# Crime Perception and Victimization in Europe: Does Immigration Matter?

Luca Nunziata\*

Department of Economics, University of Padua and IZA

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Abstract We present an empirical analysis of the consequences of the recent immigration waves in Western European regions in terms of crime victimization and perception. Our research strategy is twofold. We first estimate a linear probability model of the likelihood of being a crime victim (and of feeling unsafe) on immigration by region using individual data and a set of regional fixed effects and country specific time effects plus controls. In addition, in order to account for possible measurement errors of regional immigration and possible regional specific time varying unobservable factors, we instrument regional immigration in a model in differences using an exogenous measure of immigration flows induced by push factors in world areas of origin. Our empirical results suggest that immigration does not have any significant impact on criminality in destination regions. We find some effects on crime perception that disappear when immigration is instrumented. This result is at odds with our finding that crime perception is an important driver of the attitude of European citizens towards immigration.

**Keywords:** Crime, Immigration, Crime Perception, Victimization, Safety, Security.

JEL Classification Numbers: F22, J15, K42, O15, R23.

<sup>\*</sup>Address: Dept. of Economics, University of Padua, Via del Santo 33, 35121, Padua, Italy, e-mail: luca.nunziata@unipd.it. The author is grateful to Tommaso Frattini for advice and suggestions, to seminar participants at the CSEA workshop on Migration for helpful comments and to Veronica Toffolutti for research assistance. The usual disclaimer applies.

## 1 Introduction

One of the issues that has dominated the political debate in most OECD countries in recent years pertains to the economic and social implications of increasing immigration intakes in affluent economies. This debate has been particularly relevant in Europe, where immigration flows, especially from less developed areas of the world, have steadily increased over the past few years. In addition, whereas countries such as Germany, the UK and Belgium are not new to the immigration phenomenon, other continental countries have only recently become destinations of significant migration inflows.

Economic theory provides some guidance as regards how immigration affects host countries, with the literature largely focusing on labour markets outcomes and welfare state provision. One dimension which has attracted less attention, at least among economists, attains to the implications of immigration in terms of criminality. Nevertheless, this aspect is one of the most important when evaluating European natives' attitudes towards immigrants (see Boeri, 2009; Card, Dustmann, and Preston, 2009). Indeed, many European countries have witnessed various attempts at exploiting a supposed link between immigration and criminality to gain political prominence, sometimes with success<sup>1</sup>.

A possible channel associating immigration and criminality originates from the different opportunity costs of committing a crime experienced by immigrants with respect to natives (Becker, 1968). Whereas immigrants face reduced economic opportunities in host countries, they may be more prone to engage in criminal activities with respect to more integrated natives.

On the other hand, natives and immigrants experience different costs of being subject to trial and conviction, stemming from unequal access to quality legal defense to more dramatic consequences in case of unfavorable verdict. By internalizing these costs, immigrants may be less likely to become criminals.

Considering those conflicting factors, it is not clear what the net implications are in terms of effective criminality patterns among immigrants with respect to natives. The empirical literature on the relationship between criminality and immigration has a long tradition in Criminology and Sociology and only recently has developed in Economics too. Most analyses are based on US data and focus on actual crime outcomes only, in terms of crime reported,

<sup>&</sup>lt;sup>1</sup>See, for example, Mayer and Perrineau (1992); Norris (2005).

convictions or victimization, without paying much attention on crime perception. However, crime perception patterns may not necessarily be in line with actual reported crime for a number of reasons. On the one hand citizens may be subject to cognitive bias in their representation of the amount of crime experienced in their local area. On the other hand, the traditional media attention to crime phenomena may lead to an over-representation bias in their portrait of security issues. Crime perception may then provide a useful measure of how citizens internalize social fears about criminality, and whether those fears are actually justified in terms of actual criminality outcomes.

This paper provides the first attempt, to our knowledge, to investigate this topic with a European focus, providing some insights on crime victimization as well as crime perception. We exploit the recent years' increase in immigration flows into European countries to assess whether immigration affects criminality and the perception of insecurity among European natives. By matching individual crime victimization and crime perception data with immigration penetration in European regions we estimate the effect of changes in immigration patterns on the likelihood of being a crime victim and on the subjective representation of criminality in local area of residence. In order to account for possible endogeneity and measurement issues, we provide a set of estimates including fixed effects by regions and country\years as well as instrumenting immigration in a specification in differences using exogenous supply-push changes in migration patterns. As a result, we cannot find any evidence of an increase in criminality nor in crime perception induced by the recent immigration waves in Europe. Some preliminary empirical findings show that perceptions are altered via media consumption, suggesting a possible role played by media in representing immigration as a crime generating phenomenon.

Section 2 presents a review of the existing empirical literature, section 3 introduces the research design and discusses the potential problems created by mis-measurements of immigration by region, section 4 provides a description of the patterns in the data and presents our empirical findings, section 5 concludes.

## 2 Literature Review

Most of the empirical literature in Sociology, Criminology and more recently Economics analyze US data. For example, Butcher and Piehl (1998) analyze Uniform Crime Reports

and CPS data and identify a cross sectional correlation between criminality and immigration rates across US cities. However, the correlation disappears after controlling for the cities' demographic characteristics. No correlation is found by exploiting within city variation in crimes and immigration.

Looking at three US border cities (Miami, El Paso and San Diego) Lee, Martinez, and Rosenfeld (2001) find that immigration does not increase the number of homicides among Latinos and African Americans.

Butcher and Piehl (2007) show that immigrants in the US have much lower incarceration rates than natives (around one fifth). This difference increased from 1980 to 2000 and does not appear to be driven by increase deportation. The authors suggest instead that the migration process selects individuals who are less prone to be criminal or who respond more to deterrence than the average native born.

Moehling and Piehl (2007) use early 20th century US prison data and find analogous crime patterns for natives and immigrants, with minor exceptions. More specifically, 1904 prison commitment rates for more serious crimes are similar for all ages except ages 18 and 19 which are instead characterized by higher commitment rates for immigrants with respect to natives.

Researchers have only recently drawn their attention to European data. Bianchi, Buonanno, and Pinotti (2008) provide an empirical examination of the relationship between crime and immigration across Italian provinces from 1990 to 2003 using police administrative data. Exploiting the within variation across provinces the authors find a positive correlation between the size of immigrant population and the incidence of property crimes and the overall crime rate. However, the relationship disappears when immigration is properly instrumented, suggesting a significant effect on robberies only. The effect on the overall crime rate is therefore negligible since robberies are only a tiny fraction (1.5%) of total criminal offences.

Mastrobuoni and Pinotti (2010) look at the implications of immigrants' legal status on criminal behavior by using exogenous variation in migration restriction laws in Italy. They exploit the last round of European Union enlargement that took place in 2007 when Romania and Bulgaria entered the European Union to show that obtaining legal status reduces the propensity to commit a crime by raising its opportunity cost.

