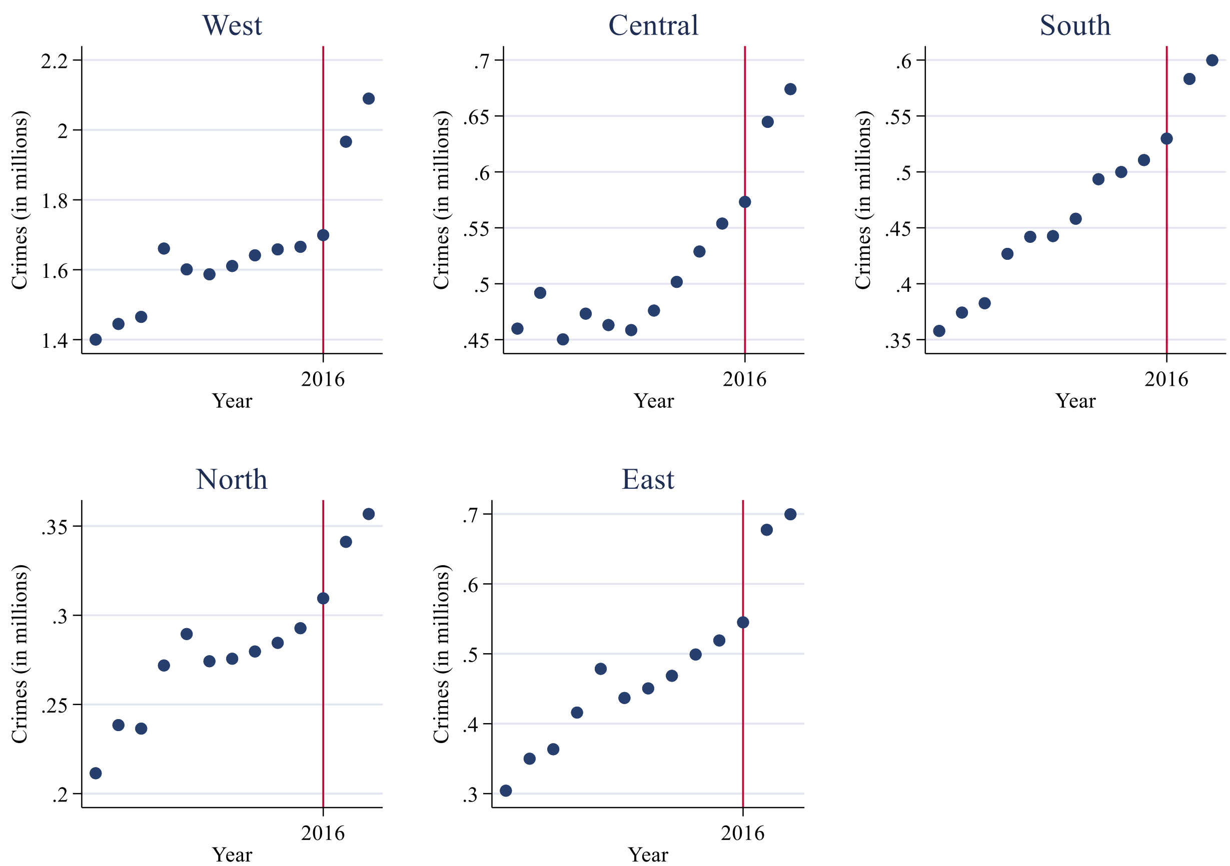
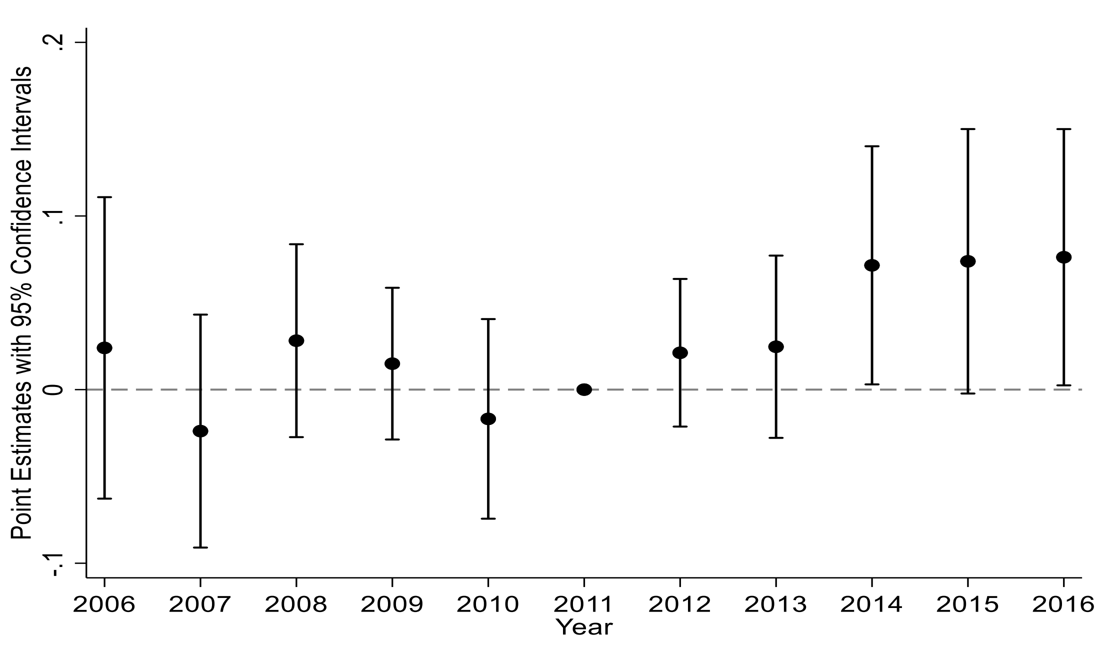
APPENDIX A

Appendix Figure A.F1
Crimes at Prosecutors' Offices by Region

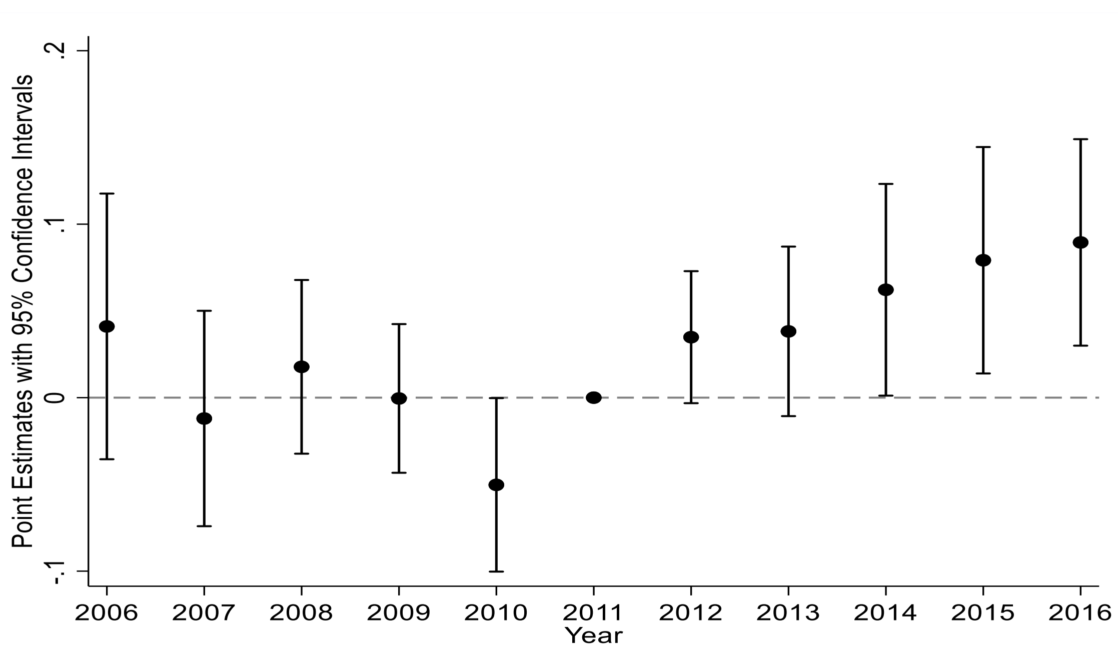


Source: TURKSTAT.

