment in column 2 (estimated effect=-0,001, se=0.001). Robust standard error are used in these estimations. We use data on smuggling activity at island level for the year 2015, which we obtained from the Hellenic Port Police.

of a shift-share IV (predicted stock of refugees) with the distance of each island from the Turkish coast. To construct the predicted stock of refugees in each island, we use the following strategy. First, we run a regression of the stock of refugees in each island in 2012 against the distance of each island from the Turkish coast and predict the 2012 stock of refugees. These predicted refugee stocks are less likely to be affected by island-specific economic indicators. We then use the share of the population (share of refugees and natives) who live on each island i in 2012 to calculate ϕ_i:

$$\phi_i = \Big(Nat_{i,2012} + Stock_{i,2012}\Big) \Big/ \Big(\sum_i (Nat_{i,2012} + Stock_{i,2012})\Big), \tag{3}$$

where $Nat_{i,2012}$ is the number of Greek natives and $Stock_{i,2012}$ is the number of refugees who live in island i in year 2012. Once we have calculated ϕ_i, we use the equation below to calculate the predicted stock of refugees in time t:

$$\widehat{Stock}_{i,t} = Stock_{i,2012} + \phi_i(Stock_t - Stock_{2012}), \tag{4}$$

where $Stock_{i,t}$ is the stock of refugees who reside in island i in year t. Finally, we use the predicted stock of refugees $\widehat{Stock}_{i,t}$ interacted with the distance of each island from the Turkish Coast as in instrumental variable.

The DiD and IV identification strategies are considered to be complementary. We believe the DiD strategy might be more efficient, and identifies the average treatment effect for the exposed islands. We show later that crime rates are identical in exposed and unexposed islands in the absence of the treatment. In contrast, the IV strategy holds many potential confounders constant by design, but relies on the exclusion restriction (Angrist, Guido, and Donald, 1996)—namely, the assumption that proximity to the Turkish coast does not affect crime incidents in any other way. We provide evidence later to support the claim that there are no confounding factors that could invalidate our identification strategies.[29] In general, one worry might be that islands with more refugees from a particular ethnicity attract more refugees of the same ethnicity. If refugees from a specific ethnicity are more violent than others, then crime activity would increase on this island simply because there are many refugees from this ethnicity on the island. If refugees were selecting their destination route based on preexisting same-ethnicity immigrants' settlement patterns or on preexisting crime rates in the destination region, that would bias our estimates. However,

[29] An alternative identification method would be to compare crime rates within the number of exposed islands. In particular, we would exploit the random component in refugee arrivals generated by the geographic closeness of the islands to the Turkish coast to compare islands with many and only few refugee arrivals. The limitation with this approach is that we end up with few observations and not enough statistical power.

the institutional setting here avoids such a threat. In other words, the nature of their trip is such that it does not allow asylum seekers to be selective. Refugees simply jumped into boats that departed from various locations along the Turkish coast and headed to the closest Greek island, depending on weather conditions (waves, wind, etc.). This makes it highly likely that refugees have no impact on which island they are going to end up on, and that renders the destination island a random outcome.[30]

We show evidence to support our findings using two placebo exercises. The first reassures us that unexposed islands provide credible counterfactuals for exposed islands. For this, we select an alternate group of islands to examine whether the foreign-born and native populations on these islands exhibit criminal activity similar to that on the exposed islands. In the second placebo exercise, we consider whether there were preexisting trends in the different crime incidents. In particular, we show that pre-exposure trends in criminal behavior for exposed and unexposed islands are identical.

5 Results

We start by examining the impact of refugees' presence on Greek islands on total crime rates using our DiD specification and the official police data. Table 3 presents estimates for specification (1). In column 1, the average treatment effect is estimated to be 1.73, which indicates that total crime rates increased by approximately 1.73 percentage points in the exposed islands relative to the unexposed islands. We also include time and island fixed effects. The coefficient estimate is statistically significant at the 1% significance level. Consequently, the presence of asylum seekers on Greek islands stimulated a considerable increase in the total crime rate. Next, we classify the total crime rate into different forms: personal robberies (or knife attacks); vehicle theft; other types of crime, such as protests or property damage; property robberies; drug-related crimes; and rape. We replace the outcome variable of total crime with each of the subcategories of crime and rerun the regression. Estimated effects are reported in Table 3 in columns 2-7. The choice of crimes we include is motivated by recent findings in the literature (Dehos, 2017; Spenkuch, 2013).

[30] We provide further evidence to support this hypothesis. First, Table 2 shows that exposed and unexposed islands have similar economic indicators, size and native population. This renders exposed and unexposed islands relatively comparable. Second, we examine whether refugees are more likely to end up on richer islands or islands in which the unemployment rate is low, or simply on the closest islands to the Turkish coast. In Table A.1 we show that economic conditions are similar betweens exposed and unexposed islands using OLS (column 1) and probit (column 2). Island-specific economic conditions do not drive refugees into specific destination islands. In particular, we show that refugees end up on islands that are closer to the Turkish coast, and there are no statistically significant differences in island unemployment rates and income levels between destination islands and unexposed islands. The only statistically significant variable that affects refugees' destination is distance from the Turkish coast. A similar exercise is used by McGowan and Vasilakis (2019) and Danisewicz, McGowan, Onali, and Schaeck (2017) to show that economic conditions are similar between treatment and control groups.

Column 2 shows DiD estimates of the effects of exposure to refugees on personal robberies (or knife attack rates). We find that the interaction of the *Post* dummy and *Treatment* is statistically significant at the 1% level, which demonstrates that the personal robberies rate increased by approximately 0.67 percentage points in the treatment group relative to the counterfactual group. Similar estimates appear to exist for the other types of crime, such as vehicle theft (see column 3); other types of crime such as protests/property damage (column 4); property robberies (column 5); drug-related crimes (column 6); and rape (column 7).[31] All estimates (but one) are positive in columns 2-7. The largest coefficients of the interaction term between the post dummy and the island exposed group are for personal and property robberies (columns 2 and 5). In contrast, we find a zero relationship between refugees and drug-related crimes, which is not statistically distinguishable from zero (column 6). Evidence in the literature suggests that exposure to refugees does not have a statistically significant effect on drug-related crimes (Dehos, 2017).

The data allows us to distinguish crimes based on whether they are committed by the foreign-born population (refugees) or natives. Table 4 presents estimates for the different crime types committed by the foreign-born population (Panel A) and natives (Panel B). We notice that the estimated effects in Panel A reveal that there is a substantial increase in crime committed by the foreign-born population being hosted on Greek islands. Coefficients of the interaction terms appear to be positive and statistically significant for all types of crime except drug-related crimes. This pattern is similar to the pattern in the main results shown in Table 3. The magnitude of the interaction terms in Table 4 is very similar to the magnitude of the interaction terms in Table 3, in which we present our main estimates. For instance, the interaction term for the total crime rate is now equal to 1.298 (se=0.200), while in Table 3 it was equal to 1.733 (se=0.439). This result is different from prior studies, in which regions exposed to refugees or immigrants do not have a higher likelihood of experiencing an increase in the crime rate (Nowrasteh, A., 2018; Huang and Kvasnicka, 2019; Hines and Peri, 2019; Masterson and Yasenov, 2019). In contrast, in Table 4 Panel B, we find that there is not a statistically significant difference in crimes committed by natives between exposed and unexposed islands before and after 2015. Coefficients of the interaction terms are much smaller, close to zero for most types of crime, and not significantly different from zero.

This main analysis is conducted using official police data. We also replicate our DiD analysis using the newspaper data instead. As explained in Section 3.1, we collected information on crimes committed on the islands from several daily and weekly newspapers. Each incident in our data is assigned the same

[31] Dehos (2017) finds that high exposure to refugees increases robbery rates in Germany.

weight, no matter how severe the crime or the number of perpetrators. We provide evidence that the two datasets are highly correlated in Tables A.3 and A.4, where we show that Pearson correlations between the two measures (one reported by the police and the other by newspapers) for the same type of crime are quite high (above 0.9 in many cases). We also show that this is the case across most types of crime.

In Table A.5 we repeat our main analysis, but now we use newspaper data instead of official police data. We find that coefficients of the interaction terms between Post and Treatment across different columns are positive and statistically significant for all types of crimes committed by the foreign-born population except for personal robberies. These estimates are close in magnitude to the estimates reported in Table 4. In particular, the coefficient of the interaction term for total crime is now 1.737 (se=0.282), but was 1.298 (se=0.200) in Table 4. In line with the evidence provided in Table 4, there is no impact on crimes committed by natives. It is worth noting that there is no statistically significant difference in drug-related crimes between exposed and unexposed islands before or after 2015. This result is consistent with the findings reported in Table 4.