Bell, Machin, and Fasani (2010) analyze two recent large immigration waves in the UK to analyze the implications in terms of changes in crime rates. Considering the large immigration

wave of asylum seekers in the late 1990s/early 2000s and the large inflow of workers from EU accession countries from 2004 onward, the authors argue that the opportunity costs of engaging in criminal offenses were radically different for the two groups of migrants. The asylum wave was associated with low labor force participation, high unemployment and low wages, while the EU enlargement wave was characterized by participation rates higher than natives. The empirical analysis is consistent with the standard economic theory of crime, with non-violent crime rates found to be significantly higher in areas in which asylum seekers are located and not in areas affected by the EU enlargement wave.

Overall the existing literature on the US plus selected European countries points to a non significant effect of migration on crimes, except minor occurrences. No evidence is generally provided as regards the implications of immigration in terms of crime perception. However, various studies in criminology focus on the fear of crime, defined as the fear to be a crime victim as opposed to the actual probability to be a crime victim (Hale, 1996; Jackson and Stafford, 2009).

Fitzgerald, Curtis, and Corliss (2009) suggest fear of crime as being a predictor of attitude towards immigration in Germany, with a larger effect during election years. It is not clear what are the actual drivers of these fears if the relationship between immigration and crime is not supported by most studies. Possible answers could be cultural factors and, according to the analysis by Fitzgerald, Curtis, and Corliss, political and media representation.

In what follows we provide further empirical evidence on the relationship between immigration and crime with a comprehensive analysis of Western European data from 2002 to 2008, i.e. a period characterized by large migration inflows to the regions object of our analysis. Our focus will be both on crime victimization and perception.

## 3 Research Design

#### 3.1 Fixed Effects Model

We analyze data from the four waves of the European Social Survey (ESS henceforth) covering a large number of European countries from 2002 to 2008, every two years. The time span of the analysis covers a crucial period for immigration in Europe, characterized by a significant increase in immigration penetration in most countries, although with a certain

degree of regional heterogeneity within and across countries.

We first adopt a fixed effects approach by matching individual level crime victimization and perception with regional variation in immigration penetration in order to investigate if a relationship exists. The analysis exploits the different patterns in immigration penetration across geographical areas, for different levels of regional disaggregation.

Despite the ESS providing information on both Western and Eastern European countries, we choose to focus on the former only, in order to capture the relationship between immigration and outcomes of interest within an homogeneous economic and social environment. In addition Eastern European countries are often subject to migration outflows towards West Europe, and therefore do not qualify for our empirical test.

Alternative sources of information on immigration penetration in Europe are used, both by country and region. These are Census 2001 data, European Labour Force Survey (LFS), and OECD Database on Immigrants in OECD Countries (DIOC).

The ESS contains information on whether the respondent or household member has been a victim of assault or burglary in the last 5 years, and the degree of perceived insecurity (when walking alone after dark in local area) that represents a measure of individual crime perception.

In addition, we observe the respondents' region of residence, that is classified according to various degrees of geographical aggregation (NUTS I, II or III) according to country. The latter can be matched with a set of measures of immigration penetration by regions, from different sources, and the within regional variation in immigration can be exploited to address the questions of interest.

The advantage of using survey data consists in relaying on a measure of crime victimization that it is not affected by the problem of under-reporting of crimes typical of administrative and judicial sources. In addition, survey data information on regional immigration does not necessarily include legal immigrants only, as in the case of official administrative sources.

However, as previously recognized in the literature, illegal immigrants may have a lower propensity to participate to interviews with respect to natives and legal immigrants. As a consequence, immigration patterns by regions may still be under-estimated. The extent to which this is a problem for our estimates will depend on whether the propensity to participate is related to the propensity to commit a crime. In that case the immigration penetration figures across regions may be endogenously mis-measured. One of our major difficulties is therefore to

deal with the problem of measurement errors of immigration penetration across regions.

Apart from measurement issues, immigration may also be endogenously driven by factors directly affecting criminality and crime perception, resulting in biased estimates and wrong policy implications. Ideally, one would need to randomly assign different levels of immigration to different European regions and check if criminality is significantly affected. From an observational perspective, we choose to deal with the problems above in two ways. A first empirical strategy is to pool the 4 ESS waves (2002-2008), gather measures of immigrants across European regions in each wave year, and exploit the within regional variation of immigration to estimate the effect on the likelihood of being a crime victim (or feeling not secure). In other words, we specify a model with regional fixed effects and clustering, as well as country-specific time dummies (plus observable individual and structural regional characteristics), assuming that both endogenous factors and measurement errors are constant by region and or country-year.

Our linear probability model is therefore:

$$crime_{crit} = \beta m_{crt} + \lambda' \mathbf{X}_{it} + \gamma' \mathbf{W}_{crt} + \mu_r + \mu_{ct} + \varepsilon_{it}$$
 (1)

where  $crime_{crit}$  is a dummy variable indicating whether the individual i, living in country c and region r is a crime victim (or whether the individual fears crime),  $\mathbf{X}_{it}$  is a matrix of individual characteristics,  $\mathbf{W}_{crt}$  is a matrix of regional characteristics,  $\mu_r$  are regional fixed effects and  $\mu_{ct}$  are country-specific time dummies.

This approach is successful if no time varying unobservable regional characteristics affect both crime (or perception of insecurity) and immigration, therefore inducing spurious correlation between the two variables (whereas country-level changes in unobserved country characteristics are admitted).

If the assumptions above hold, the estimates of model (1), presented in section 4.2.1, are able to capture the causal impact of immigration on our variables of interest.

#### 3.2 Measurement Issues

We may think about two sources of error affecting our measure of the proportion of immigrants by regions. On the one hand we have illegal immigration that is either not counted in the data (for example when considering administrative sources) or less represented in the

interviewed sample. On the other hand, legal migrants may be less inclined to participate to a survey than native born.

As far as illegal immigration is concerned, previous analysis show that the relative dimension of illegal immigration with respect to legal immigration is fairly stable. For example, Bianchi, Buonanno, and Pinotti (2008) use regularization episodes in Italy to show that the ratio of illegal to legal immigrants is very stable within Italian provinces and regularization years. If this is the case, the inclusion of regional and country-specific dummies should account for the first source of error.

As regards the second possible source of measurement error, model (1) implicitly assumes that the different propensity to participate to the survey of legal immigrants is either constant, or it changes across regions and\or across time. If it changes across time, the change follows country-specific motives. All these possible scenarios are accounted by the fixed effects specification in (1) and more specifically by regional and country-specific time dummies.

In analytical terms, we may think that the proportion of immigrants on resident population  $M^{total}$  in each region consists of legal plus illegal migrants, so that:

$$M_{crt}^{total} = M_{crt}^{legal} + M_{crt}^{illegal} \tag{2}$$

where  $M_{crt}^{legal}$  and  $M_{crt}^{illegal}$  are, respectively, the number of legal and illegal immigrants on resident population in region r and time t, with c denoting the country to which region r belongs.