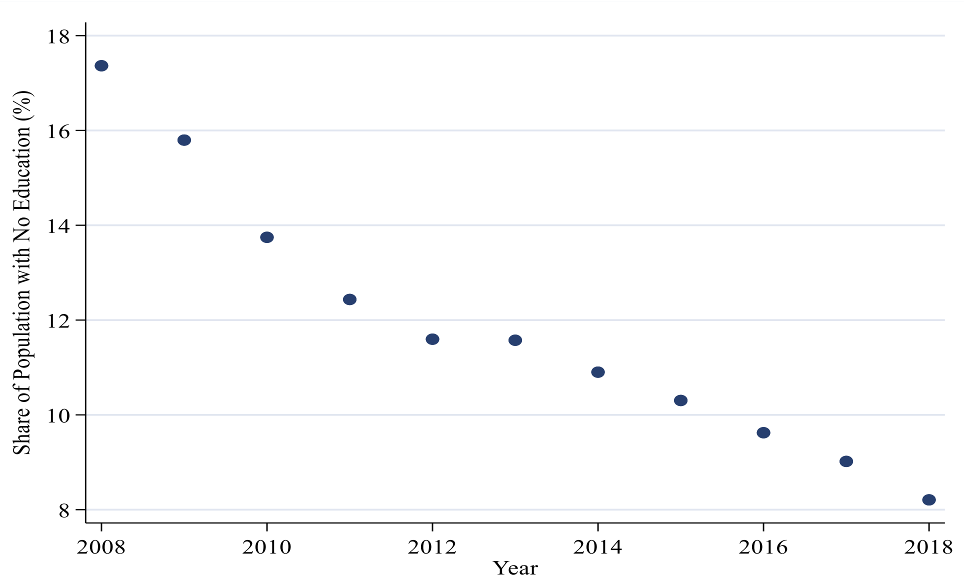
Appendix Figure A.F2 Event Study: The Difference in Refugee Impact between High vs. Low Refugee Exposure Provinces (Cutoff: 15th Percentile)



Appendix Figure A.F3 Event Study: The Difference in Refugee Impact between High vs. Low Refugee Exposure Provinces (Cutoff: 25th Percentile)

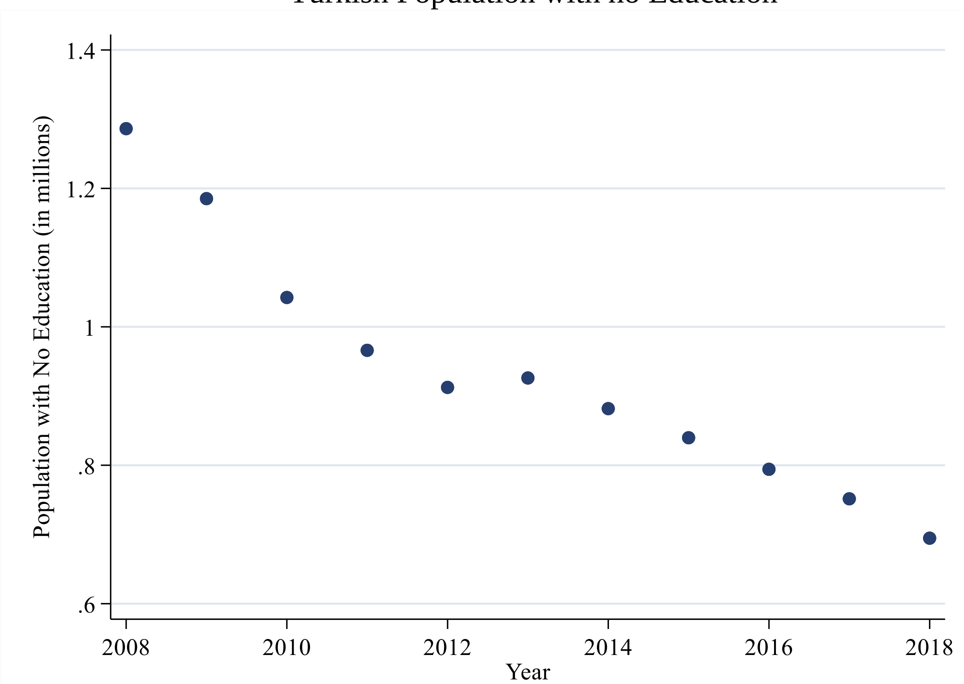


Appendix Figure A.F4
The Share of Turkish Population with no Education



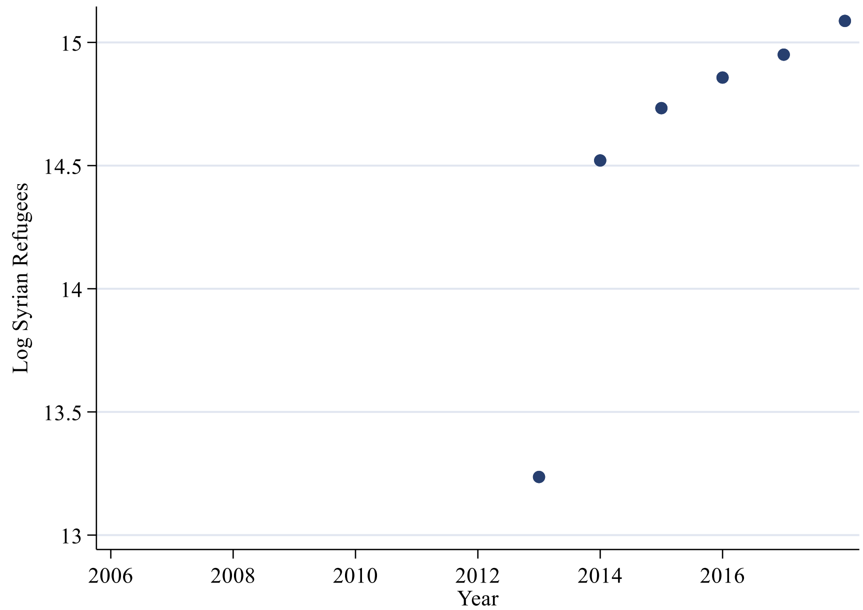
The graph plots the share of the population who are illiterate or without any diploma.
Source: TURKSTAT.

Appendix Figure A.F5
Turkish Population with no Education



The graph plots the size of the population who are illiterate or without any diploma.
Source: TURKSTAT.

Appendix Figure A.F6
Logarithm of the Number of Syrian Refugees



Source: TURKSTAT.