Our estimates are comparable to those found in other studies, although our estimated effects are on the upper bound. This could be explained by the institutional characteristics of those countries and the agreements with refugees' origin countries, as well as local economic conditions in destination counties. The most closely related studies are probably those that examine the impact of the same refugee crisis on crime in Germany or Turkey (Akbulut-Yuksel, Mocan, Tumen, and Turan, 2022; Dehos, 2017). Both studies find a positive association between the influx of refugees and crime incidents.[32] Akbulut-Yuksel, Mocan, Tumen, and Turan (2022) study the impact of refugees in Turkey and find that a 1-percentage-point increase in the share of refugees increases crime by 0.6-1.3 percentage points. This is a smaller magnitude than ours; we find that a 1-percentage-point increase in the share of refugees increases crime by 1.7-2.5 percentage points. This could be explained by several reasons, including the fact that Turkey and Syria signed an agreement that gave refugees access to public health, public education, and social protection early on, which could lead to lower motivation to commit crime. Our estimated effect is also larger than the effect found in Germany, where a 1 % increase in the share of recognized refugees is found to be associated with a 3% increase in crime (Dehos, 2017). In our study, we find that an 1 percent increase in the share of refugees on the destination island increases crime incidents by 5%-9% compared with neighboring unexposed islands.

[32] Turkey shares a land border with some of the origin countries of refugees, and thus received a massive influx of refugees. Germany also received a large number of refugees (the most in Europe), as one of the few countries in Europe that had the financial and administrative resources to deal with these large numbers of newcomers.

Several reasons could explain why the impact in the case of Greece is higher than in other countries. For instance, local market conditions in Greece were not particularly good during the period the migration flow occurred; which was just after the end of a prolonged and severe financial crisis. The unemployment rate was very high, even for locals, during the study period and local governments were unable to fully support refugees despite financial aid from the European Union. Refugees in Greece had limited access to formal employment while their asylum applications were being examined, and they faced mobility restrictions. Limited labor market opportunities for asylum seekers could explain our findings, and policies that improve their attachment to the labor market may also reduce crime. Our findings highlight the need for government provision in terms of infrastructure, social benefits, quicker examination of asylum applications, and social security.

5.1 Placebo Exercises

To further test whether our identification assumptions and main DiD results are robust, we conducted an extensive battery of placebo exercises. The first shows that in the pre-refugee period, time trends in crime rates for exposed and unexposed islands are identical. In this test, we use only pre-2015 data and show that there are no changes in crime rates between exposed and unexposed islands in the absence of the treatment. The second placebo exercise shows that there are no confounding factors that could have affected crime rates. We find this by looking at a complex of islands that belong to the same geographic and electoral unit and have the same characteristics, but are a few miles farther from the Turkish coast than the exposed islands. These are necessary conditions for the validity of our assumption that the arrival of refugees resembles an exogenous shock to crime rates on Greek islands.

5.1.1 Pre-exposure Years

To provide additional evidence in support of the parallel trends assumption, we use data only for years 2012, 2013, and 2014. We create a placebo treatment in 2014, which we call *Placebo Post*. This dummy indicator takes the value 1 in 2014 and 0 in 2013 and 2012. This does not indicate real exposure to refugees, but it does capture changes in crime rates between exposed and unexposed islands in the pre-exposure period. We then re-estimate equation (1), but we use data only for the period before refugees arrived on Greek islands. Interacting this Placebo Post dummy for 2014 and the original Treatment variable allows us to test whether there are differential time trends in different types of crime in the pre-refugee period.

In Table 5, we report DiD estimates for crimes committed by the foreign-born population (Panel A) and natives (Panel B) in the pre-refugee period (prior to 2015). We notice that all interaction terms are small—practically zero and statistically insignificant. This implies that there are no differences in crime rates for the foreign-born population between exposed and unexposed islands in the years before 2015. We therefore conclude that there is no evidence that trends in crime were different between exposed and unexposed islands before refugees arrived in Greece. The implication of this evidence is that in the pre-exposure period, time trends in crime rates between exposed and unexposed islands were identical. This provides additional validity for our identification strategy. The pattern is similar in Panel B, which further reassures us that crime rates across exposed and unexposed islands for natives were identical in the absence of refugees.

5.1.2 Placebo Islands

Next, we examine the robustness of our results to alternative definitions of treatment status. The idea here is to investigate whether other potential reasons that are not related to the arrival of refugees could affect the different types of crimes. To investigate this, we focus on a neighboring group of islands that are in the same electoral and administrative district as the exposed islands. These islands are in the Aegean Sea and are located a few miles farther from the Turkish coast and closer to mainland Greece. This complex of islands is called *Cyclades*.[33]

We create a dummy we call "Placebo Treatment," which takes the value 1 if the island belongs to this neighboring complex and 0 for all other islands. Table 6 shows DiD estimates based on equation (1) for the different crime incidents committed by foreign-born (Panel A) and natives (Panel B) for the placebo treatment islands of Cyclades compared with the unexposed islands. Panels A and B report estimates of the effect of exposure to the foreign-born population on the different types of crime committed by the foreign-born population and natives, respectively. For all interaction terms the estimates are small—close to zero and statistically insignificant. These findings provide further support for our hypothesis that there are no other confounding factors that could affect crime rates on the treatment islands compared with others. Taking into account the estimates in Table 6, we conclude that the influx of refugees on exposed islands is the main determinant of the increase in crime rates on the exposed islands compared with the unexposed islands.

[33]The following islands are included: Amorgos, Anafi, Andros, Antiparos, Delos, Ios, Kea, Kimolos, Kythnos, Milos, Mykonos, Naxos, Paros, Folegandros, Serifos, Sifnos, Sikinos, Syros, Tinos, Santorini, Donousa, Eschati, Gyaros, Irakleia, Koufonisia, Makronisos, Rineia, and Schoinousa. Smaller islands are also included in Cyclades, but they are uninhabited.

5.2 IV methodologies

The IV approach has frequently been used in the migration literature (Saiz, 2007; Bell, Machin, and Fasani, 2013; Gonzalez and Ortega, 2011; Tabellini, 2020), in which the share of refugees is often considered to be an endogenous variable. This is likely if unobserved factors are expected to affect both the share of refugees and crime incidents. In some settings, we might expect OLS estimates to be downwardly biased if, for instance, refugees tend to prefer islands with lower unemployment rates (better job opportunities); islands with lower unemployment rates might be more developed and thus less prone to crime. In other settings, we might expect OLS estimates to be upwardly biased if, for instance, refugees tend to prefer islands with a higher income level that might be more populated, and thus more prone to crime. Our OLS estimates are presented in Table A.6. In Panel A, we examine crimes committed by both natives and refugees. We find that an increase of 1 percentage point in the share of refugees is associated with an increase in the percentage of total crime, personal robberies, vehicle theft, other crimes, property robberies, and rape by 4.57, 2.13, 0.50, 0.67, 1.11, and 0.19 percentage points on average, respectively. The effect on drug-related crimes is still practically zero and statistically insignificant. In Panel B, we focus on crimes committed by refugees and find a pattern similar to that for DiD estimates. In particular, an increase in the share of refugees increases crimes committed by refugees, whereas in Panel C we show that crime rates committed by natives remain insensitive to changes in the share of refugees. For instance, the interaction term when the outcome is total crime in Panel A is 4.566 (se=1.506) and is very close to 4.371 (se=1.1464) in Panel B, while it drops to 0.195 (se=0.153) in Panel C.

To alleviate remaining concerns about endogeneity in the OLS specification, we present our IV estimates in Appendix Table A.7. We instrument the endogenous variable (i.e., share of refugees) with the interaction term between the distance of islands from the closest Turkish border and year dummies, which conceptually satisfies the exclusion restriction. For our first stage to be strong, islands that are closer to the Turkish coast are expected to receive a higher number of refugees after 2015 compared with islands that are far from the Turkish coast. We report the F-statistic for the related first-stage regression at the bottom of this table. A common concern in IV estimation is bias due to weak instruments, as highlighted by Stock, Wright, and Yogo (2002), and Bound, Jaeger, and Baker (1995). In this regression, there is one endogenous variable (i.e., share of refugees) and four instrumental variables (i.e., distance from the Turkish coast interacted with the four time dummies.). Our F-statistic for the first stage (13.56) clearly exceeds the critical value, so it allows us to limit potential weak-instrument concerns.[34]

[34] Staiger and Stock (1997) suggest that the rule of thumb to avoid a weak IV issue when there is a single endogenous

The impact of the presence of refugees on crime rates is large and statistically different from zero, as suggested by the IV estimates in Appendix Table A.7. This indicates slight downward bias in the OLS estimates (in Table A.6) in five of the six significant estimates. This finding highlights the fact that of the sources of bias, those that cause attenuation bias, such as measurement error and/or reverse causality, are likely to play a role. For property crimes, the OLS estimate is larger than the IV estimate. In Appendix Table A.7 we find that an increase of 1 percentage point in the share of refugees is associated with an increase in the percentage of total crime, personal robberies, vehicle theft, other crimes, and rape by 4.99, 2.94, 0.73, 0.90, and 0.29 percentage points on average, respectively. This pattern is very similar to that in Table 3, in which we applied a DiD identification approach. The estimate for drug-related crime is negative and remains statistically insignificant, while the estimate for property crimes is now imprecise. Thus, exposure to refugees seems to persistently affect personal robberies, vehicle theft, and rape, but does not seem to affect drug-related crime rates.