On the lines with the findings of Bianchi, Buonanno, and Pinotti (2008), illegal immigration is proportional to legal immigration according to the following relationship:

$$M_{crt}^{illegal} = M_{crt}^{legal} \left( \theta_j + \theta_{it} \right) \tag{3}$$

Assuming that only a fraction of legal immigrants accepts to participate to the survey, what we observe is not  $M_{crt}^{legal}$  but:

$$M_{crt}^{survey} = M_{crt}^{legal} \nu_{crt}^{-1} \tag{4}$$

Combining (5) and (4) with (2) we obtain:

$$M_{crt}^{total} = M_{crt}^{survey} \nu_{crt} \left( 1 + \theta_r + \theta_{ct} \right) \tag{5}$$

Assuming that the propensity to participate of migrants varies by region and time and that these differences are fixed but allowed to vary across countries, we have:

$$M_{crt}^{total} = M_{crt}^{survey} \left( 1 + v_r + v_{ct} \right) \left( 1 + \theta_r + \theta_{ct} \right) \tag{6}$$

Taking logs, equation (6) becomes:

$$m_{crt}^{total} = m_{crt}^{survey} + \mu_r + \mu_{ct} + \varepsilon_{crt} \tag{7}$$

which is the rationale for the specification of our fixed effects model (1).

Another way at looking at the measurement problem is to think about the error as being random. In this case, it is not unreasonable to assume that the error, consisting in the proportion of migrants who are not surveyed, is correlated with the true stock of migrants and uncorrelated to the observed measure of migration. In other words, the proportion of those who participate to the survey is random but correlated to the proportion of migrants who live in the region, so that, for example, in regions where migrants are more (few) they will tend to be more (less) surveyed. If this is the case, the OLS estimation of (1) will deliver consistent estimates of  $\beta$  and only the error variance will be positively affected.

On top of these considerations, we use different data sources on regional immigration patterns, in order to check if our results are robust. Section 4.1 provides a detailed description of the data and of the consistencies across sources.

### 3.3 Instrumental Variable Model

Unobservable factors correlated to immigration patterns may vary over time in a way not captured by country-specific time effects, in which case our fixed effects specification may still produce biased estimates. In addition, the assumptions implied by model (1) on the measurement errors of immigration by regions may not be supported by the data. An instrumental variable approach may then be advisable in this setting for two order of reasons. On the one hand in order to account for regional-specific omitted time-varying factors (not therefore cap-

tured by regional dummies or by country-specific time-dummies) that may affect both migration patterns and the likelihood of being a crime victim or the perception of insecurity among respondents. On the other, in order to account for possible measurement errors in the accounts of immigration presence by region. This aspect is potentially relevant if we consider that immigrants are a small fraction of the total population in each European region. The measures provided by all our data sources on the presence of immigrants in each region may be therefore affected by measurement error, due to small sample size, especially at more disaggregated regional levels.

In this case, a classic remedy suggested by the literature is to instrument the variable affected by measurement error (Reiersol, 1941; Durbin, 1954). Various instruments have been suggested by the literature. For example, Lemos and Portes (2008) and Bell, Machin, and Fasani (2010) instrument recent migration patterns from eastern Europe towards UK regions by using the availability of flights from Eastern Europe to the UK. Card (2001), Dustmann, Frattini, and Preston (2008) and Bianchi, Buonanno, and Pinotti (2008) consider instead the geographical distribution of previous immigrants from flow areas as an instrument for following flows.

We follow this second approach, and similarly to what Bianchi, Buonanno, and Pinotti (2008) do for Italy, we use exogenous migration flows to Europe as instrument. These are measured by changes in migration flows towards other European countries (or regions) from different world areas of provenience, weighted by the predetermined share of previous immigrants by world flow areas in each country (or region). In other words, changes in migration towards other European countries (or regions) account for the exogenous push factors inducing an increase in migration from world areas of provenience. These supply-push factors can be wars, political repression, famine, economic stagnation or else in areas of origin, and therefore exogenous with respect to our analysis. They affect immigration in each region according to the predetermined share of previous immigrants by flow area in that region since immigrants tend to locate in areas previously penetrated by individuals from the same area of provenience (Munshi, 2003).

Assuming we have N possible world flow areas a and that prior to the period under investigation each region r in country c is characterized by a certain share  $s_{cr}^a$  of immigrants from each area, the change in migration in that region will be approximately equal to:

$$\Delta m_{crt} \approx \sum_{a=1}^{N} s_{cr}^{a} \Delta m_{crt}^{a} - \Delta pop_{crt}$$
 (8)

In order to construct an instrument for  $\Delta m_{crt}$ , we define the exogenous changes in migration from each flow area induced by supply-push factors as the changes in all countries other than c, where r belongs, i.e. we substitute  $m_{crt}^a$  with  $m_{kt}^a$ , where  $k \neq c$ . Our instrument therefore becomes:

$$z_{crt} = \sum_{a=1}^{N} s_{cr}^{a} \Delta m_{kt}^{a} - \Delta pop_{crt}$$

$$\tag{9}$$

In order to avoid to incorrectly measure the predetermined shares of migrants  $s_{cr}^a$  we choose not to be too disaggregated in both our definitions of flow areas a, and in our definition of region r. In our baseline specification we therefore consider N=5 flow areas, corresponding to the 5 continents, and we calculate the predetermined share at a country level, i.e.  $s_c^a$ . For robustness, we repeat the analysis for N > 5, i.e. introducing a finer geographical classification including sub-continents, and considering regional shares instead of country shares. The instrument in the baseline IV model is therefore:

$$z_{crt} = \sum_{a=1}^{N} s_c^a \Delta m_{kt}^a - \Delta pop_{crt}$$
 (10)

We can therefore estimate a model of crime victimization (or perception) in differences like:

$$\Delta c_{crt} = \beta \Delta m_{crt} + \gamma' \mathbf{W}_{crt} + \varepsilon_{crt}$$
 (11)

by instrumenting  $\Delta m_{crt}$  with (10). The estimates of this model are reported in section 4.2.4.

# 4 Empirical Analysis

## 4.1 The Data

The only coherent administrative measure of immigration presence across European regions is Census data, which is available for selected years only. Last available Census data for some but not all European countries is dated 2001. Accordingly, we rely on a number of alternative data sources on regional immigration presence in European regions, i.e. ESS, LFS, and DIOC,

and check how they compare with 2001 Census data.

In general, two different levels of regional disaggregation are considered, i.e. NUTS I and NUTS II<sup>2</sup>. Figure (1) displays the percentage of immigrants over total residential population in European regions (NUTSII) according to alternative data sources (European Social Survey, Eurostat Census 2001 and European Labour Force Survey) and according to alternative definitions of immigrants (born abroad and non-nationals). In principle, Census data is the most reliable source as regards official figures on legal immigrants. Survey data should instead be able to capture the presence of illegal immigration, if well designed. In practice, as noted above, it is quite likely that both measures underestimate the number of illegal immigrants by region.