Table A1
The Impact of Refugees on Crime- Using Alternative Instruments
Dependent Variable: The Number of New Crimes Handled by Prosecutors' Offices

	(1)	(2)	(3)	(4)	(5)
					Reduced
	Panel A: Modified Shift IV				Form
Ln (Refugees)	0.059***	0.056***	0.064*	0.061***	
	(0.024)	(0.022)	(0.040)	(0.022)	
Ln (Natives)	-0.027	-0.011	0.093	0.440**	
	(0.384)	(0.379)	(0.312)	(0.217)	
F-test for first-stage	47.86	46.04	39.06	49.00	
Instrument/1000					0.036***
					(0.014)
Ln (Natives)					0.305
					(0.196)
	Panel B: Arabic IV				
Ln (Refugees)	0.055***	0.050***	0.085**	0.070**	
	(0.009)	(0.007)	(0.036)	(0.028)	
Ln (Natives)	-0.250	-0.108	-0.070	0.371	
	(0.299)	(0.250)	(0.337)	(0.234)	
F-test for First-stage	48.79	46.69	35.71	42.54	
Instrument/10000					0.003***
					(0.001)
Ln (Natives)					0.328*
					(0.178)
Observations for Panel A	810	810	810	810	810
Observations for Panel B	737	737	737	737	737
Year FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Time-Varying Province Controls	No	Yes	Yes	Yes	Yes
5 Region Linear Trend	No	No	Yes	Yes	Yes
12 Region-Year FE	No	No	Yes	Yes	Yes
Trends by pre-Syrian Province Crime	No	No	No	Yes	No

Standard errors, clustered at province level, are in parentheses. Asterisks denote significance levels (*=.10, **=.05, ***=.01). Time-varying province controls include the log of hospitals per 100K population, the presence of natural gas lines in the province in a given year, the log of public expenditures per 100K population, and the lag of prison intake.

Table A2
The Impact of Refugees on Crime- Using Alternative Instruments
Dependent Variable: The Number of Charges in Court Cases

	(1)	(2)	(3)	(4)	(5)
	Panel A: Modified Shift IV				Reduced Form
Ln (Refugees)	0.053**	0.047**	0.090*	0.090**	
	(0.022)	(0.016)	(0.049)	(0.042)	
Ln (Natives)	0.026	0.084	0.378	0.702	
	(0.475)	(0.407)	(0.530)	(0.502)	
F-test for First-stage	26.99	26.51	27.62	33.12	
Instrument/1000					0.035**
					(0.012)
Ln (Natives)					0.595*
					(0.354)
	Panel B: Arabic IV				
Ln (Refugees)	0.057**	0.044***	0.100	0.091	
	(0.027)	(0.016)	(0.067)	(0.055)	
Ln (Natives)	-0.095	0.076	0.075	0.838	
	(0.602)	(0.441)	(0.799)	(0.540)	
F-test for first-stage	31.03	30.36	28.43	33.33	
Instrument/10000					0.003**
					(0.001)
Ln (Natives)					0.700**
					(0.275)
Observations for Panel A	486	486	486	486	486
Observations for Panel B	469	469	469	469	469
Year FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Time-Varying Province Controls	No	Yes	Yes	Yes	Yes
5 Region Linear Trend	No	No	Yes	Yes	Yes
12 Region-Year FE	No	No	Yes	Yes	Yes
Trends by pre-Syrian Province Crime	No	No	No	Yes	No

Standard errors, clustered at province level, are in parentheses. Asterisks denote significance levels (*=.10, **=.05, ***=.01). Time-varying province controls include the log of hospitals per 100K population, the presence of natural gas lines in the province in a given year, the log of public expenditures per 100K population, and the lag of prison intake.

Table A3
The Impact of Refugees on Crime Using Refugee-to-Native Ratio
Dependent Variable: The Number of New Cases Handled by Prosecutors' Offices

	(1)	(2)	(3)	(4)	(5)
	Panel A: OLS				Reduced Form
Refugees/Natives	0.675***	0.670***	0.469***	0.426***	
	(0.048)	(0.048)	(0.097)	(0.101)	
Ln (Natives)	0.544***	0.560***	0.311	0.443**	
	(0.202)	(0.212)	(0.188)	(0.185)	
Observations	891	891	891	891	
	Panel B: IV				
Refugees/Native	0.893***	0.888***	0.551***	0.545**	0.017**
	(0.209)	(0.202)	(0.197)	(0.214)	(0.007)
Ln (Natives)	0.512**	0.531**	0.313*	0.442**	0.29
	(0.203)	(0.210)	(0.186)	(0.183)	(0.194)
Observations	891	891	891	891	891
	Panel C: Modified Shift IV				
Refugees/Native	0.934***	0.932***	0.613***	0.603**	0.036***
	(0.198)	(0.190)	(0.193)	(0.216)	(0.014)
Ln (Natives)	0.518**	0.547**	0.340*	0.467**	0.305
	(0.204)	(0.211)	(0.184)	(0.184)	(0.196)
Observations	810	810	810	810	810
	Panel D: Arabic IV				
Refugees/Native	1.299***	1.256***	1.239***	1.191***	0.003***
	(0.301)	(0.293)	(0.299)	(0.291)	(0.001)
Ln (Natives)	0.242	0.363**	0.219	0.298*	0.328*
	(0.171)	(0.165)	(0.172)	(0.178)	(0.178)
Observations	737	737	737	737	737
Year FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Time-Varying Province Controls	No	Yes	Yes	Yes	Yes
5 Region Linear Trend	No	No	Yes	Yes	Yes
12 Region-Year FE	No	No	Yes	Yes	Yes
Trends by pre-Syrian Province Crime	No	No	No	Yes	No

Standard errors, clustered at province level, are in parentheses. Asterisks denote significance levels (*=.10, **=.05, ***=.01). Time-varying province controls include the log of hospitals per 100K population, the presence of natural gas lines in the province in a given year, the log of public expenditures per 100K population, and the lag of prison intake.

Table A4
The Impact of Refugees on Crime Using Refugee-to-Native Ratio
Dependent Variable: The Number of Charges in Court Cases

	(1)	(2)	(3)	(4)	(5)
					Reduced Form
	Panel A: OLS				
Refugees/Natives	0.505***	0.524***	0.537***	0.520***	
	(0.072)	(0.081)	(0.156)	(0.159)	
Ln (Natives)	0.646**	0.610**	0.579*	0.627*	
	(0.293)	(0.290)	(0.319)	(0.331)	
Observations	567	567	567	567	
	Panel B: Shift IV				
Refugees/Native	0.598***	0.636***	0.607***	0.616**	0.018***
	(0.164)	(0.173)	(0.222)	(0.239)	(0.007)
Ln (Natives)	0.623**	0.579**	0.574*	0.618*	0.569*
	(0.292)	(0.287)	(0.320)	(0.331)	(0.320)
Observations	567	567	567	567	567
	Panel C: Modified Shift IV				
Refugees/Native	0.582***	0.622***	0.596***	0.594***	0.035***
	(0.162)	(0.167)	(0.198)	(0.208)	(0.012)
Ln (Natives)	0.680**	0.653**	0.617*	0.685*	0.595*
	(0.317)	(0.313)	(0.353)	(0.360)	(0.354)
Observations	486	486	486	486	486
	Panel B: Arabic IV				
Refugees/Native	0.965*	0.974**	1.339**	1.307**	0.003**
	(0.490)	(0.369)	(0.655)	(0.587)	(0.001)
Ln (Natives)	0.600**	0.595**	0.485	0.708**	0.700**
	(0.251)	(0.252)	(0.329)	(0.339)	(0.275)
Observations	469	469	469	469	469
Year FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Time-Varying Province Controls	No	Yes	Yes	Yes	Yes
5 Region Linear Trend	No	No	Yes	Yes	Yes
12 Region-Year FE	No	No	Yes	Yes	Yes
Trends by pre-Syrian Province Crime	No	No	No	Yes	No

Standard errors, clustered at province level, are in parentheses. Asterisks denote significance levels (*=.10, **=.05, ***=.01). Time-varying province controls include the log of hospitals per 100K population, the presence of natural gas lines in the province in a given year, the log of public expenditures per 100K population, and the lag of prison intake.