Next, we look at the effects of exposure to refugees on crimes committed by the foreign-born population and native population separately, using the same IV approach as in Table A.7. We report these IV estimates in Appendix Table A.8. In particular, we report estimates for the effect of the share of refugees on the different types of crime committed by refugees (Panel A) and natives (Panel B). The pattern is the same as before: The increase in crime incidents is driven by crimes committed by refugees, while there is no change in the crimes committed by natives. In particular, in Panel A, all estimated effects are positive and statistically significant, except for drug-related crimes. A 1-percentage-point increase in the share of refugees leads to an increase in the percentage of total crime, personal robberies, vehicle theft, other crimes, property crimes, and rape by 5.97, 2.53, 0.62, 1.04, 1.52, and 0.28 percentage points on average, respectively. The overall effect is clearly driven by crimes committed by refugees. Panel B indicates that the crime rates committed by natives do not follow a different pattern between exposed and unexposed islands when we instrument the share of refugees with proximity to the Turkish coast interacted with time dummies, consistent with DiD results.

We then turn to additional IV methodologies. Tables A.9 and A.10 show the estimated effects when our instrument is the distance from the Turkish coast interacted with the actual stock of refugees in each year and island. The endogenous variable is the share of refugees in each year and island. Table A.9 presents estimated effects on crime committed by both refugees and natives. The pattern remains similar

variable is that the first-stage F-statistic must be greater than 10. Also, when there is one endogenous variable and four instruments, the critical value for the relative bias weak instrument test with b=0.1 is 10.27 at a 5% significance level (Stock and Yogo, 2005).

to previous IV estimates and there is a positive association between the share of refugees and crime. In particular, an increase of 1-percentage-point in the share of refugees increases total crime, personal robberies, vehicle theft, other crimes, property crimes, and rape by 1.5, 0.68, 0.13, 0.22, 0.39, and 0.07 percentage points on average, respectively. In Table A.10 we report estimates for the impact of refugees on crime committed by refugees (Panel A) and natives (Panel B). Consistent to findings in previous tables, these positive associations between presence of refugees and crime are driven by crimes committed by refugees, as shown in Panel A, Table A.10. Crimes committed by natives remain similar in the exposed compared with unexposed islands across periods (Panel B).

We then present additional estimation results in which we interact the distance from the Turkish coast of each island with a shift-share IV (using the predicted refugee stocks in 2012), which we discuss in Section 4.2.2. The endogenous variable is the share of refugees in each island and year. In Table 7 we report the first-stage estimate. Consistent with our understanding of the institutional setting, we observe a strong relationship between distance from the Turkish coast and the share of refugees in a Greek island. This relationship is strong and also statistically significant, with an F-statistic above 80; this indicates that the estimates do not suffer from a weak instrument problem.[35] In Tables 8 and 9 we show similar estimation results using the shift-share IV that relies on the predicted stock of migrants based on 2012 (Saiz, 2007; Bell, Machin, and Fasani, 2013; Gonzalez and Ortega, 2011; Tabellini, 2020; Docquier, Turati, Valette, and Vasilakis, 2019), and our findings point in the same direction as before: an increase of 1 percentage point in the share of refugees increases total crime, personal robberies, vehicle theft, other crimes, property crimes, and rape by 2.56, 1.15, 0.23, 0.36, 0.68, and 0.11 percentage points on average, respectively. We also find that the increase in crime incidents is driven by crimes committed by refugees (Panel A in Table 9) and not by natives (Panel B in Table 9). All these different methodologies yield similar results.

5.3 Robustness Exercise

In Table A.13 we report the main estimates using an IV approach, but now we use newspaper data instead of official police data. Estimates are very similar to the main results we obtained when we used

[35]For completeness, we also use the same methodology in our DiD specification (1) discussed in Section 4.1. In particular, we interact the distance from the Turkish coast for each island with a shift-share IV (using the predicted stocks); the endogenous variable is no continuous, but it is binary instead. We show the estimated effects in Tables A.11 and A.12. Table A.11 shows the impact of exposure to refugees on crime rates. All estimated coefficients (except one) are positive and statistically significant at 1% level, which indicates a positive relationship between exposure to refugees and crime activity. In Table A.12 we split the crimes into those committed by refugees and by natives (in Panels A and B), and find the same pattern as before—i.e., the increase in crime activity is driven by crimes committed by refugees; there is no impact on the crimes committed by natives.

official police data in Table A.8. The effects on crime seem to also be considerable when the newspaper data are used. In particular, a 1-percentage-point increase in the share of refugees yields an increase in the total crime rate by 8.71 percentage points (Panel A, Table A.13) instead of 5.96 percentage points (Panel A, Table A.8). This pattern is the same for other types of crime, except property crime which has an imprecise estimated coefficient in Table A.13. Drug-related crimes do not seem to be affected by the arrival of refugees, and this finding is consistent across specifications and different identification strategies. The arrival of refugees does not seem to affect crimes committed by natives, regardless of which dataset we use. These IV results follow the same pattern as the DiD results in Table 4. The conclusions drawn using the IV approach are very similar to those drawn using the DiD approach.

We also replicate our main results using data on reported crime instead of data on arrested offenders as the outcome variable and present these results in Tables A.14 and A.15. In Table A.14 we use a DiD methodology and obtain results in a pattern similar to the main analysis when arrest data were used as an outcome variable instead of reported crime data. Using reported crime data, we find that exposure to refugees increases total crime, personal robberies, vehicle theft, other crimes, and property robberies by 3.81, 0.54, 0.43, 0.52, and 2.26 percentage points on average, respectively. These results point in the same direction as the data on arrested offenders, which we used in the main analysis. For instance, the overall effect of exposure to refugees on total crime when arrest data were used was 1.733 (se=0.439, Table 3), but increases to 3.809 (se=1.487) when reported crime data are used.

In Table A.15 we reproduce the estimation results of Table 8, but the outcome variable is now crime incidents based on reported crime data instead of arrest data. Again, the pattern of the estimated results is the same as when we used arrest data. Using reported crime data, we find that an increase of 1 percentage point in the share of refugees increases total crime, personal robberies, vehicle theft, other crimes, and rape by 2.91, 0.92, 0.58, 0.95 and 0.65 percentage points on average, respectively. The pattern is similar to that when arrest data were used. For instance, the overall effect of exposure to refugees on total crime when arrest data were used was 2.559 (se=0.559, Table 8), but it increases to 2.908 (se=1.071) when reported crime data are used. The pattern across different types of crime is similar, except for drugs and property crime; The effect of refugees is imprecise and approximately zero when arrest data on drugs are used and negative when reported crime data are used. The effect on property robberies is of a similar magnitude, but it becomes imprecise when arrest data are used.

6 Conclusions

Understanding the impact of forced migration on crime is important. This relationship has attracted great attention in public debates as well as in the labor economics literature, although it is based on limited credible scientific evidence of the causal relationship between crime and immigration. In this paper, we exploit an exogenous increase in the foreign-born population in some islands in Greece. The civil war and terror in Syria, Iraq, and Afghanistan caused people to become fugitives. Refugees first reached Turkey, then crossed the Aegean Sea to seek asylum in European countries. Refugees typically used boats that departed from various locations along the Turkish coast, heading toward the closest Greek islands. Thus, this unprecedented refugee flow disproportionally affected Greek islands that neighbor Turkey. The 2015 agreement between Greece, the European Union, and Turkey forced the presence of refugees on Greek islands until a decision regarding their asylum applications could be made. This renders this natural experiment appropriate for studying the effect of exposure to refugees on crime incidents on those islands and tackling the endogeneity issues previous studies have faced.

To investigate our research questions, we construct a comprehensive dataset of crime activity committed by natives and the foreign-born population living on all inhabited Greek islands using official police data. We also construct a data set on crime rates by year, type, and island from newspapers. To the best of our knowledge, no similar dataset with comprehensive information on refugees and their criminal activities in Greece has been created or used. The two datasets are highly correlated. Greece provides an ideal setting to study these questions, since it is in the most southeastern corner of the European Union and is the country most affected by the refugee crisis.

We use two complementary empirical methods: difference-in-differences and instrumental variable approaches. The difference-in-differences approach compares crime rates across islands that received and hosted refugees with islands that did not receive and host refugees before and after 2015. The main idea is to exploit differences in exposure to refugees over time on islands closer to the Turkish coast (exposed islands) and islands farther from the Turkish coast (unexposed islands). We enhance the credibility of our identification strategy by showing the existence of common trends between exposed and unexposed islands. Then we exploit differences in the intensity of refugees across islands and over time and employ instrumental variables. We use time interacted with proximity from the Turkish border across islands as an instrumental variable. This relies on the assumption that distance from the Turkish coast had no effect on islands' crime incidents other than through its effect on the number of refugees who landed on a given island. We use two more instrumental variables. First, we interact the distance of each island from the Turkish coast with the overall number of refugees, then interact the distance of each island from the Turkish coast with a shift-share instrument. Our first stage relies on the assumption that the proximity of an island to the Turkish coast determines the degree of its exposure to refugees, since refugees are more likely to head to islands closer to the Turkish coast.