Table 1: Correlations between alternative measures of % immigrants in NUTSII European regions in 2002

Variables	Census 01	ESS, non-nat	ESS, b.abr.	LFS, non-nat	LFS, b.abr.
Census 01	1.000				
ESS, non-nat	0.865	1.000			
ESS, b.abr.	0.913	0.820	1.000		
LFS, non-nat	0.942	0.877	0.762	1.000	
LFS, b.abr.	0.973	0.747	0.821	0.899	1.000

Table 2: Correlations between alternative measures of % born-abroad immigrants in NUTSII European regions

zaropean regions				
Variables	ESS, b.abr.	LFS, b.abr.	ESS, b.abr. non-eu cnt	ESS, b.abr. non-eu lng
ESS, b.abr.	1.000			
LFS, b.abr.	0.821	1.000		
ESS, b.abr. non-eu cnt	0.801	0.711	1.000	
ESS, b.abr. non-eu lng	0.652	0.639	0.749	1.000

The correlation among these measures is pretty high, as shown in Table 1. LFS figures are generally closer to Census than ESS. The same is true for born-abroad counts versus non-national.

In what follows we mainly focus on the definition of immigrant as an individual who is born abroad, rather than using the information on citizenship, in line with most of the literature in order to avoid distortions induced by differences in legislation on naturalizations across countries. However we also provide a set of estimates using alternative definitions of who

<sup>&</sup>lt;sup>2</sup>According to the NUTS classification, NUTSI regions are characterized by a population between 3 and 7 millions individuals, whereas NUTSII regions are between 800,000 and 3 millions.

the immigrant is. As noted by Boeri (2009) the born abroad concept may induce some bias in countries with former colonies, where nationals born in those colonies and returning to the home country may be wrongly counted as immigrants. However, if we look at the data, the definition based on citizenship seriously underestimate regional immigration, even by comparison with the 2001 Census data. In general, ESS and LFS measures based on whether respondents are born abroad are closer to Census that those based on nationality only. We therefore believe that in our setting the second type of bias is less relevant than the first type<sup>3</sup>. In addition to using alternative data sources, we adopt various levels of regional disaggregation, i.e. country, NUTS I and NUTS II level.

Figure (2) presents the distribution of born-abroad immigrants across European regions by different individual characteristics and data sources. More specifically, both individuals born in Non-European countries and those who do not speak European languages at home are displayed. The figure points to a strong cross-sectional correlation among alternative measures, that is also displayed in Table 2. Tables 3 and 4 provide some summary statistics across alternative definitions and data sources, respectively over the whole sample and by country.

Table 3: Summary statistics for alternative immigration definitions and data sources

Variable	Mean	Std. Dev.	N
Census 01	10.65	8.44	23438
ESS, non-nat	4.87	5.68	117064
ESS, b.abr.	9.08	6.78	117064
LFS, non-nat	6.57	5.63	101906
LFS, b.abr.	10.44	7.28	91138

Figure (3) provides a summary of crime victimization across European regions as portrayed by ESS data. Here a crime victim is an individual who reports to have been victim of burglary or assault in the last five years. The figure provides clear patterns in crime victimization. The regions most affected seem to be Central UK, Southern France, Belgium, Luxemburg and Finland. A bit less affected are Southern Spain, Norway, Sweden and Denmark. Overall, Germany appears to be the country affected the least.

The ESS measure of fear of crime is a variable depicting the feeling of safety when walking alone in local area after dark, with 4 categories stemming from very safe to very unsafe. Figure

<sup>&</sup>lt;sup>3</sup>In this paper we only consider first generation immigrants, as the second generation is counted as native. The implication of second versus first generation immigration on criminality and perception of insecurity may be a topic of a paper on its own.

Table 4: Summary statistics, by country

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FR 9.933784 8.726927 11.15412 GB 7.652652 9.700822 9.828049 GR . 9.833959 6.049255 IE 10.30851 8.661308 8.236203 IT 3.70842 2.229532 . LU 32.45491 30.42424 . NL . 8.418588 11.93144 NO 6.728887 7.261103 7.338271 PT 6.932284 5.852096 6.475953 SE 10.95735 10.75253 13.37496	ES	5.388701	7.369424	10.07911
GB       7.652652       9.700822       9.828049         GR       .       9.833959       6.049255         IE       10.30851       8.661308       8.236203         IT       3.70842       2.229532       .         LU       32.45491       30.42424       .         NL       .       8.418588       11.93144         NO       6.728887       7.261103       7.338271         PT       6.932284       5.852096       6.475953         SE       10.95735       10.75253       13.37496	FI	2.694695	2.662394	2.523992
GR.9.8339596.049255IE10.308518.6613088.236203IT3.708422.229532.LU32.4549130.42424.NL.8.41858811.93144NO6.7288877.2611037.338271PT6.9322845.8520966.475953SE10.9573510.7525313.37496	FR	9.933784	8.726927	11.15412
IE       10.30851       8.661308       8.236203         IT       3.70842       2.229532       .         LU       32.45491       30.42424       .         NL       .       8.418588       11.93144         NO       6.728887       7.261103       7.338271         PT       6.932284       5.852096       6.475953         SE       10.95735       10.75253       13.37496	GB	7.652652	9.700822	9.828049
IT       3.70842       2.229532       .         LU       32.45491       30.42424       .         NL       .       8.418588       11.93144         NO       6.728887       7.261103       7.338271         PT       6.932284       5.852096       6.475953         SE       10.95735       10.75253       13.37496	GR		9.833959	6.049255
LU       32.45491       30.42424       .         NL       8.418588       11.93144         NO       6.728887       7.261103       7.338271         PT       6.932284       5.852096       6.475953         SE       10.95735       10.75253       13.37496	IE	10.30851	8.661308	8.236203
NL       .       8.418588       11.93144         NO       6.728887       7.261103       7.338271         PT       6.932284       5.852096       6.475953         SE       10.95735       10.75253       13.37496	$\operatorname{IT}$	3.70842	2.229532	
NO       6.728887       7.261103       7.338271         PT       6.932284       5.852096       6.475953         SE       10.95735       10.75253       13.37496	LU	32.45491	30.42424	
PT 6.932284 5.852096 6.475953 SE 10.95735 10.75253 13.37496	NL		8.418588	11.93144
SE 10.95735 10.75253 13.37496	NO	6.728887	7.261103	7.338271
	PT	6.932284	5.852096	6.475953
Total 10.65026 9.083977 10.44251	SE	10.95735	10.75253	13.37496
10000 10000 0000 100000 100000 100000 100000 100000 100000 100000 10000 10000 10000 10000 10000 10000 10000 10000 10000 10000 100000 10000 100000 10000 10000 10000 10000 10000 10000 10000 10000	Total	10.65026	9.083977	10.44251

4 gives a picture of crime perception across European regions, measured by individual feeling of safety. This is measured by the percentage of residents who feel safe and very safe when walking alone after dark. Not surprisingly, Germany is a country where citizens feel safe. Less clear is the pattern in the other countries with, for example, Norway, Sweden and Finland being countries where citizen feel safe despite the relatively high rate of crime victimization.