Table A5
Heterogeneity in Estimated Effects of Refugees on Crime: IV Results
Models Estimated for Different Time Periods

	2006-2016	2006-2015	2006-2014
	(1)	(2)	(3)
Panel A: Number of Crimes handled by the Prosecutors' Office			
Ln (Refugees)	0.054**	0.063**	0.051**
	(0.021)	(0.024)	(0.020)
Ln (Natives)	0.424**	0.338	0.283
	(0.201)	(0.210)	(0.188)
Observations	0.993	0.992	0.994
	891	810	729
Panel B: Number of Criminal Charges in Courts			
Ln (Refugees)	0.084*	0.077*	0.034
	(0.044)	(0.039)	(0.025)
Ln (Natives)	0.642	0.61	0.518
	(0.472)	(0.503)	(0.393)
Observations	567	486	405
Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Time-Varying Province Controls	Yes	Yes	Yes
5 Region Linear Trend	Yes	Yes	Yes
12 Region-Year FE	Yes	Yes	Yes
Trends by pre-Syrian Province Crime	Yes	Yes	Yes

Standard errors, clustered at province level, are in parentheses. Asterisks denote significance levels (*=.10, **=.05, ***=.01). Time-varying province controls include the log of hospitals per 100K population, the presence of natural gas lines in the province in a given year, the log of public expenditures per 100K population, and the lag of prison intake.

Table A6

Heterogeneity in Estimated Effects of Refugees on Crime: IV Results

Models Estimated for Different Locations of the Country

	Excluding					Only	
	West	Central	South	North	East	South	East
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Number of Crimes handled by the Prosecutors' Office							
Ln (Refugees)	0.052**	0.052**	0.061**	0.055**	0.051**	0.050*	0.055**
	(0.020)	(0.022)	(0.026)	(0.021)	(0.025)	(0.025)	(0.026)
Ln (Natives)	0.399*	0.546**	0.369*	0.489**	0.279	0.51	0.630*
	(0.232)	(0.225)	(0.200)	(0.226)	(0.244)	(1.510)	(0.359)
Observations	649	770	803	715	627	88	264
Panel B: Number of Criminal Charges in Courts							
Ln (Refugees)	0.067*	0.087*	0.122*	0.087*	0.06	0.054*	0.098
	(0.034)	(0.044)	(0.073)	(0.048)	(0.039)	(0.027)	(0.068)
Ln (Natives)	1.016**	0.605	0.409	0.652	0.539	1.167	0.999
	(0.457)	(0.529)	(0.480)	(0.625)	(0.490)	(2.329)	(0.897)
Observations	413	490	511	455	399	56	168
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Varying Province Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5 Region Linear Trend	No	No	No	No	No	No	No
12 Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trends by pre-Syrian Province Crime	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors, clustered at province level, are in parentheses. Asterisks denote significance levels (*=.10, **=.05, ***=.01). Time-varying province controls include the log of hospitals per 100K population, the presence of natural gas lines in the province in a given year, the log of public expenditures per 100K population, and the lag of prison intake.

Table A7
Sensitivity of Estimated Effect of Refugees on Crime: IV Results
Models Estimated by Excluding Various Provinces

		Excluding		
	Baseline	Istanbul	3 Major Provinces	Kilis and Sirnak
	(1)	(2)	(3)	(4)
Panel A: Number of Crimes handled by the Prosecutors' Office				
Ln (Refugees)	0.054**	0.054**	0.053**	0.042*
	(0.021)	(0.021)	(0.021)	(0.024)
Ln (Natives)	0.424**	0.424**	0.440**	0.468**
	(0.201)	(0.200)	(0.200)	(0.197)
Observations	891	880	858	869
Panel B: Number of Criminal Charges in Courts				
Ln (Refugees)	0.084*	0.084*	0.083*	0.059
	(0.044)	(0.043)	(0.042)	(0.049)
Ln (Natives)	0.642	0.642	0.618	0.635
	(0.472)	(0.469)	(0.473)	(0.434)
Observations	567	560	546	553
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Time-Varying Province Controls	Yes	Yes	Yes	Yes
5 Region Linear Trend	Yes	Yes	Yes	Yes
12 Region-Year FE	Yes	Yes	Yes	Yes
Trends by pre-Syrian Province Crime	Yes	Yes	Yes	Yes

Standard errors, clustered at province level, are in parentheses. Asterisks denote significance levels (*=.10, **=.05, ***=.01). Time-varying province controls include the log of hospitals per 100K population, the presence of natural gas lines in the province in a given year, the log of public expenditures per 100K population, and the lag of prison intake.

Table A8
Sensitivity of Estimated Effect of Refugees on Crime: IV Results
Models Estimated by Controlling Initial Province Education and Wealth

	Crimes in the Prosecutors' Office (1)	Criminal Charges in Courts (2)
	Panel A: by Initial Education	
Ln(Refugees) *Least Educated	0.054**	0.089**
	(0.022)	(0.044)
Ln(Refugees) *Mid Educated	0.052**	0.084*
	(0.021)	(0.044)
Ln(Refugees) *Most Educated	0.049**	0.092**
	(0.021)	(0.046)
	Panel B: by Initial Wealth	
Ln(Refugees) *Least Wealth	0.048**	0.082*
	(0.021)	(0.044)
Ln(Refugees) *Mid Wealth	0.054***	0.086**
	(0.020)	(0.042)
Ln(Refugees) *Most Wealth	0.046**	0.084*
	(0.021)	(0.043)
Year FE	Yes	Yes
Province FE	Yes	Yes
Time-Varying Province Controls	Yes	Yes
5 Region Linear Trend	Yes	Yes
12 Region-Year FE	Yes	Yes
Trends by pre-Syrian Province Crime	Yes	Yes

Standard errors, clustered at province level, are in parentheses. Asterisks denote significance levels (*=.10, **=.05, ***=.01). Time-varying province controls include the log of hospitals per 100K population, the presence of natural gas lines in the province in a given year, the log of public expenditures per 100K population, and the lag of prison intake.

APPENDIX B

In this appendix we synthesize two recent papers which addressed the same research question we ask in our paper, but reached the conclusion that an increase in refugees *lowered* crime in Turkey. Specifically, Kirdar et al. (2022) and Kayaoglu (2022) both employ the same refugee data we use in this paper, and they implement an instrumental variables analysis using the same or very similar instruments to ours. They, however, approximate the criminal activity by different measures, as opposed to using the number of offenses reported to the prosecutors' offices as was done in our paper. Kayaoglu (2022) uses a noisy indicator of crime which leads to underestimating criminal activity and misrepresentation of the true crime trend in the country. Kirdar et al. (2022) use an erroneous approximation of crime which is incorrect conceptually, and which woefully underreports its true prevalence. More importantly, both papers estimate a particular empirical specification which produces a downwardly-biased estimate of the impact of refugees on crime. Put differently, the econometric model used by these papers mechanically produces a negative relationship between refugees and crime, when in fact the true relationship is positive. In this appendix we describe these pitfalls in some detail although we discussed them throughout the paper.