Both empirical methods point in the same direction: Islands that are exposed to a higher share of refugees exhibit an increase in crime activity (property theft, vehicle theft, personal robberies, and rape), while there is no effect on drug-related crimes. In particular, a 1-percentage-point increase in the share of refugees increases total crimes by 1.7 percentage points in the difference-in-differences specification and 2.5 percentage points in the instrumental variables specification. We also find that these results are driven by crimes committed by the foreign-born population and not natives.

We also conduct several placebo exercises to support the validity of our identification assumptions and main results. We first provide evidence that in the absence of refugees, exposed and unexposed islands exhibit the same trends in crime rates. Then we show that proximity to the Turkish coast is a significant determinant of refugees' exposure: When a different group of islands is used, the estimated effects do not exhibit the same pattern. Also, we show that our results hold for the case in which we use our newly constructed newspaper datasets and also when we use the official police data.

Our results highlight the need for policy measures that support better integration of refugees into society and attachment to the labor market. Our findings imply that more attention should be paid to potential localized crime risks involved in the concentrated dispersal policy adopted by the government and migration authorities. Improving the limited labor market opportunities for asylum seekers may in turn reduce crime. To better integrate refugees into society, it might be beneficial for the government to provide language courses and job training. Such an approach could significantly tilt the labor market opportunities of migrants relative to illegal activities.

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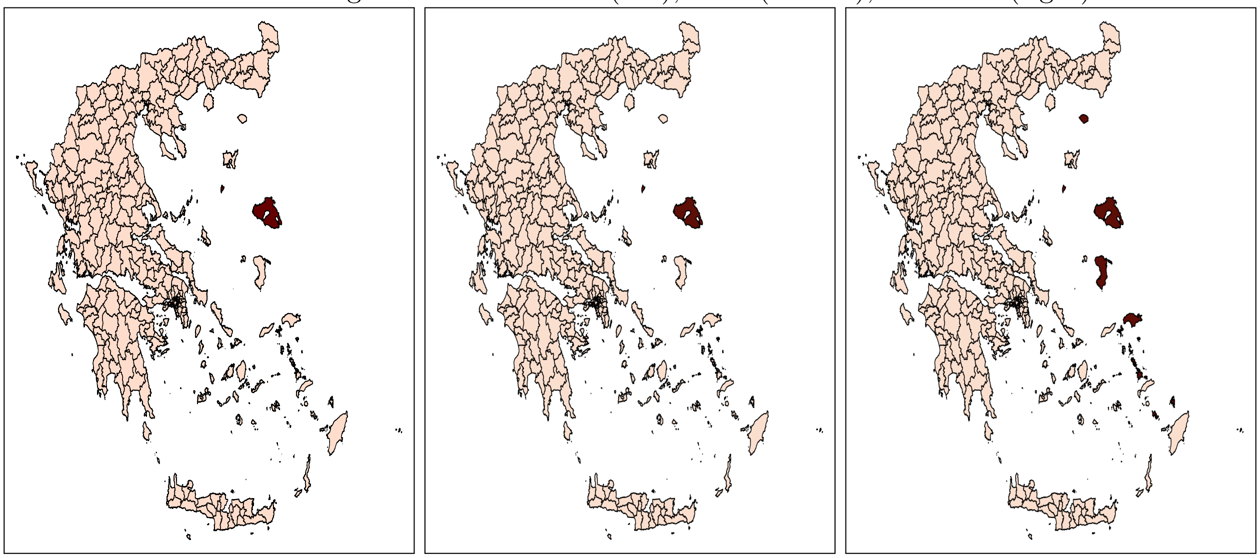
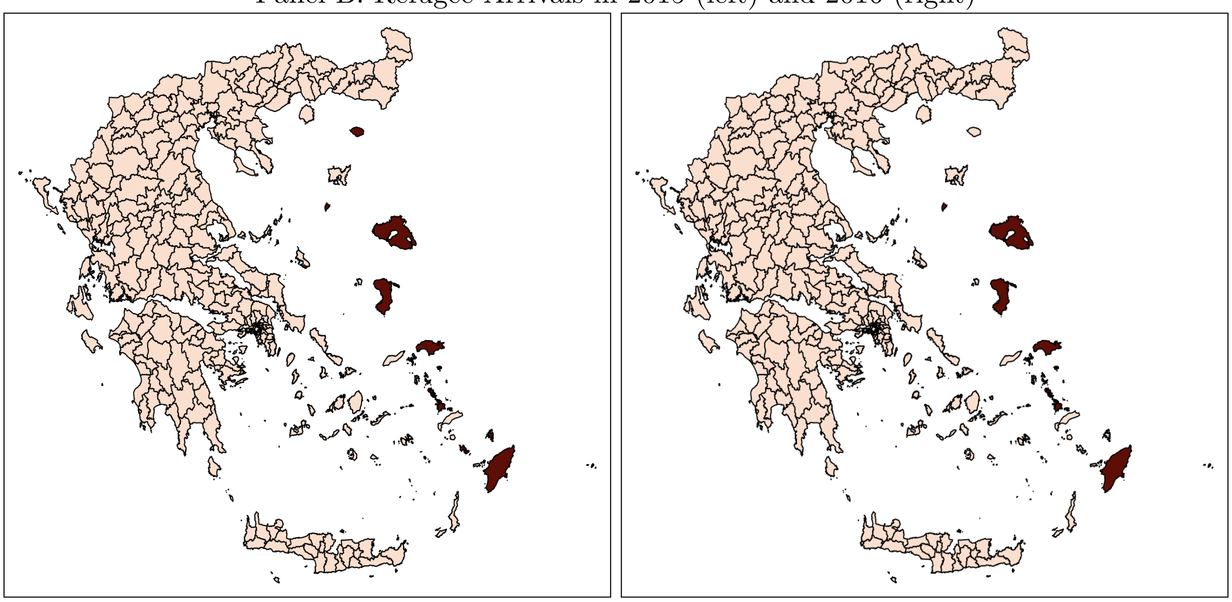
Figure 2: Annual Arrival of Refugees to Greek islands in 2012-2016

Panel A: Refugee Arrivals in 2012 (left), 2013 (middle), and 2014 (right)



Panel B: Refugee Arrivals in 2015 (left) and 2016 (right)



Note: This is the map of Greece. Each bounded area represents a county. Greece is bordered to the east by Turkey. The map shows refugee arrivals in 2012 (top left), 2013 (top middle), 2014 (top right), 2015 (bottom left), and 2016 (bottom right). Higher intensity of refugees is indicated by darker color. Refugees cross the Aegean Sea to land on Greek islands from Turkey. The closest islands to the Turkish coast are those in the Dodecanese Archipelago, but also large outcrops such as Chios, Samos, and Lesvos. These eastern islands are more exposed to refugees over time, as indicated by the intensity of refugee arrivals. The level of exposure increased dramatically between 2014 and 2015, as indicated by the intensity of the islands that are dark. The southern and western islands seem to be unaffected by refugee arrivals across all years.

Table 1: Summary Statistics

	Mean	Std. Dev.	Min.	Max.
	(1)	(2)	(3)	(4)
Number of Refugees	193.144	1613.050	0	28684
Population of Natives	15827.931	70523.812	1	682900
Island Size	232.867	893.266	0.355	8336
Share of Refugees	0.009	0.066	0	0.980
Personal Robberies				
Personal Roberries Rate for Natives (police)	0.074	0.446	0	6.667
Personal Roberries Rate for Refugees (police)	0.097	0.399	0	6.822
Personal Roberries Rate for Natives (newspaper)	0.003	0.018	0	0.179
Personal Roberries Rate for Refugees (newspaper)	0.079	0.280	0	3.232
Vehicle Theft				
Vehicle Theft for Natives (police)	0.017	0.111	0	1.818
Vehicle Theft for Refugees (police)	0.019	0.092	0	1.795
Vehicle Theft for Natives (newspaper)	0.010	0.059	0	0.909
Vehicle Theft for Refugees (newspaper)	0.020	0.106	0	2.154
Other Crimes				
Other Types of Crime Rate for Natives (police)	0.041	0.130	0	1.333
Other Types of Crime Rate for Refugees (police)	0.031	0.159	0	3.232
Other Types of Crime Rate for Natives (newspaper)	0.018	0.073	0	0.935
Other Types of Crime Rate for Refugees (newspaper)	0.034	0.169	0	3.232
Property Robberies				
Roberries Rate for Natives (police)	0.097	0.383	0	4.651
Roberries Rate for Refugees (police)	0.037	0.236	0	5.027
Roberries Rate for Natives (newspaper)	0.051	0.200	0	2.326
Roberries Rate for Refugees (newspaper)	0.082	0.905	0	19.390
Drugs Crimes				
Drugs Rate for Natives (police)	0.075	0.171	0	1.333
Drugs Rate for Refugees (police)	0.018	0.085	0	1.068
Drugs Rate for Natives (newspaper)	0.049	0.198	0	2.326
Drugs Rate for Refugees (newspaper)	0.012	0.034	0	0.287
Rapes				
Rape Rate for Natives (police)	0.001	0.006	0	0.064
Rape Rate for Refugees (police)	0.004	0.035	0	0.718
Rape Rate for Natives (newspaper)	0.016	0.168	0	3.333
Rape Rate for Refugees (newspaper)	0.006	0.046	0	0.718

Note: We use annual data for all (=107) inhabited Greek islands in the period between 2012 and 2016. The number of observations is 535 (5 years of data, 107 islands in each year). For each type of crime, two measures are used: (a) official police rates for each type of crime, and (b) those derived from newspapers. Island size is measured in km^2. Crime rates are per 100,000 total population.