Table 5 shows the rate of victimization by country, together with the proportion of individuals who feel unsafe and very unsafe when walking alone after dark. Finally, Figure 5 provides a summary of the attitude towards immigrants across European regions. This is measured by the average score assigned by natives to the question asking whether immigrants make country worse or better place to live (from worse to better). Sweden, Denmark, Finland, Poland, Ireland and Eastern Spain (Cataluna) are very pro-immigrant regions. In Germany there is a clear difference between West and East, with Eastern Germany being significantly less positive towards the role of immigration than the West.

Immigrants as % of resident population in Europe

ESS, 2002-2008, NUTS 2

Shon nationals

One of the state of

Figure 1: Immigrants (non-nationals and born abroad) as percentage of resident population in Europe from alternative data sources

Note: figures are drawn by the author using, respectively, data from the European Social Survey from 2002 to 2008, the European census in 2001, and Eurostat European Labour Force Survey from 2002 to 2008. Regions are NUTS 2 level.

## 4.2 Empirical Findings

#### 4.2.1 Fixed Effects Estimations

We first estimate equation (1) by calculating the proportion of immigrants by region using alternative data sources and definitions of immigrant. In order to have a large enough number of observations by region we adopt a regional disaggregation which differs across countries, according to the information available from ESS, and the dimension of the sample by regions under alternative NUTS levels of disaggregation. We end up having 115 western European regions<sup>4</sup> with a number of observations per region that goes from a minimum of 207 for the German region of Hamburg, to a maximum of 4451 for the Belgian Flemish region.

Table 6 reports the effect of immigration in region of residence on the probability of being a crime victim, using alternative definitions of immigrant (born abroad and non-national) and using both ESS and LFS data to calculate immigration presence by regions.

<sup>&</sup>lt;sup>4</sup>We use NUTSII for AT, CH, DK, FI, IE, NO, PT, SE and NUTSI for BE, DE, ES, FR, IT, LU, NL, GR, GB. We drop two regions, i.e DE5 (Bremen) and DEC (Saarland) because the number of observations are lower than 200.

Immigrants as % of resident population in Europe

ESS, 2002-2008, NUTS 2

| Market |

Figure 2: Immigrants (born abroad) as percentage of resident population in Europe from alternative data sources and using alternative definitions

Note: figures are drawn by the author using, respectively, data from the European Social Survey from 2002 to 2008 and Eurostat European Labour Force Survey from 2002 to 2008. Regions are NUTS 2 level.

Columns (1) to (3) report the effect of immigration on crime using ESS data, where an immigrant is defined, respectively, as a non-national, a born-abroad and a born outside Europe. In all cases the coefficient of immigration is not significant. Models in columns (4) to (7) use LFS measures of regional immigration. These are, respectively, non-national, non-European national, born abroad and born outside Europe. The only measure which is only weakly significant (at the 10% level) is LFS non-national, whose coefficient would suggest that a one percentage point increase in immigration is associated with a 1.6% increase in the likelihood of being a crime victim. In each column we control for educational attainment, degree of urbanization of local area, gender, age, age squared and if main source of income is financial. Standard errors are clustered by regions

Overall, the estimates do not point to a significant effect of immigration on criminality. Males are more likely to be crime victims than females (typically by around 1%), whereas if main source of income is financial the likelihood of being crime victim increases by around 7%. As regards the other controls, in a typical regression the further from big city the individual is, the lower the probability of being a crime victim, with rural areas having around a 8%

Table 5: Summary statistics, by country

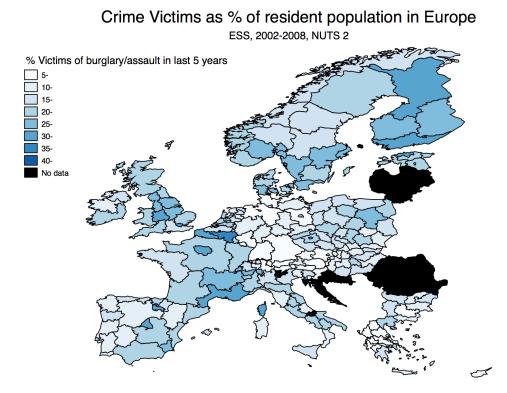
	$\operatorname{crimevictim}$	unsafefeel	veryunsafefeel
AT	.0981961	.1649321	.02573
BE	.2546412	.2017968	.0402211
СН	.1724005	.1661968	.022937
DE	.1018875	.2400489	.0485335
DK	.2455996	.1309758	.0345449
ES	.2176749	.2377613	.0471698
FI	.3063263	.1120424	.0145446
FR	.2615782	.2585505	.0935125
GB	.2498561	.3575618	.1084531
GR	.1796419	.3016895	.0878922
IE	.1883202	.2984344	.0802348
$\operatorname{IT}$	.1890311	.2953216	.0635965
LU	.2429201	.2384688	.0624412
NL	.188622	.1955258	.0309656
NO	.2277856	.1030303	.0191684
PT	.1648203	.2609176	.0458783
SE	.2585176	.1665369	.0382918
Total	.2060919	.2162085	.0492921

lower probability than big cities. Education level is significant, with higher education being correlated with a higher likelihood of being a crime victim. In addition, crime victimization decreases with age. Note that on average the likelihood of being a crime victim decreased in Western Europe by around 5% from 2002 to 2008.

Table (7) reports the estimation of equation (1) without including regional fixed effects. In this case, all specifications report a significant effect of regional immigration on the likelihood of being crime victims, ranging from around 2% to 6%. The comparison of the results in tables (6) and (7) may help explaining why some commentators view the increase in immigration as being related to criminality. Indeed, regions with more immigrants are regions where it is more likely to be crime victims. However, this relationship is altered by the regional characteristics (unobserved in our specification) that in turn attract immigration and affect criminality, rather than pointing to a casual relationship from immigration to crime.

Tables 8 and 9 reports the effect of immigration on crime perception (or crime fear) where the latter is defined, respectively, as feeling unsafe or very unsafe when walking alone after dark, or just very unsafe. In other words, the dependent variables in the tables indicate different

Figure 3: Victims of burglary or assault in the last five years in Europe as percentage of resident population in Europe



Note: the figure is drawn by the author using data from the European Social Survey from 2002 to 2008.

Regions are NUTS 2 level.