Problems with Crime Indicators

Kirdar et al. (2022)

Kirdar et al. (2022) use the number of individuals who enter the prison as the measure of criminal activity. The first author of Kirdar et al. (2022) graciously shared their data with us. Thus, we are able to confirm that the authors, in fact, used as their crime indicator *the number of convicted felons who entered the prison system* as reported by the Turkish Statistical Institute (Prison Statistics, Table 2.7: *Convicts Received into Prison*, for all years until 2013. The data post-2013 can be downlaoded from https://data.tuik.gov.tr/Bulten/DownloadIstatistikselTablo?p=I9Aqz2QqBid7/f56YuhmhdeColBqAVuq1GPADbvDU3k9M1zQSSLpMo7Mz9gs0pEN)

As the vast literature in economics of crime reveals, however, prison intake is not a valid proxy for criminal activity for a number of important reasons. First, incarceration has an impact on crime itself. This is both because of the incapacitation effect of incarceration (incarcerated individuals being unable to commit crime while in prison), and because incarceration is a deterrent to crime. This means that prison population is a determinant of crime, rather than being an indicator of crime itself (Barbarino and Mastrobuoni 2014; Johnson and Raphael 2012; Drago et al. 2009; Corman and Mocan 2005; Levitt 1996). Prison population is, of course, influenced by the extent of criminal activity. However, that incarceration is impacted by crime does not imply that the former can be used as a proxy for the latter. This is described in Figure 3 of our paper. In 2013, there were about 3.4 million recorded criminal acts in Turkey, but that same year only 161,711 individuals entered prisons. This is because, as shown in Figure 3, not all crimes end up in courts to be adjudicated (because of unknown suspects, lack of evidence, and so on). Furthermore, if a case goes to trial, not all defendants are convicted; and only some of the convicted criminals are imprisoned (due to other resolutions implemented by the courts such as suspended sentences, fines, probations, etc.)

Using the number of convicted felons who enter prison as a proxy for the incidence of crime lead the authors to report the crime rate of Turkey as **<u>196</u>** offenses per 100,000 people (Kirdar et al. 2022, Table 1). The true crime rate of the country, based on crimes handled by the offices of the prosecutors is 4,500 per 100,000 population. It should be noted that with a few exceptions with questionable crime reporting, there is virtually no country with a crime rate in the range of a few hundred per 100,000 people. The crime rate in the EU was 7,000 in 2010 (Buonano et al. 2018). The current crime rate in EU countries ranges from 1,500 in Bulgaria, to 3,500 in Portugal, to 4,500 (Italy) to 7,500 in Germany (European Sourcebook of Crime and Criminal Justice Statistics, 2021. Sixth Edition). The crime rate in the U.S. was 3,500 in 2010, and 2,500 in 2019 (FBI, Uniform Crime Reports).

Relatedly, Kirdar et al. (2022) claim that the crime rate for most felony crimes are in the single digits. For example, the authors argue that the homicide rate is **8** per 100,000 people, and the robbery rate is **6.6**. They also argue that with the exception of assault, there are provinces with **<u>zero crime</u>** for all other crime categories (see Kirdar et al. (2022), Table 1). This peculiar picture emerges because there are in fact very few individuals who enter prison for narrow crime categories in a given province.

Another issue with the attempt to use prison intake in a particular year as a proxy for crime for that year lies in the fact that the timing of prison entry does not match the timing of the commission of the crime. Judicial process is slow, which translates into a mismatch between the year in which a crime is committed and when the offender enters prison. In Turkey, the average time for the office of the prosecutors to process files with known suspects was 91 days in 2013, and it steadily rose over time, reaching 131 days in 2016 (Turkish Judicial Statistics Yearbook, 2016). The average duration of cases at the courts was 231 days for cases adjudicated in 2013, rising to 274 days in 2016 (Turkish Justice Statistics Yearbook 2016). This means that the time span between a crime reported to the office of the prosecutors and its final court resolution was 322 days in 2013, and 405 days in 2016. This, in turn, implies that perpetrators who got arrested for their offense in March or later in a particular year are expected to enter prison (if convicted) during the following year. A perpetrator who committed a crime in December 2014 is expected to hear the decision of the judge in January 2016.

To make matters worse, the manner in which the prison intake is reported in the Correction Statistics of the Turkish Statistical Institute *does not* refer to defendants who are convicted and received a prison sentence in that year. Rather, prison intake refers to the resolution of cases after they have completed the appeal process. More specifically, although the defendant stays in prison while his case is evaluated by the relevant Appellate Court, this individual is not counted as a "prison entry" until after the final decision of the Appellate court.[41] The average duration of the appellate process in criminal cases is over 1,000 days (Akdeniz 2019). Thus, the interval between the commission of a crime and the time the perpetrator shows up in prison statistics as "prison intake" could be four years or longer. Clearly, the timing of prison intake does not match the timing of the criminal activity.

There are other concerns as well. The delays in the judicial process are not exogenous, nor are they time-invariant. Rather, judicial delays depend on the caseload of the system, which in turn is a function of the extent of criminal activity. Put differently, a rise in crime increases the caseload of the criminal justice system, which leads to further delays in processing the defendants, and widens the time span between arrest and prison entry.[42]

A final complication pertains to prison capacity. It is well-established that prison infrastructure and physical capital cannot be expanded quickly (Boylan and Mocan 2014; Levitt 1996). This implies that judicial decisions are expected to be impacted by prison overcrowding, and judicial leniency goes up when prisons are operating at or near full capacity. This in turn has

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[41] This is explained on page XV of the of the Prison Statistics 2013, Turkish Statistical Institute.

[42] Each year Turkish criminal courts roll over about 1.7 million cases to the following year (Turkish Judicial Statistics Yearbooks, various years)

a positive impact on crime as it signifies a reduction in deterrence. In summary, prison intake should not be used as a proxy for the extent of criminal activity.

Kayaoglu (2022)

Kayaoglu (2022) uses the number of cases in criminal courts as her crime indicator. As we discussed in Section IV, the number of cases in courts is not a good proxy for the incidence of crime for a number of reasons. First, the number of cases is, by definition, smaller than the number of offenses because some defendants are charged with multiple offenses. Second, some suspects and arrestees are not pursued further by prosecutors because of insufficient evidence. In these situations, the case files are not forwarded to the courts although there were suspects in these cases. Finally, there are offenses with unknown suspects. This means that, although a crime has been committed and that there is a record in the files of the police and the prosecutors' offices, no perpetrator has been identified. The upshot is that the number of court cases underestimates the true incidence of crime.