Table 2: Balancing Tests Between Exposed and Unexposed Islands

	(1) Exposed Islands Mean s.d.	(2) Unexposed Islands Mean s.d.	(3) Difference (1)-(2) s.e.
Island Characteristics			
Unemployment Rate (%)	23.149	18.335	4.814
	7.877	9.940	2.514
P-value			0.056
Log Income (in Euro)	6.359	6.298	0.061
	0.440	0.353	0.091
P-value			0.504
Population of Natives	28325.312	15442.655	12882.657
	28209.818	71408.797	17908.752
P-value			0.472
Island Size	428.939	226.823	202.116
	546.681	901.495	226.776
P-value			0.373
Distance and Share of Refugees			
Log-Distance from Turkish Coast	1.507	4.934	-3.426
	1.595	1.456	0.371
P-value			0.000
Share of Refugees	0.263	0.001	0.262
	0.284	0.010	0.012
P-value			0.000

Note: Columns (1) and (2) show the means and standard deviations for the available variables in exposed and unexposed islands, respectively. Column (3) shows the differences between the means of exposed islands and means of unexposed islands and corresponding standard errors in parentheses. Island characteristics include island-specific economic performance indexes (unemployment rate and log income), island-specific native population, and island-specific size. We also report the P-value for the difference between columns (1) and (2).

Table 3: Impact of Exposure to Refugees on Crime Rates, Difference-in-Differences

	Total Crime	Personal Robberies	Vehicle Theft	Other Types	Property Robberies	Drugs Crimes	Rape
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post x Treatment	1.733	0.666	0.181	0.282	0.531	0.000	0.055
	(0.439)***	(0.282)**	(0.073)**	(0.077)***	(0.187)***	(0.034)	(0.010)***
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓

Notes: We use a weighted least square and the weighting is proportional to the share of refugees in each island-year configuration. Rates for the different types of crimes are used as outcome variables. Official data reported by police are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4: Impact of Exposure to Refugees on Crime Committed by Refugees (Panel A) and Natives (Panel B), Difference-in-Differences

	(1) Total Crime	(2) Personal Robberies	(3) Vehicle Theft	(4) Other Types	(5) Property Robberies	(6) Drugs Crimes	(7) Rape
	Panel A: Different Types of Crime Committed by Refugees						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post x Treatment	1.298	0.466	0.159	0.231	0.411	-0.018	0.052
	(0.200)***	(0.089)***	(0.022)***	(0.036)***	(0.050)***	(0.013)	(0.008)***
	Panel B: Different Types of Crime Committed by Natives						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post x Treatment	0.122	0.058	0.018	-0.000	0.025	0.020	-0.000
	(0.154)	(0.108)	(0.038)	(0.027)	(0.074)	(0.032)	(0.002)
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓

Note: We use a weighted least square and the weighting is proportional to the share of refugees in each island-year configuration. Difference-in-differences estimates of the effect of exposure to refugees on crimes committed by refugees and natives are presented in Panels A and B, respectively. Rates for the different types of crimes are used as outcome variables. Official data reported by police are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Table 5: Placebo Exercise: Impact of Refugees in the Absence of the Treatment (Before 2015) on Crime committed by Refugees (Panel A) and Natives (Panel B), Difference-in-Differences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total Crime	Personal Robberies	Vehicle Theft	Other Types	Property Robberies	Drugs Crimes	Rape
	Panel A: Different Types of Crime Committed by Refugees						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Placebo Post x Treatment	0.00016	-0.00002	-0.00000	-0.00000	0.00005	0.00013	-0.00000
	(0.00155)	(0.00017)	(0.00002)	(0.00004)	(0.00049)	(0.00139)	(0.00000)
	Panel B: Different Types of Crime Committed by Natives						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Placebo Post x Treatment	-0.00005	-0.00003	-0.00000	-0.00000	-0.00000	0.00001	-0.00003
	(0.00039)	(0.00031)	(0.00001)	(0.00001)	(0.00001)	(0.00009)	(0.00020)
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓

Note: We use a weighted least square and the weighting is proportional to the share of refugees in each island-year configuration. Placebo effects of difference-in-differences DiD estimates of the effects of exposure to refugees on crime rates committed by refugees and natives are presented in Panels A and B, respectively. For this table, we use only pre-exposure data, namely, for years 2012, 2013 and 2014. The variable "Placebo Post" takes the value 1 in 2014, and 0 in 2013, and 2012. Rates for the different types of crimes are used as outcome variables. Official data reported by police are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 6: Placebo Exercise: Impact of Refugees in Placebo Islands (Cyclades) on Crime Committed by Refugees (Panel A) and Natives (Panel B), Difference-in-Differences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total Crime	Personal Robberies	Vehicle Theft	Other Types	Property Robberies	Drugs Crimes	Rape
	Panel A: Different Types of Crime Committed by Refugees						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post x Placebo Treatment	-0.01408	-0.00476	-0.00156	-0.00353	-0.00342	0.00071	-0.00079
	(0.08703)	(0.03632)	(0.00977)	(0.01786)	(0.02279)	(0.01187)	(0.00329)
	Panel B: Different Types of Crime Committed by Natives						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post x Placebo Treatment	0.05722	0.06043	-0.02115	0.01142	0.04028	-0.03523	0.00164
	(0.21246)	(0.15016)	(0.03649)	(0.03689)	(0.10276)	(0.04385)	(0.00203)
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓

Notes: The placebo treatment group includes a group of islands in Cyclades. Panel A reports crime rates committed by the foreign-born population and Panel B reports crime rates committed by the native population. Rates for the different types of crimes are used as outcome variables. Data collected from newspaper reports are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property roberries, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 7: Firs-Stage, Shift-Share IV Estimates

	First Stage Share of Refugees
	(1)
Distance x Predicted Refugee Arrivals	1.893
	(0.289)***
Time FE	✓
Island FE	✓
F-statistics First Stage	86.67
Observations	535

Note: This shift-share IV methodology uses the predicted stock of refugees in each year and island (based on 2012) interacted with distance from the Turkish coast. This table presents the first-stage estimate. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 8: Impact of Exposure to Refugees on Crime Rates, Shift-Share IV Estimates

	Total Crime	Personal Robberies	Vehicle Theft	Other Types	Property Robberies	Drugs Crimes	Rape
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of Refugees	2.559	1.145	0.233	0.363	0.679	0.026	0.112
	(0.559)***	(0.187)***	(0.062)***	(0.127)***	(0.203)***	(0.033)	(0.016)***
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓
F-statistics First Stage	86.67	86.67	886.67	86.67	86.67	86.67	86.67
Observations	535	535	535	535	535	535	535

Note: This shift-share IV methodology uses the predicted stock of refugees in each year and island (based on 2012) interacted with distance from the Turkish coast. Rates for the different types of crimes are used as outcome variables. Official data reported by police are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 9: Impact of Exposure to Refugees on Crime Committed by Refugees (Panel A) and Natives (Panel B), Shift-Share IV Estimates

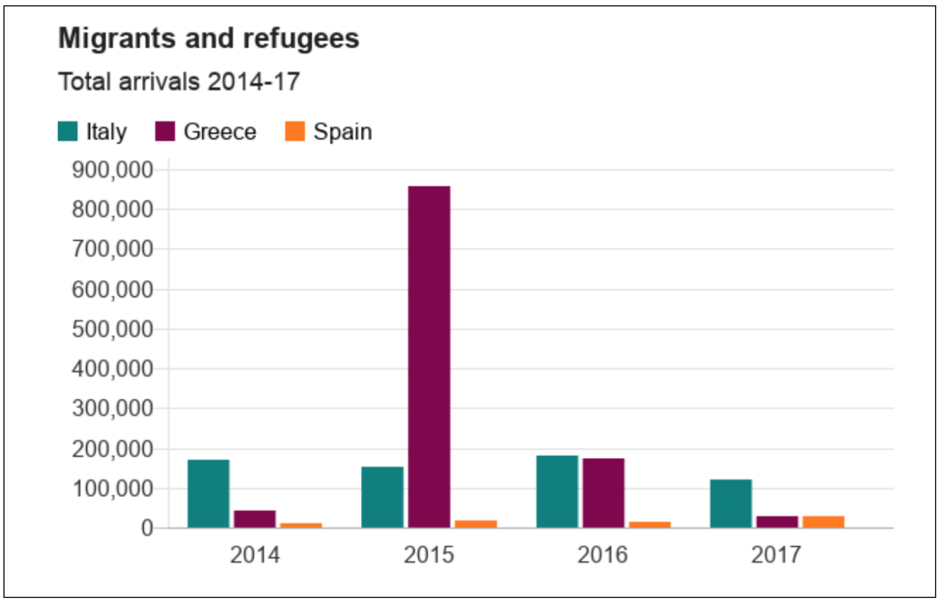
	Total Crime	Personal Robberies	Vehicle Theft	Other Types	Property Robberies	Drugs Crimes	Rape
	Panel A: Different Types of Crime Committed by Refugees						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of Refugees	2.328	1.033	0.270	0.352	0.572	-0.012	0.113
	(0.433)***	(0.106)***	(0.067)***	(0.123)***	(0.134)***	(0.011)	(0.017)***
	Panel B: Different Types of Crime Committed by Natives						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of Refugees	0.231	0.112	-0.037	0.011	0.107	0.039	-0.001
	(0.199)	(0.122)	(0.034)	(0.028)	(0.097)	(0.035)	(0.001)
Observations	535	535	535	535	535	535	535
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓