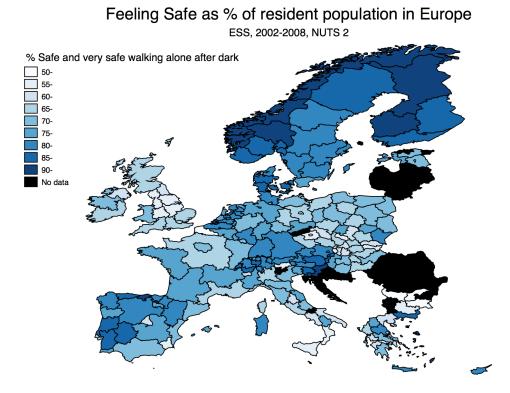
degrees of crime perception by respondents. Here we find signs of a significant positive effect of immigration on crime perception, although the effect is not robust across all definitions of immigration. In particular, we find a significant effect of born abroad and born in non-European countries immigration on the very unsafety feeling in table 9, but only when using the LFS measure. The LFS born abroad measure is instead significant in table 8 too.

As regards the other controls, in general male feel more safe when walking alone after dark in local area (around 18% more than females) together with more educated respondents and those living in less urbanized areas. In addition, as expected, crime perception increases with age.

#### 4.2.2 Crime Perception and Attitude Towards Immigration

So far we have analyzed the implications of changes in regional immigration on crime victimization and perception. The models in Table 12 revert this logic by considering the implications of crime victimization and perception on the attitude of natives towards immigrants.

Figure 4: Percentage of respondents feeling "safe" or "very safe" when walking alone after dark in local area



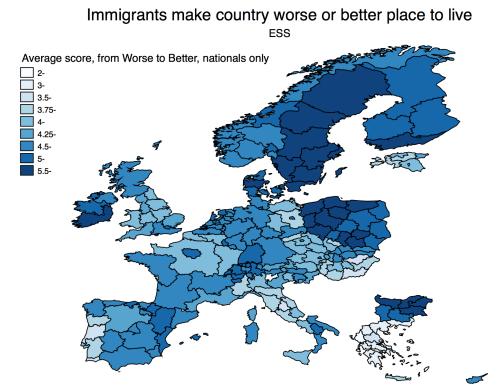
Note: the figure is drawn by the author using data from the European Social Survey from 2002 to 2008.

Regions are NUTS 2 level.

Here we consider two different measures of attitude that can be potentially affected by crime victimization and fear. The dependent variable in columns (1) and (3) is whether immigrants make country worse according to respondents (i.e. the variable is a dummy equal to 1 for respondents who answer less than or equal 4, on a scale from 0 to 10, from worse to better). The dependent variable in columns (2) and (4) indicates whether many or some immigrants from poorer countries outside Europe should be allowed to come and live in the country (as opposed to few or none).

The regressions are estimated both on individual data (columns 1 and 2) and on data collapsed at regional level (columns 3 and 4). The linear probability models in the first two columns have the disadvantage of not controlling for individual fixed effects. This may potentially harm our estimates since, differently from all previous models above, the regressors of interest here are defined at the individual level, rather than at the regional level. The estimates on regional data in the last columns do instead control for regional unobservables, as well as country-specific time dummies as in the previous regressions.

Figure 5: Average score to question "Is country made a worse or better place to live by people coming to live here from other countries?", where answer can go from 0 (worse) to 10 (better)



Note: the figure is drawn by the author using data from the European Social Survey from 2002 to 2008. Regions are NUTS 2 level.

All models point to a significant and positive effect of crime perception on the belief that immigrants make the country a worse place to live. According to model (1), feeling unsafe increases by 12% the probability of seeing immigration as making the country worse. According to model (3) instead, a 1% increase of individuals who feel unsafe in the region induces a 0.4% increase in negative attitude towards immigrants. Crime perception also significantly affects the attitude towards the openness of the country for immigrants coming from poor regions outside Europe. Here the number become -8% and -0,3%, respectively. Crime victimization is only significant in the first column, where having been a crime victim increases by almost 2% the probability of seeing immigration as making the country worse.

Overall, these result point to a clear and robust effect of crime perception on the attitude of natives versus immigration.

## 4.2.3 Media Consumption, Immigration and Crime Perception

Previous studies such as Fitzgerald, Curtis, and Corliss (2009) show how the link between fear of crime and worries about immigration is stronger in election years. This suggests how the public perception of social phenomena can be influenced by the political discourse or media representation.

If the relationship between immigration and crime perception is somehow mediated by the portrait of the immigration phenomenon depicted by the media we should observe an heterogeneous effect of immigration on the crime perception of individuals, according to the quantity and quality of media consumed. The ESS provides some useful information in this respect, since we have information both on the quality and the quantity of the media consumed, i.e. the time spent per day in watching television or reading newspapers.

Table 10 interacts the coefficient of regional immigration with the per-day consumption of television of each individual. Crime perception is measured by whether individuals feel unsafe or very unsafe when walking alone after dark in local area. Table 11 reports the same regressions using a different definition of crime fear, including only those who feel very unsafe. Television consumption is likely to be correlated to unobservable individual characteristics that directly affect crime perception. Since we cannot control for individual fixed effects but only for regional fixed effects, we allow the immigration coefficient to be heterogeneous according to educational attainment, to disentangle the implications of television consumption versus the individual characteristics embodied by educational attainment.

Television consumption is measured by three categories, i.e. the consumption of up to one hour per day, from one hour to three hours, and of more than three hours. Educational attainment has instead six categories, i.e. Primary, Lower secondary, Upper secondary, Post secondary, non-tertiary, First stage of tertiary and Second stage of tertiary.

In general, we find that an higher educational attainment implies a lower coefficient of immigration on crime perception. Spending longer time watching television is instead directly positively correlated with crime fear. In addition it increases the coefficient of immigration on crime perception in around half of the specifications, after we control for education both in levels and in interactions.

Similar estimates have been conducted including newspaper consumption in addition to television consumption, with analogous results. In this case, more time spent reading newspaper have a negative effect on crime perception, after controlling for education in a similar fashion.

Unfortunately we are not able to give a clear causal interpretation to these results, but they seem promising in indicating that the effect of immigration patterns on crime perception is heterogeneous across different social groups and that media consumption may play a role in shaping the individual perception of the consequences of immigration flows.

### 4.2.4 IV Estimations

Our fixed effects estimates may suffer from the problems discussed in section 3. A possible answer to these problems is to use instrumental variables, as discussed in section 3.2. We estimate model (11) instrumenting the change in immigration with our instrument (10). We classify immigrants' flow areas using UN classification of composition of macro geographical (sub-continental) regions (M49 code), with minor differences<sup>5</sup>. I end up having N possible origins for immigrants, according to the chosen aggregation criteria of macro areas. Then i calculate the predetermined share of immigrants by geographical areas of origin in each European country. This is done by using the Database on Immigrants in OECD Countries (DIOC), provided by the OECD, that contains information on several demographical dimensions (including country of birth and citizenship) of the population of 28 OECD countries in 2000, i.e. prior to the timeframe of our analysis. Since the DIOC does not contain any information on the distribution of immigrants across regions within each country, we assume that the proportion of immigrants by areas of origin is common to all regions in each country.