Box II of Figure 3 of our paper reveals that there were about 3.4 million new crimes handled by the prosecutors' offices in 2013. In contrast, Box III shows that there were about 1.3 million new cases that came into the dockets of criminal courts in that year. Kayaoglu (2022) uses the sum of cases in basic criminal courts and criminal courts of peace as her main outcome. In 2013, there are about 1.17 Million new cases in these courts (The upper line in Figure 2 of Kayaoglu (2022) presents the behavior of these court cases per 100,000 people).[43]

The middle (dashed) line in Figure B.F1 below replicates the crime rate in Figure 2 of Kayaoglu (2022), which is the sum of the number of cases in basic criminal courts and criminal courts of peace. Figure B.F2 presents the same information using the actual number of cases, rather than rates per 100,000 people. According to these figures, there was a steady decline in the number of court cases (Figure B.F2) between 2012 and 2017, the period during which Syrian refugee influx took place.[44] The solid lines in both figures display the cases in prosecutors' offices with unknown

[43] In Figure 2 of Kayaoglu (2022) this variable is titled "Basic Criminal Court Cases" although it consists of the sum of cases in basic criminal courts and cases in criminal courts of peace. The bottom line of the same Figure represents the number of cases for felonies with associated sentences of 10 years and longer. The author calls these High Criminal Court Cases. There were 69,732 of such cases in 2013.

[44] The decline in the number of court cases in Figure B.F2 translates into a decline in the crime rate based on these court cases in Figure B.F1.

perpetrators. These cases are not forwarded to the courts because there were no defendants identified. There has been a steady increase in the number of cases with unknown perpetrators over time. These are criminal acts reported by the police to the prosecutors' offices, but ultimately no suspects were identified. These unresolved cases may reflect the resource constraint faced by law enforcement agencies during a period of rising crime.

The true number of criminal cases can be portrayed by the sum of the cases in courts (the middle lines in Figures B.F1 and B.F2; as used by Kayaoglu, 2022) and the number of cases with unknown offenders (the bottom, solid line in Figures B.F1 and B.F2). This total is shown by the top line (the broken line) in both Figures, which still does not represent the actual criminal activity, but it brings the calculated crime rate and its evolution over time closer to reality.

Figure B.F1: The Number of Cases in Some Courts per 100K Population, and Cases with Unknown Perpetrators per 100K Population

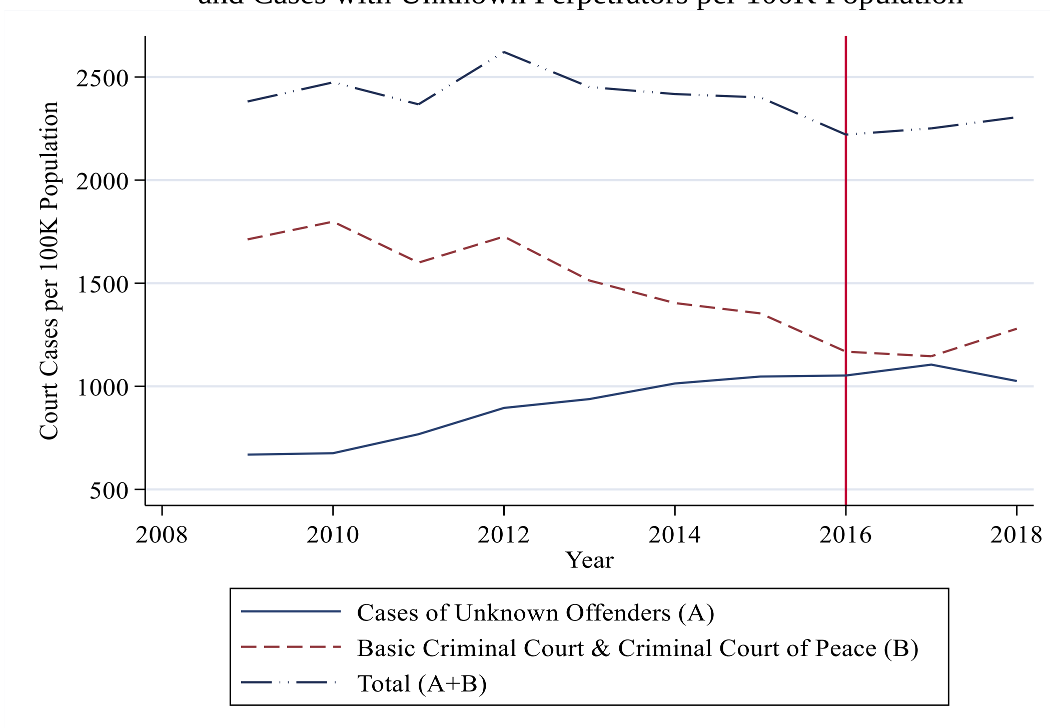
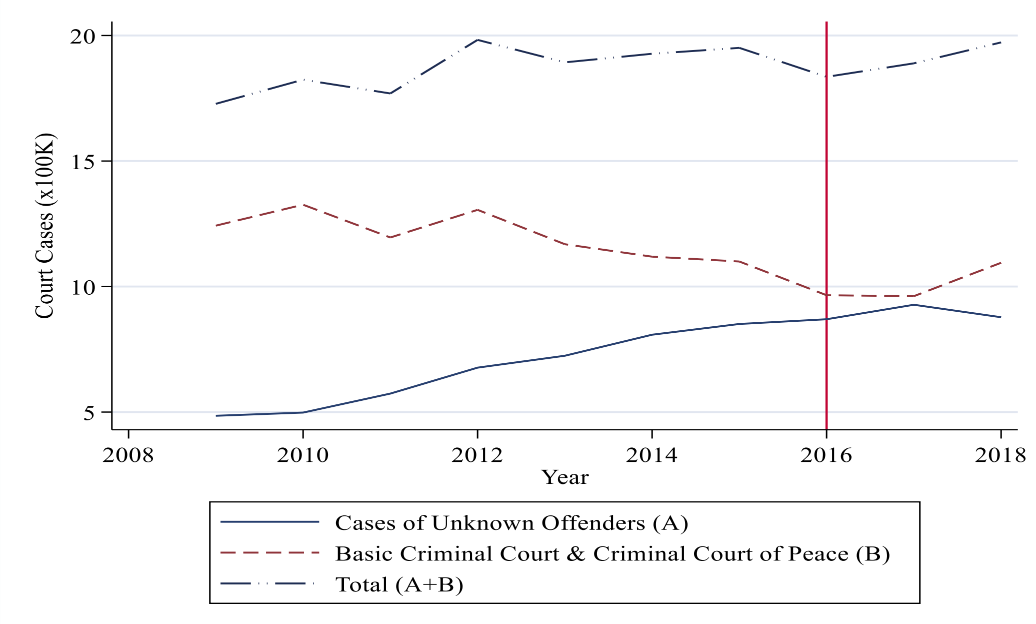


Figure B.F2: The Number of Cases in Some Courts
and Cases with Unknown Perpetrators



Nevertheless, we used the same crime rate proxy employed by Kayaoglu (2022), and estimated our model depicted by Equation (6). That is, we used the sum of the number of cases in basic criminal courts and cases in criminal courts of peace (i.e., the middle line in Figure B.F2), and estimated our instrumental variables specification. The results, reported in Table B1 below reveal that an increase in refugee population has a positive and significant impact on crime even when this particular crime proxy is employed as the outcome. This result confirms the theoretical discussion in Section VI of the paper which reveals that the specific empirical model used by both Kayaoglu (2022) and Kirdar et al. (2022) imposed a mechanical negative relationship between refugees and crime. We repeat the explanation of this pitfall below.