Note: This shift-share IV methodology uses the predicted stock of refugees in each year and island (based on 2012) interacted with distance from the Turkish coast. Rates for the different types of crimes are used as outcome variables. This table reports 2SLS estimates. Official data reported by police are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Online Appendix A

Not For Publication

Figure A1: Refugee Sea Arrivals to Greece, Italy, and Spain in the Period 2014-2017



Note: The data used in this figure come from UNHCR. This figure shows arrivals by sea for Greece, Italy, and Spain in the period 2014-2017. Greece received the highest number of refugees. The highest number of refugee arrivals to Greece was recorded in 2015, when more than 800,000 refugees traveled by sea from Turkey. Since 2015, the number of refugees and migrants arriving in Greece has fallen dramatically, after the EU and Turkey signed an agreement.

Figure A2: List of Newspapers Used to Construct the Dataset on Crime Incidents by Geographic Region

Νομός Λέσβου

Εμπρός
Δημοκράτης

Νομός Χίου

Πολίτης
Η Αλήθεια online edition

Νομός Σάμου

Σαμιακή Γνώμη
Σαμιακός Τύπος (weekly newspaper)

Νομός Κυκλάδων

Κυκλαδική (daily newspaper)
Κυκλαδικόν Φως
Κοινή Γνώμη (weekly newspaper)

Νομός Δωδεκανήσου

Πρόοδος online
Η Ροδιακή
Η Δράσις
Γνώμη News
Η δημοκρατική της Ρόδου
Νησιά Ιονίου

Νομός Ζακύνθου

Ημερα Ζακύνθου

Νομός Κέρκυρας

Ενημέρωση

Νομός Κεφαλληνίας

Ανεξάρτητος (daily newspaper)
Εφημερίδα των Κεφαλληνίων
Ημερήσιος

Νομός Λευκάδας

Τα ΝΕΑ της Λευκάδας

Figure A2: List of Newspapers Used to Construct the Dataset on Crime Incidents by Geographic Region

Νομός Ηρακλείου

Πατρίς (daily newspaper)
Νέα Κρήτη

Νομός Λασιθίου

Ανατολή online

Νομός Ρεθύμνου

Ρεθεμνιώτικα Νέα

Νομός Χανίων

Χανιώτικα Νέα (daily newspaper)
Αγώνας της Κρήτης online edition

Νομός Σποράδων

Καθημερινή Εφημερίδα της Μαγνησίας
Ταχυδρόμος
Νέα Μαγνησίας
Βόρειες Σποράδες

Table A.1: Correlation between Exposed Islands, Distance to Turkish Coast, and Economic Indicators

Outcome Variable: A Binary Indicator for Exposed Islands		
	(1) OLS	(2) Probit
	(1)	(2)
main		
Log-Distance from Turkish Coast	-0.112	-0.748
	(0.024)***	(0.203)***
Unemployment Rate	0.002	0.013
	(0.002)	(0.015)
Log Income (in Euro)	0.002	-0.780
	(0.068)	(0.839)
Island Size	0.000	-0.000
	(0.000)	(0.001)
Population of Natives	-0.000	0.000
	(0.000)	(0.000)
Constant	0.575	5.994
	(0.426)	(5.531)
Observations	92	92

Note: This table shows the correlation between the treatment status of an island, distance from the Turkish coast, and economic indicators. The outcome (treatment) variable is a binary indicator that takes the value 1 if the island is exposed to refugees and 0 otherwise. Economic indicators are the island-specific unemployment rate and the island-specific log income (in euro). Robust standard errors are reported in parentheses. We obtained information on economic indicators for 92 out of 107 islands due to data availability issues. The remaining 15 islands have omitted observations in national statistics for island-specific economic performance. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.2: Relationship Between Smuggling Presence, Distance, and Economic Indicators

	Outcome: Share of Smugglers	
	(1)	(2)
Log-Distance from Turkish Coast	-0.001	-0.001
	(0.001)	(0.001)
Unemployment Rate		-0.000
		(0.000)
Log Income (in Euro)		-0.003
		(0.003)
Observations	107	92

Notes: This table presents the estimated effects of distance (log) of each island from the Turkish coast and other island-specific economic indicators on the share of smugglers in each island. The outcome variable is the share of smugglers at island level, which is generated as the ratio of number of smugglers over total population. Economic indicators are the island-specific unemployment rate and island-specific income (log). We use data obtained from the Hellenic Port Police for the year 2015. Robust standard errors are reported in parentheses.

Table A.3: Correlations between Crime Committed by Refugees Reported in Newspapers and Official Police Records

Variables	Total Crime Refugees (New/per)	Personal Robberies Refugees (New/per)	Vehicle Theft Refugees (New/per)	Other Crime Refugees (New/per)	Property Crime Refugees (New/per)	Drugs Refugees (New/per)	Rape Refugees (New/per)	Total Crime Refugees (Police)	Personal Robberies Refugees (Police)	Vehicle Theft Refugees (Police)	Other Crime Refugees (Police)	Property Crime Refugees (Police)	Drugs Refugees (Police)	Rape Refugees (Police)
Total Crime Refugees (New/per)	1.000													
Personal Robberies Refugees (New/per)	0.744	1.000												
	(0.000)													
Vehicle Theft Refugees (New/per)	0.985	0.767	1.000											
	(0.000)	(0.000)												
Other Crime Refugees (New/per)	0.977	0.792	0.985	1.000										
	(0.000)	(0.000)	(0.000)											
Property Robberies Refugees (New/per)	0.966	0.551	0.931	0.907	1.000									
	(0.934)	(0.000)	(0.000)	(0.000)										
Drugs Refugees (New/per)	0.214	0.580	0.244	0.277	0.031	1.000								
	(0.000)	(0.000)	(0.000)	(0.000)	(0.479)									
Rape Refugees (New/per)	0.837	0.567	0.838	0.871	0.803	0.047	1.000							
	0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.273)								
Total Crime Refugees (Police)	0.976	0.871	0.973	0.978	0.872	0.361	0.818	1.000						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)							
Personal Robberies Refugees (Police)	0.940	0.910	0.946	0.963	0.824	0.429	0.796	0.991	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
Vehicle Theft Refugees (Police)	0.973	0.796	0.985	0.986	0.902	0.298	0.853	0.985	0.966	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
Other Crime Refugees (Police)	0.980	0.780	0.987	0.981	0.920	0.286	0.818	0.980	0.955	0.992	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
Property Crime Refugees (Police)	0.975	0.712	0.980	0.968	0.940	0.172	0.856	0.959	0.918	0.978	0.983	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
Drugs Refugees(Police)	0.232	0.741	0.229	0.258	0.030	0.589	0.046	0.393	0.462	0.247	0.232	0.151	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.484)	(0.000)	(0.291)	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)		
Rape Refugees (Police)	0.894	0.612	0.902	0.889	0.871	0.068	0.898	0.883	0.833	0.906	0.900	0.947	0.066	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.119)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.128)	

Note: This table presents Pearson correlation coefficients between the same type of crime reported in newspapers and official police records. These crimes are committed by foreigners. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.4: Correlations between Crime Committed by Natives reported in Newspapers and Official Police Records