Table 13 provides a set of regressions in differences analogous to the fixed effects regressions of the previous section where the data has been collapsed at NUTSI regional level. The first column presents a simple OLS difference regression where the victimization rate by regions is regressed on the log change in immigrants from outside Europe, i.e. those affected by supply-push factors, on population at country level. Here the coefficient of the log change in immigration is positive but not significant.

Column (2) presents the IV estimation where the change in immigration is instrumented by means of (10), showing no effect of immigration on crime. Column (3) provides an analogous IV

<sup>&</sup>lt;sup>5</sup>In order to obtain macro areas of comparable importance, I aggregate some regions that are disaggregated in the original UN classification. More specifically, I use Oceania instead of considering Australia, New Zealand, Melanesia, Micronesia and Polinesia separately. In addition, Middle and Southern Africa go together, similarly to Caribbean, Central and South America

estimate but with the instrument defined at the regional instead of the country level. The effect of immigration on crime is again not statistically significant. Columns (4) and (5) display the first stage regressions for, respectively, models (2) and (3), showing the positive and significant correlation between the instrument and our immigration measure.

Table 14 display similar results for the proportion of regional citizens feeling unsafe or veryunsafe when walking alone after dark. Here, again, we do not find any significant effect of regional immigration.

# 5 Concluding remarks

We presented an empirical analysis of the consequences of the recent immigration waves in Western European regions in terms of crime victimization and perception. To our knowledge this is the first comprehensive analysis on the topic using European data.

Our research strategy is twofold. We first estimate a linear probability model of the like-lihood of being a crime victim (and of feeling unsafe) on immigration by region (variously defined) using individual data and a set of regional fixed effects and country specific time effects plus controls. Our individual data come from the European Social Survey and cover 17 Western European countries from 2002 to 2008, a period characterized by large immigration inflows for most countries. The individual data is matched with other data sources such as the European Labour Force Survey and a set of measures of immigration by European regions are calculated using different data sources and definitions.

In addition, in order to account for possible measurement errors of regional immigration and possible regional specific time varying unobservable factors, we also use instrumental variables. We instrument regional immigration in a model in differences on regional data using an exogenous measure of immigration flows induced by push factors in world areas of origin.

Our empirical results suggest that immigration does not have any significant impact on criminality in destination regions once we control for unobservable regional characteristics. Immigration is positively and significantly correlated with crime only when we exclude the regional fixed effects from the linear probability model. In other words, the correlation between immigration and crime is likely to be induced by third unobservable factors at the regional level.

This result suggests that the frequently debated relationship between immigration and crime in western Europe maybe originated by a wrong interpretation of the empirical evidence available to the public. The observation by some commentators that criminality is higher where immigrants are more present may be biased by the omission of relevant elements at the regional level that may influence both immigration and crime.

Our fixed effects analysis provides some evidence that immigration may induce an increase in crime perception (or crime fear), but the result is not robust across alternative definitions of immigration. When instrumented, we do not find any significant effect of regional immigration on crime perception.

We provide also some tentative analysis of the drivers of the relationship between immigration and crime perception. When allowing an heterogeneous effect of immigration on crime perception, we find significant effects of the interactions with educational attainment and media consumption. In general, our regressions point to a lower effect of immigration on fear for higher levels of education and for lower level of television consumption, although the results are not significant for all definitions of immigration. Despite being hard to assess as causal effects, these findings seem promising in indicating that the effect of immigration patterns on crime perception is heterogeneous across different social groups and that media consumption may play a role in shaping the individual perception of the consequences of immigration flows.

Finally, we estimate whether crime victimization and perception affect the attitude of European citizens versus immigration using our panel of European regions. The attitude versus immigration is measured by a general judgment about immigrants making the country a worse or better place to live, and by the individual opinion versus the country being more or less open to migration inflows from poor non-European countries. Our findings suggest that crime perception is an important driver of the attitude towards immigration, with higher crime fear being related to a worse evaluation of the immigration phenomenon by European citizens.

Overall, only some of our results are robust to alternative data sources, definitions of regional immigration and estimation methods. More specifically, our instrumental variable model suggest no causal effect of immigration on both crime victimization and perception. However, crime perception seems to be an important driver of the attitude of European citizens towards immigration. We only provide some tentative descriptive analysis on the role of the media that deserve further investigation.

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# A Appendix

## A.1 European Regions

1. AT11 2. AT12 3. AT13 4. AT21 5. AT22 6. AT31 7. AT32 8. AT33 9. AT34 10. BE1 11. BE2 12. BE3 13. CH01 14. CH02 15. CH03 16. CH04 17. CH05 18. CH06 19. CH07 20. DE1 21. DE2 22. DE3 23. DE4 24. DE5 25. DE6 26. DE7 27. DE8 28. DE9 29. DEA 30. DEB 31. DEC 32. DED 33. DEE 34. DEF 35. DEG 36. DK01 37. DK02 38. DK03 39. DK04 40. DK05 41. ES1 42. ES2 43. ES3 44. ES4 45. ES5 46. ES6 47. ES7 48. FI13 49. FI18 50. FI19 51. FI1A 52. FR1 53. FR2e 54. FR2w 55. FR3 56. FR4 57. FR5 58. FR6 59. FR7 60. FR8 61. GR1 62. GR2 63. GR30 64. GR4 65. IE01 66. IE02 67. IE02d 68. ITC 69. ITD 70. ITE 71. ITF 72. ITG 73. LU0 74. NL11 75. NL12 76. NL13 77. NL21 78. NL22 79. NL23 80. NL31 81. NL32 82. NL33 83. NL34 84. NL41 85. NL42 86. NO01 87. NO02 88. NO03 89. NO04 90. NO05 91. NO06 92. NO07 93. PT11 94. PT15 95. PT16 96. PT17 97. PT18 98. SE11 99. SE12 100. SE21 101. SE22 102. SE23 103. SE31 104. SE32 105. SE33 106. UKC 107. UKD 108. UKE 109. UKF 110. UKG 111. UKH 112. UKI 113. UKJ 114. UKK 115. UKL 116. UKM 117. UKN

Table 6: Linear probability models of crime victimization using alternative definitions of presence of immigrants by regions crimevictim 0.010\*\*\*0.074\*\*(0.023)(0.024)(0.003)LFSb 0.05882881 YES YES YES crimevictim ).010\*\*\* ).074\*\* (0.031)(0.003)(0.023)LFSb 0.0320.05882881 YESYES YES crimevictim 3.009\*\*\* 3.068\*\* (0.003)(0.021)(0.007)LFSn0.00990497 0.062YES YES crimevictim 3.009\*\*\* \*\*\*890°C (0.000)(0.003)(0.021)0.016\*LFSn90497 0.062YESYESYES crimevictim 0.010\*\*\* ).061\*\*\* (0.004)(0.003)(0.021)-0.001100891 ESSP 0.057YES YES YES crimevictim 0.010\*\* ).061\*\*\* (0.003)-0.008 (0.005)(0.021)101371 (2)ESSb 0.057YES YES YES crimevictim 0.010\*\*\*3.065 (0.004)(0.003)(0.021)-0.004ESSn 97495 0.057YESYES YES Country X Year FE log(IMM/POP) VARIABLES Clustered SE Observations Regional FE R-squared wealth\_fin male

Immigration definitions by column are, respectively, ESS non-national, ESS born abroad, ESS born outside Europe, LFS \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Robust standard errors in parentheses

DK, FI, IE, NO, PT, SE and NUTSI for BE, DE, ES, FR, IT, LU, NL, GR, GB. Regional and country-specific year fixed effects non-national, LFS non-national and non-European, LFS born abroad, LFS born outside Europe. Regions are NUTSII for AT, CH, are included. Controls include educational attainment, degree of urbanization of local area, gender, age, age squared, if main source of income is financial. Standard errors are clustered by regions.