Table B1
The Impact of Refugees on Crime, 2006-2016
Dependent Variable: The Number of Cases in Basic Criminal Courts and Criminal Courts of Peace

	(1)	(2)	(3)	(4)	(5)
					Reduced
		Panel A: OLS			Form
Ln(Refugees)	0.005	0.005	0.002	0.009	
	(0.005)	(0.005)	(0.005)	(0.006)	
Ln(Natives)	0.471*	0.419	0.131	0.215	
	(0.238)	(0.253)	(0.234)	(0.257)	
		Panel B: IV			
Ln(Refugees)	0.027	0.027	0.075*	0.074**	
	(0.019)	(0.017)	(0.044)	(0.032)	
Ln(Natives)	0.220	0.163	-0.099	0.188	
	(0.301)	(0.308)	(0.296)	(0.286)	
Instrument/1000					0.023***
					(0.009)
Ln(Natives)					0.125
					(0.223)
F-test for first-stage	43.12	50.20	16.31	16.15	
Mean of the Dependent Variable	13,569	13,569	13,569	13,569	13,569
Mean of Refugees	8,892	8,892	8,892	8,892	8,892
Mean of Natives	922,180	922,180	922,180	922,180	922,180
Observations	891	891	891	891	891
Year FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Time-Varying Province Controls	No	Yes	Yes	Yes	Yes
5 Region Linear Trends	No	No	Yes	Yes	Yes
12 Region-Year FE	No	No	Yes	Yes	Yes
Trends by pre-Syrian Province Crime	No	No	No	Yes	No

Standard errors, clustered at province level, are in parentheses. Asterisks denote significance levels (*=.10, **=.05, ***=.01). Time-Varying province controls include the log of hospitals per 100K population, the presence of natural gas lines in the province in a given year, the log of public expenditures per 100K population and the lag of prison intake.

Incorrect Empirical Model that Produces a Negative Bias on the Estimated Refugee Effect

This material is presented in Section VI of the paper. We summarize it again here for completeness.

This production function of crime can be specified as

$$(A1) \qquad CR = A\, R^{\beta} N^{\gamma} e^{\varepsilon}$$

where CR stands for the number of offenses, R represents the number of refugees, and N is the size of the native population. The empirical counterpart of Equation (A1) is:

$$(A2)\ \ lnCR = \alpha + \beta\ lnR + \gamma\ lnN + \varepsilon$$

where α contains observable exogenous characteristics of the province, as well as various fixed effects that soak up unobservable province and regional attributes. Province and time subscripts are suppressed.

Equation (A2) can be converted into different forms. For example, adding $[-\beta\ ln\ \ (N+R)\ -\ \ ln\ \ (N+R)\ ]$ to both sides and rearranging terms yields

$$(A3) \quad ln\left(\frac{CR}{N+R}\right) = \alpha + \beta\ ln\left(\frac{R}{N+R}\right) + \gamma\ ln\ N + [(\beta - 1)\ ln\ (N+R)] + \varepsilon,$$

which can also be written as

$$(A4)\ \ ln\left(\frac{CR}{N+R}\right) =\ \alpha +\ \beta\ ln\ \left(\frac{R}{N+R}\right) +\ \gamma\ ln\ N\ \ + \nu$$

$$where\ \ \nu = \varepsilon + (\beta - 1)\ ln\ (N+R)$$

The left-hand-side of Equation (A4) is (log of) the crime rate, and the key explanatory variable on the right-hand side is the (log of) share of refugees in total population as used by both Kayaoglu (2022) and Kirdar et al. (2022) to estimate the impact of refugees on crime.

Although Equation (A4) is a rearrangement of Equation (A2), it is not appropriate to use Equation (A4) in an effort to estimate the impact of refugees on crime. This is because of the following reasons:

(i) Suppose there is no true relationship between the refugee share $\left(\frac{R}{N+R}\right)$ and the crime rate; that is, assume that β=0 in Equation (5). The error term of Equation (A4) reveals, however, that an increase in the number of refugees (R) will nevertheless produce a negative relationship between refugees and the crime rate. This mechanical negative relationship, imposed by the transformation of Equation (A2) to Equation (A4) persists as long as the elasticity of the crime rate with respect to refugee share (β) is less than one. Put differently, fitting equation (A4) to data underestimates β.

(i) Ignoring the issue highlighted in point (i), another problem in using Equation (A4), as was done by Kayaoglu (2022) and Kırdar et al. (2022), is that the variable of interest, R, is both in the numerator of the key explanatory variable, and in the denominator of the dependent variable. This property of Equation (A4) also imposes a mechanical negative relationship between refugees and the crime rate by construction.

(ii) Related to points (i) and (ii) above, any instrument that is correlated with R is invalid in Equation (A4) because the exclusion restriction is violated and the estimated β is biased. More specifically, consider Equation (A4) again. The probability limit of the instrumental variables estimate of β is: $plim\,\hat{\beta} = \beta + \frac{Cov\,(lnZ,\upsilon)}{Cov(ln\left(\frac{R}{N+R}\right),lnZ)}$, where Z is the instrument. Any instrument Z, which would generate a movement in R, is also correlated with the error term (υ) of Equation (A4) as the error term contains R. More specifically, if Cov (Z, R)>0, this would imply that Cov(Z, ν)<0 if β<1, and Cov(Z, ν)>0 if β>1. The instrument is uncorrelated with the error term only if β=1, but even in this special case the instrument is invalid, because the endogenous variable (R) also appears in the denominator of the dependent variable.

(iii) Finally, even if none of these vital issues existed, a basic problem would have been the use of the same divisor both in the dependent and the independent variable. More specifically, using the crime rate as the dependent variable, and then using population (which is the denominator of the dependent variable) as the deflator of the key explanatory variable creates bias.[45]

[45] More specifically, consider the model [CR/(N+R)]= α+β [R/N]+ε, where CR stands for crime, R is the refugee population, N is the native population, and (R/N) represents the refugee share. Because (N+R)≈N, this regression would produce a spurious relationship between the crime rate and refugee share because both the dependent variable and the explanatory variable have (almost) the same denominator. As explained by Kronmal (1993) and Bazzi and Clemens (2013), and as highlighted with examples by Clemens and Hunt (2019), the denominators that are the same or very similar will generate a spurious correlation between the two variables when the true β is zero. See Kronmal (1993) for theoretical and empirical examples, and proposed solutions.

In summary, estimating the specification shown in Equation (A4) produces a downward bias which explains the surprising result reported by Kayaoglu (2022) and Kırdar et al. (2022) that refugee inflows have a crime-reducing effect. To demonstrate this point empirically, we used the same crime indicators employed by these papers (prison intake as used by Kırdar et al (2022); and the sum of the number of cases in basic criminal courts and cases in criminal courts of peace as used by Kayaoglu 2022). We first replicated their results, and then demonstrated how they changed under correct model specification. This exercise is summarized in Table B2 below.

Panel A of Table B2 reports the instrumental variables results using the same crime proxy (prison intake) and the same instrument of Kırdar et al. (2022). These authors used data spanning 2008-2019, but they dropped the year 2012 from the analysis sample. We employed the same sample as they did, used the same incorrect empirical specification (Equation A4), and replicated their results as was reported in the first row of their Table 3 (Kırdar et al 2022, p. 576). This replication, displayed in the top section of Panel A, reveals a negative impact of the refugee ratio on the crime rate, as reported by the authors. The bottom section of Panel A, uses the same data and the same instrument, but employs the correct empirical model (Equation A2) as discussed above. Doing so reverses the results and reveals that an increase in refugees leads to more crime.