Variables	Total Crime Natives (New/per)	Personal Robberies Natives (New/per)	Vehicle Theft Natives (New/per)	Other Crime Natives (New/per)	Property Crime Natives (New/per)	Drugs Natives (New/per)	Rape Natives (New/per)	Total Crime Natives (Police)	Personal Robberies Natives (Police)	Vehicle Theft Natives (Police)	Other Crime Natives (Police)	Property Crime Natives (Police)	Drugs Natives (Police)	Rape Natives (Police)
Total Crime Natives (Newspaper)	1.000													
Personal Robberies Natives (Newspaper)	0.001	1.000												
	(0.983)													
Vehicle Theft Natives (Newspaper)	0.611	0.038	1.000											
	(0.000)	(0.379)												
Other Crime Natives (Newspaper)	0.653	0.012	0.715	1.000										
	(0.000)	(0.790)	(0.000)											
Property Robberies Natives (Newspaper)	0.919	-0.003	0.506	0.557	1.000									
	(0.000)	(0.952)	(0.000)	(0.000)										
Drugs Natives (Newspaper)	0.913	-0.001	0.488	0.529	0.980	1.000								
	(0.000)	(0.982)	(0.000)	(0.000)	(0.000)									
Rape Natives (Newspaper)	0.314	-0.012	-0.014	-0.022	-0.023	-0.022	1.000							
	(0.000)	(0.778)	(0.743)	(0.614)	(0.600)	(0.615)								
Total Crime Natives (Police)	0.787	0.014	0.478	0.583	0.689	0.687	0.295	1.000						
	(0.000)	(0.753)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)							
Personal Robberies Natives (Police)	0.176	0.007	0.013	-0.007	-0.011	-0.010	0.547	0.599	1.000					
	(0.000)	(0.867)	(0.767)	(0.874)	(0.799)	(0.824)	(0.000)	(0.000)						
Vehicle Theft Natives (Police)	0.633	0.042	0.950	0.752	0.532	0.517	-0.012	0.491	-0.007	1.000				
	(0.000)	(0.332)	(0.000)	(0.000)	(0.000)	(0.000)	(0.776)	(0.000)	(0.866)					
Other Crime Natives (Police)	0.376	-0.035	0.408	0.572	0.325	0.316	-0.028	0.565	0.008	0.420	1.000			
	(0.000)	(0.458)	(0.000)	(0.000)	(0.000)	(0.000)	(0.675)	(0.000)	(0.714)	(0.000)				
Property Crime Natives (Police)	0.890	-0.010	0.382	0.532	0.981	0.972	-0.023	0.683	-0.008	0.405	0.314	1.000		
	(0.000)	(0.810)	(0.000)	(0.000)	(0.000)	(0.000)	(0.596)	(0.000)	(0.849)	(0.000)	(0.000)			
Drugs Natives (Police)	0.333	0.062	0.299	0.483	0.292	0.314	-0.040	0.590	0.062	0.317	0.743	0.303	1.000	
	(0.000)	(0.154)	(0.000)	(0.000)	(0.000)	(0.000)	(0.361)	(0.000)	(0.153)	(0.000)	(0.000)	(0.000)		
Rape Natives (Police)	-0.005	0.061	0.012	0.002	-0.015	-0.012	0.013	-0.029	-0.023	0.023	-0.015	-0.032	-0.039	1.000
	(0.965)	(0.436)	(0.886)	(0.953)	(0.706)	(0.851)	(0.000)	(0.515)	(0.642)	(0.785)	(0.619)	(0.502)	(0.306)	

Note: This table presents Pearson correlation coefficients between the same type of crime reported in newspapers and official police records. These crimes are committed by natives. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.5: Impact of Exposure to Refugees on Crime Committed by Refugees (Panel A) and Natives (Panel B), Difference-in-Differences, Newspaper Data instead of Official Police Data

	Total Crime	Personal Robberies	Vehicle Theft	Other Types	Property Robberies	Drugs Crimes	Rape
	Panel A: Different Types of Crime Committed by Refugees						
Post x Treatment	1.737***	0.261***	0.162***	0.219***	1.056***	-0.013	0.059***
	(0.282)	(0.070)	(0.023)	(0.037)	(0.185)	(0.009)	(0.010)
Observations	535	535	535	535	535	535	535
Island FE							
Time FE							
	Panel B: Different Types of Crime Committed by Natives						
Post x Treatment	0.035	0.003	0.011	-0.009	0.001	0.012	0.024
	(0.098)	(0.002)	(0.020)	(0.015)	(0.039)	(0.039)	(0.046)
Observations	535	535	535	535	535	535	535
Island FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓

Note: We use a weighted least square and the weighting is proportional to the share of refugees in each island-year configuration. Difference-in-differences estimates of the effect of exposure to refugees on crime rates committed by refugees and natives are presented in Panels A and B, respectively. Rates for the different types of crimes are used as outcome variables. Data collected from newspaper reports are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Table A.6: Impact of Exposure to Refugees on Crime Rates, OLS Estimates

	(1) Total Crime	(2) Personal Robberies	(3) Vehicle Theft	(4) Other Types	(5) Property Robberies	(6) Drugs Crimes	(7) Rape
	Panel A: Different Types of Crime Committed						
Share of Refugees	4.566***	2.129***	0.496**	0.666**	1.108***	-0.023	0.189***
	(1.506)	(0.669)	(0.235)	(0.294)	(0.339)	(0.056)	(0.032)
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓
Observations	534	535	534	535	535	535	535
	Panel B: Different Types of Crime Committed by Refugees						
Share of Refugees	4.371***	2.018***	0.467***	0.669**	1.070***	-0.041	0.188***
	(1.464)	(0.638)	(0.161)	(0.311)	(0.372)	(0.045)	(0.031)
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓
Observations	535	535	535	535	535	535	535
	Panel C: Different Types of Crime Committed by Natives						
Share of Refugees	0.195	0.111	0.029	-0.003	0.038	0.019	0.001
	(0.153)	(0.104)	(0.081)	(0.031)	(0.084)	(0.029)	(0.002)
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓
Observations	534	535	534	535	535	535	535

Note: OLS is used to produce these estimates. Rates for the different types of crimes are used as outcome variables. Official police data are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.7: Impact of Exposure to Refugees on Crime Rates, IV Estimates

	Total Crime	Personal Robberies	Vehicle Theft	Other Types	Property Robberies	Drugs Crimes	Rape
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of Refugees	4.992	2.935	0.727	0.899	0.257	-0.124	0.292
	(2.709)*	(1.255)**	(0.398)*	(0.466)*	(1.145)	(0.189)	(0.089)***
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓
F-statistics First Stage	13.56	13.56	13.56	13.56	13.56	13.56	13.56
Observations	428	428	428	428	428	428	428

Note: This table shows IV estimated effects when the IV is distance from the Turkish coast interacted with time dummies. The endogenous variable is the share of refugees in each island. Rates for the different types of crimes are used as outcome variables. Official data reported by police are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.8: Impact of Exposure to Refugees on Crime Committed by Refugees (Panel A) and Natives (Panel B), IV Estimates

	Total Crime	Personal Robberies	Vehicle Theft	Other Types	Property Robberies	Drugs Crimes	Rape
	Panel A: Different Types of Crime Committed by Refugees						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of Refugees	5.964	2.528	0.615	1.040	1.520	-0.022	0.284
	(2.413)**	(1.063)**	(0.265)**	(0.467)**	(0.619)**	(0.075)	(0.089)***
	Panel B: Different Types of Crime Committed by Natives						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of Refugees	-0.975	0.407	0.112	-0.141	-1.263	-0.102	0.008
	(1.257)	(0.654)	(0.176)	(0.156)	(1.025)	(0.181)	(0.014)
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓
Observations	535	535	535	535	535	535	535

Note: This table presents IV estimated effects when the IV is distance from the Turkish coast interacted with time dummies. The endogenous variable is the share of refugees in each island. Rates for the different types of crimes are used as outcome variables. This table reports 2SLS estimates. Official data reported by police are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.9: Impact of Exposure to Refugees on Crime Rates, IV Estimates

	Total Crime	Personal Robberies	Vehicle Theft	Other Types	Property Robberies	Drugs Crimes	Rape
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of Refugees	1.491	0.680	0.128	0.223	0.388	0.007	0.066
	(0.401)***	(0.144)***	(0.051)**	(0.094)**	(0.141)***	(0.026)	(0.011)***
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓
F-statistics First Stage	552.7	552.7	552.7	552.7	552.7	552.7	552.7
Observations	535	535	535	535	535	535	535

Note: This table shows IV estimated effects when the IV is distance from the Turkish coast interacted with the actual stock of refugees in each year and island. The endogenous variable is the share of refugees in each island. Rates for the different types of crimes are used as outcome variables. Official data reported by police are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.10: Impact of Exposure to Refugees on Crime Committed by Refugees (Panel A) and Natives (Panel B), IV Estimates

	Total Crime	Personal Robberies	Vehicle Theft	Other Types	Property Robberies	Drugs Crimes	Rape
	Panel A: Different Types of Crime Committed by Refugees						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of Refugees	1.341	0.591	0.165	0.217	0.315	-0.012	0.066
	(0.325)***	(0.081)***	(0.051)***	(0.093)**	(0.098)***	(0.011)	(0.011)***
	Panel B: Different Types of Crime Committed by Natives						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of Refugees	0.151	0.090	-0.037	0.006	0.074	0.018	0.000
	(0.145)	(0.095)	(0.035)	(0.022)	(0.069)	(0.025)	(0.001)
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓
Observations	535	535	535	535	535	535	535

Note: This table shows IV estimated effects when the IV is distance from the Turkish coast interacted with the actual stock of refugees in each year and island. The endogenous variable is the share of refugees in each island. Rates for the different types of crimes are used as outcome variables. This table reports 2SLS estimates. Official data reported by police are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.11: Impact of Exposure to Refugees on Crime Rates, Shift-Share Instrument for the Difference-in-Differences Specification

	Total Crime	Personal Robberies	Vehicle Theft	Other Types	Property Robberies	Drugs Crimes	Rape
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post x Treatment	1.534	0.686	0.140	0.218	0.407	0.016	0.067
	(0.339)***	(0.200)***	(0.039)***	(0.042)***	(0.077)***	(0.018)	(0.020)***
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓
F-statistics First Stage	12.39	12.39	12.39	12.39	12.39	12.39	12.39
Observations	535	535	535	535	535	535	535

Note: We use a shift-share instrument (using the predicted stock in 2012) interacted with distance from the Turkish coast for each island. The endogenous variable is binary and is from the difference-in-differences specification (it is the interaction term between *Post* and *Treatment*). Rates for the different types of crimes are used as outcome variables. Official data reported by police are used here and refer to arrested offenders. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.12: Impact of Exposure to Refugees on Crime Committed by Refugees (Panel A) and Natives (Panel B), Shift-Share Instrument for the Difference-in-Differences Specification

	(1) Total Crime	(2) Personal Robberies	(3) Vehicle Theft	(4) Other Types	(5) Property Robberies	(6) Drugs Crimes	(7) Rape
	Panel A: Different Types of Crime Committed by Refugees						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post x Treatment	1.395	0.619	0.162	0.211	0.343	-0.007	0.068
	(0.343)***	(0.196)***	(0.035)***	(0.039)***	(0.068)***	(0.006)	(0.020)***
	Panel B: Different Types of Crime Committed by Natives						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post x Treatment	0.139	0.067	-0.022	0.007	0.064	0.023	-0.000
	(0.097)	(0.066)	(0.018)	(0.017)	(0.048)	(0.018)	(0.001)
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓
F-statistics First Stage	12.39	12.39	12.39	12.39	12.39	12.39	12.39
Observations	535	535	535	535	535	535	535

Note: We use as a shift-share instrument using the predicted stock of refugees interacted with the distance of each island from the Turkish coast. The endogenous variable is the interaction term between *Post* and *Treatment* from the difference-in-differences specification presented in Section 4. IV estimates of the effect of exposure to refugees on crimes committed by refugees and natives are presented in Panels A and B, respectively. Rates for the different types of crimes are used as outcome variables. Official data reported by police are used here and refer to arrested offenders. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.13: Impact of Exposure to Refugees on Crime Committed by Refugees (Panel A) and Natives (Panel B), IV Estimates, Newspaper Data instead of Official Police Data

	(1) Total Crime	(2) Personal Robberies	(3) Vehicle Theft	(4) Other Types	(5) Property Robberies	(6) Drugs Crimes	(7) Rape
	Panel A: Different Types of Crime Committed by Refugees						
Share of Refugees	8.712*	1.196***	0.684**	1.020*	5.380	-0.003	0.435***
	(4.997)	(0.390)	(0.326)	(0.535)	(3.746)	(0.065)	(0.127)
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓
Observations	535	535	535	535	535	535	535
	Panel B: Different Types of Crime Committed by Natives						
Share of Refugees	-0.949	0.034	0.064	-0.148*	-0.570	-0.600	0.305
	(1.011)	(0.022)	(0.088)	(0.079)	(0.503)	(0.507)	(0.197)
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓
Observations	535	535	535	535	535	535	535

Note: Rates for the different types of crimes are used as outcome variables. This table reports 2SLS estimates. Official data reported by police are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.14: Impact of Exposure to Refugees on Reported Crime Rates, Difference-in-Differences

	Total Crime	Personal Robberies	Vehicle Theft	Other Types	Property Robberies	Drugs Crimes	Rape
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post x Treatment	3.809	0.543	0.434	0.522	2.259	-0.206	0.127
	(1.487)**	(0.328)*	(0.106)***	(0.122)***	(0.919)**	(0.205)	(0.129)
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓

Notes: We use a weighted least square and the weighting is proportional to the share of refugees in each island-year configuration. Rates for the different types of crimes are used as outcome variables. Official data reported by police are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.15: Impact of Exposure to Refugees on Reported Crime Rates, Shift-Share IV Estimates

	Total Crime	Personal Robberies	Vehicle Theft	Other Types	Property Robberies	Drugs Crimes	Rape
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of Refugees	2.908	0.916	0.583	0.951	0.512	-0.702	0.648
	(1.071)***	(0.253)***	(0.153)***	(0.221)***	(0.484)	(0.195)***	(0.071)***
Time FE	✓	✓	✓	✓	✓	✓	✓
Island FE	✓	✓	✓	✓	✓	✓	✓
F-statistics First Stage	81.78	81.78	81.78	81.78	81.78	81.78	81.78
Observations	535	535	535	535	535	535	535

Note: Rates for the different types of crimes are used as outcome variables. Official data reported by police are used here. We use 7 main categories of crime: total crime, personal robberies, vehicle theft, other types, property robberies, drug-related crimes, and rape. Standard errors are clustered at island level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Online Appendix B

Not For Publication

In this section we describe how we collected the newspaper data on crime. First, newspapers were screened by a team of research assistants who became experts in recording crime incidents. Data were initially collected on a daily basis, and then crime rates were aggregated on an annual level. In this way, the newspaper data are consistent with the police records data and have the same frequency. Several research assistants were involved in the process of recording these crime incidents, and a data manager was responsible for monitoring the data collection process and ensuring that research assistants recorded the data in a consistent fashion. This process of hand collecting data helped us build a dictionary of words used by journalists when referring to different forms of crime. These data are based on arrested offenders, and thus are comparable to data used in the main analysis, which are obtained from the police. In the second step, we developed a text analytics algorithm to double-check that our hand collection was precise. Thus, we web-scraped all related newspapers' texts. The algorithm proceeded in two steps:

Step 1: The application using web scrap parsed the content of each page or uploaded image, detected the related information based on crime-related words, and stored the data.

Step 2: We stored:

- URL of the news or related image

-Title of the news

-Description of the crime incident and the municipality in which the crime took place

-Date of the newspaper publication; most crime incidents also report the approximate time each incidence took place

-Object stolen (extracted from the description and title using crime-related words)

The crime-related words we use (in Greek) are:

Ξυλοδαρμός, κλοπή, φασαρία, βιασμός, μαχαίρι, επίθεσή, ταραχή, ληστεία, σπίτι, όχημα, μηχανή, αυτοκίνητο, ληστεία, μαγαζί, χρήματα, λεφτά, εθνικότητες: από τον οργανισμό HE, ξένος, μετανάστης, πρόσφυγας, αστυνομία, φυλακή, καταστροφές, επίθεση, κλεψιά, αρπαγή, υπεξαίρεση, λεηλασία, αμάξι, λησταρχείο, λήσταρχός, ληστεύω, ληστρικός κουκούλα, ληστοφυγόδικος, παράνομη εμπορία, εισβολή, εισβάλω, ένοπλος δράστης έγχρωμος, πολιτικός πρόσφυγας, κακόβουλο τραύμα, τραυματισμός, αλλοδαπός, ημεδαπός, όπλο, περίστροφο, καταστροφή, ναρκωτικά, κάνναβη, κοκαΐνη, οπιοειδή, ηρωίνης, καθώς και συνθετικά αλκαλοειδή, διεγερτικά τύπου αμφεταμίνης (ATS), ηρεμιστικά και υπνωτικά, διαλύτες και εισπνεόμενα, εισαγγελία πλημμελειοδικών, ακριτικό νησί, ενδοοικογενειακή βία, ιατροδικαστής υποδιεύθυνση ασφαλείας, πραγματογνωμοσύνης, σεξουαλική κακοποίηση, αδίκημα, προσβολής της γενετήσιας αξιοπρέπειας, γενετήσιες πράξεις, σωματική βλάβη, πατίνι, ποδήλατο, τροχοφόρο, μηχανή, χρυσαφικά, σπίτι, κολίε, δακτυλιδι, βραχιόλι, μετανάστης, ξένος, ντόπιος

The algorithm also identified all synonyms of the above words.

The translated words in English are: beating, theft, rioting, rape, knife, assault, riot, robbery, house, vehicle, machine, car, robbery, shop, money, nationalities: from UN organization, foreigner, immigrant, refugee, police, prison, disasters, assault, theft, robbery, embezzlement, looting, car-jacking, robber, rob, hood robber, bootlegger, illegal trafficking, intrusion, intrude, armed offender of color, political refugee, malicious wounding, injury, alien, national, gun, revolver, destruction, narcotics, cannabis, cocaine, opioids, heroin, as well as synthetic alkaloids, amphetamine-type stimulants (ATS), sedatives and hypnotics, solvents and inhalants, misdemeanour prosecution, critical island, domestic violence, coroner security sub-division, expert witness, sexual abuse, crime, sexual indecency, sexual acts, bodily harm, skate, bicycle, wheeler, motorcycle, jewelery, house, necklace, ring, bracelet, refugee, migrant, native.

The match between hand-collected and data collected through web scrapping was extremely high (97%), so we are highly satisfied with the data collection protocol. Hand-collected newspaper data on crime incidents based on arrested offenders was used in the relevant analysis. Crimes for which the offenders are not caught or known were entered in our dataset.