Panel B of Table B2 repeats the same exercise for Kayaoglu (2022). The top section of Panel B replicates the author's results using the same crime proxy, the same instrument, and the same incorrect model specification as employed in that paper.[46] Here, as in Table 5 of Kayaoglu (2022), there is a negative impact of the refugee share on the crime rate. The bottom section of Panel B reports the results based on the same data and the same instrument , but here we use the correct model (Equation A2) which does not impose a negative association between refugees and crime. As was the case with the Kırdar et al (2022) in Panel A, doing so flips the sign of refugees from negative to positive.

In summary, as displayed in Table B2, the impact of refugees on crime is positive, and the results reported by these authors are an artifact of the incorrect specification employed by them.

[46] The author writes in the paper that she used the period 2009-2016, which would have produced 648 observations. However, Table 5 of Kayaoglu (2021) reports 567 observations, which implies a span of 7 years. Thus, we estimated the model between 2010-2016, which produced the results reported in the top section of Panel B. Using the time period of 2009-2016 or 2012-2018 provided the same results.

Table B2
The Impact of Refugees on Crime
The Influence of Model Specification when Using Poor/Wrong Proxies of Crime:
IV Specifications

	Panel A: Kırdar et al. (2022) Crime Proxy: Convicts Entering Prison	
Incorrect Model: Equation (A4)	(I)	(II)
Dependent Variable: ln (CR/(N+R))	-157.282*	-140.377
Explanatory Variable: ln (R/(N+R))	(89.023)	(138.970)
Correct Model: Equation (A2)	(I)	(II)
Dependent Variable: ln (CR)	0.117**	0.194*
Explanatory Variable: ln (R)	(0.046)	(0.109)

	Panel B: Kayaoglu (2022) Crime Proxy: Cases in Criminal Courts and Criminals Courts of Peace	
Incorrect Model: Equation (A4)	(I)	(II)
Dependent Variable: ln (CR/(N+R))	-0.012***	-0.006***
Explanatory Variable: ln (R/(N+R))	(0.004)	(0.002)
Correct Model: Equation (A2)	(I)	(II)
Dependent Variable: ln (CR)	0.011	0.043*
Explanatory Variable: ln (R)	(0.019)	(0.023

Following Kırdar et al (2022) Panel A models are based on 891 observations spanning 2008-2019, omitting 2012. Column (I) in Panel A corresponds to the first column in Table 3 (page 576) of Kırdar et al. (2022), and controls for province and year fixed effects and province specific controls. Column (II) corresponds to the fifth specification in Table 3 of Kırdar et al. (2022), and controls for province and year fixed effects, 5-Region time trends, NUTS1 time trends, 5-Region-year fixed effects, NUTS1-year fixed effects, and province specific controls. The correct model in Panel A also controls for population.

Following Kayaoglu (2022), the results reported in Panel B are based on 567 observations, spanning the years 2010-2016. The specification in Column (I) in Panel B corresponds to Column 4 in Table 5 (page 15) of Kayaoglu (2022), and Column (II) corresponds to Column 5 in Table 5 (page 15) of Kayaoglu (2022). The correct model in Panel B also controls for population. Standard errors are clustered at the province level in all regressions. ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5% and 1%, respectively.

APPENDIX C

Connections to the Labor Market

In the paper we demonstrated that an increase in the refugee population generates an increase in criminal activity. The same is true for an increase in the unskilled native population, although the impact of the refugee population is bigger. With this result in mind, consider that an increase in the refugee population exerts two effects on total crime: (i) non-labor market effect, which signifies the rise in total number of crimes simply because of additional individuals in the society, (ii) the labor market effect, which impacts crime through the influence of refugees on wages.

Specifically, consider

$$(A5) \qquad \frac{\partial CR - Nonlabormarket}{\partial R} + \left(\frac{\partial CR_R}{\partial w_R}\right)\left(\frac{\partial w_R}{\partial R}\right) + \left(\frac{\partial CR_N}{\partial w_R}\right)\left(\frac{\partial w_R}{\partial R}\right)$$
$$= C^* + \left(\frac{\partial w_R}{\partial R}\right)\left[\left(\frac{\partial CR_R}{\partial w_R}\right) + \left(\frac{\partial CR_N}{\partial w_R}\right)\right]$$

The first term of Equation (A5) represents the increase in crime due to the non-labor market effect of an increase in the refugee population (R). As described in the introduction, this reflects an increase in crime simply because of the increase in the number of people who have attributes (e.g., risk aversion, time preference, exposure to violence, and so on) which would influence their criminal proclivity one way or the other. The second term captures the change in crimes committed by refugees (CR_R), induced by the change in wages triggered by a rise in the refugee population. This second term summarizes the labor market effect on refugees' crime of a change in refugee wages. The third term depicts how a change in refugee wages, due to an increase in the number of refugees, impacts crime committed by natives (CR_N). Collecting terms produces the expression on the right-hand-side of the equality sign, where C^* stands for. ($\frac{\partial CR-Nonlabormarket}{\partial R}$).

Equation (A6) displays the same idea for an increase in the native population (N). The term C^{**} on the right-hand-side of Equation (A6) represents the change in crime because of an increase in native population, without altering the labor market conditions.

$$(A6) \qquad \frac{\partial CR - Nonlabormarket}{\partial N} + \left(\frac{\partial CR_N}{\partial w_N}\right)\left(\frac{\partial w_N}{\partial N}\right) + \left(\frac{\partial CR_R}{\partial w_N}\right)\left(\frac{\partial w_N}{\partial N}\right)$$
$$= C^{**} + \left(\frac{\partial w_N}{\partial N}\right)\left[\left(\frac{\partial CR_N}{\partial w_N}\right) + \left(\frac{\partial CR_R}{\partial w_N}\right)\right]$$

Our empirical analyses show that an increase in the number of refugees has a larger impact on total crime than an increase in the native population. This implies that the right-hand side of Equation (A5) is greater than the right-hand side of Equation (A6).

If native unskilled labor and refugee labor are perfect substitutes, this would imply the existence of one prevailing wage in the market for both groups ($w_R = w_N$). Under this scenario, the last terms in brackets on the right-hand-side of equations (A5) and (A6) would be the same, and it would also be the case that $\left(\frac{\partial w}{\partial R}\right) = \left(\frac{\partial w}{\partial N}\right)$. Thus, it would follow that $C^* > C^{**}$, which would in turn imply that even if there were no labor market effect on crime, an increase in refugee population generates a larger increase in crime in comparison to an equivalent increase in native population.

Alternatively, suppose that C*=C**. That is, assume that absent any labor market effect, an injection of refugees or natives in a community by a given magnitude would impact crime equally. Further assume that unskilled native workers and refugees are not perfect substitutes. In this case, our finding that the magnitude produced by Equation (A5) being greater than the magnitude generated by Equation (A6) implies that

$$\left(\frac{\partial w_N}{\partial N}\right)\left[\left(\frac{\partial CR_N}{\partial w_N}\right)+\left(\frac{\partial CR_R}{\partial w_N}\right)\right] < \left(\frac{\partial w_R}{\partial R}\right)\left[\left(\frac{\partial CR_R}{\partial w_R}\right)+\left(\frac{\partial CR_N}{\partial w_R}\right)\right]$$

This inequality depends on elements such as the elasticity of labor demand for refugee labor and for native labor, the responsiveness of refugee crime to refugee wages, and the responsiveness of native crime to native wages. It also depends on the responsiveness of refugee crime (native crime) to native wages (refugee wages), through the elasticity of substitution between refugee labor and native labor.

The upshot is that the results identified in the paper can emerge theoretically under a number of different scenarios involving the structure of the labor markets (which also reflect the production technology).