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Table 7: Linear probability models of crime victimization using alternative definitions of presence of immigrants by regions (with no regional fixed effects)

)	,						
	(1)	(5)	(3)	(4)	(5)	(9)	(7)
	$\mathrm{ESSn}$	ESSb	ESSP	m LFSn	m LFSn	LFSb	LFSb
VARIABLES	crimevictim	crimevictim	crimevictim	crimevictim	crimevictim	crimevictim	crimevictim
log(IMM/POP)	0.019***	0.025***	0.019***	***6800	0.034***	***290.0	0.047***
( / )	(0.007)	(0.008)	(0.005)	(0.009)	(0.006)	(0.010)	(0.008)
male	0.010**	0.009***	0.009***	0.009***	0.009***	0.010***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
wealth_fin	0.062***	0.056***	0.056***	$0.064^{***}$	0.064***	0.072***	0.073***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)
Observations	97495	101371	100891	90497	90497	82881	82881
R-squared	0.048	0.048	0.048	0.053	0.052	0.051	0.050
Regional FE	ON	ON	ON	ON	NO	NO	NO
Country X Year FE	m YES	m YES	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES	YES	YES
		٠ ,					

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

DK, FI, IE, NO, PT, SE and NUTSI for BE, DE, ES, FR, IT, LU, NL, GR, GB. No regional fixed effects are included, whereas Immigration definitions by column are, respectively, ESS non-national, ESS born abroad, ESS born outside Europe, LFS non-national, LFS non-national and non-European, LFS born abroad, LFS born outside Europe. Regions are NUTSII for AT, CH, country-specific year fixed effects are included. Controls include educational attainment, degree of urbanization of local area, gender, age, age squared, if main source of income is financial. Standard errors are clustered by regions.

Table 8: Linear probability models of crime perception using alternative definitions of presence of immigrants by regions

	(1)	$(1) \qquad (2) \qquad (3) \qquad (4) \qquad (5) \qquad (6) \qquad (7)$	(3)	(4)	(2)	(9)	(7)
	$ ext{ESSn}$	ESSb	ESSb	$ ext{LFSn}$	$ ext{LFSn}$	$ ext{LFSb}$	$ ext{LFSb}$
VARIABLES	unsafefeel	unsafefeel	unsafefeel	unsafefeel	unsafefeel	unsafefeel	unsafefeel
$\log(\mathrm{IMM/POP})$	*600.0	0.003	0.004	0.008		0.048*	0.057***
	(0.005)	(0.007)	(0.006)	(0.000)		(0.025)	(0.021)
male	-0.185***	-0.184***	-0.184***	-0.182***		-0.181***	-0.181***
	(0.006)	(0.006)	(0.006)	(0.006)		(0.007)	(0.007)
wealth_fin	0.016	0.020	0.020	0.019		0.017	0.017
	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.019)	(0.019)
Observations	02926	101550	101070	90651	90651	83024	83024
R-squared	0.134	0.133	0.133	0.133	0.133	0.133	0.133
Regional FE	YES	YES	YES	YES	YES	YES	YES
Country X Year FE	YES	YES	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Dependent variable is whether respondent feels unsafe or very unsafe when walking alone after dark. Immigration definitions by column are, respectively, ESS non-national, ESS born abroad, ESS born outside Europe, LFS non-national, LFS non-national and non-European, LFS born abroad, LFS born outside Europe. Regions are NUTSII for AT, CH, DK, FI, IE, NO, PT, SE and NUTSI for BE, DE, ES, FR, IT, LU, NL, GR, GB. Regional and country-specific year fixed effects are included. Controls include educational attainment, degree of urbanization of local area, gender, age, age squared, if main source of income is financial. Standard errors are clustered by regions.

Table 9: Linear	Table 9: Linear probability models of crime perception using alternative definitions of presence of immigrants by regions	els of crime perce	ption using alter	rnative definitior	is of presence of	immigrants by r	egions
	$(1) \\ \text{ESSn}$	(2) ESSb	$ \begin{array}{c} (3) \\ \text{ESSb} \end{array} $	$(4) \\ \text{LFSn}$	$ \begin{array}{c} (5)\\ \text{LFSn} \end{array} $	(6) LFSb	$\begin{array}{c} (7) \\ \text{LFSb} \end{array}$
VARIABLES	veryunsafefeel	veryunsafefeel	veryunsafefeel	veryunsafefeel	veryunsafefeel	veryunsafefeel	veryunsafefeel
$\log(\mathrm{IMM/POP})$	0.002	0.002	-0.000	0.005	0.003	0.048**	0.040***
	(0.002)	(0.003)	(0.002)	(0.006)	(0.004)	(0.020)	(0.015)
male	-0.052***	-0.052***	-0.052***	-0.051***	-0.051***	***050.0-	-0.050***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
wealth_fin	0.014	0.013	0.013	0.011	0.011	0.011	0.011
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Observations	02926	101550	101070	90651	90651	83024	83024
R-squared	0.058	0.057	0.057	0.059	0.059	0.059	0.059
Regional FE	YES	YES	YES	YES	YES	YES	YES
Country X Year FE	YES	YES	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

NUTSI for BE, DE, ES, FR, IT, LU, NL, GR, GB. Regional and country-specific year fixed effects are included. Controls include umn are, respectively, ESS non-national, ESS born abroad, ESS born outside Europe, LFS non-national, LFS non-national and non-European, LFS born abroad, LFS born outside Europe. Regions are NUTSII for AT, CH, DK, FI, IE, NO, PT, SE and educational attainment, degree of urbanization of local area, gender, age, age squared, if main source of income is financial. Standard Dependent variable is whether respondent feels very unsafe when walking alone after dark. Immigration definitions by colerrors are clustered by regions.

(2)	LEGS.
(9)	<u> </u>
(5)	1 P.S.
(4)	T T T
(3)	HOO!
(2)	F C C C C C C C C C C C C C C C C C C C
(1)	TAG.
	) (2) (3) (4) (5) (6) (

	(1)	(2)	(3)	(4)	(5)	(9)	(7)
VARIABLES	unsafefeel	unsafefeel	unsafefeel	unsafefeel	unsafefeel	Lr 3D unsafefeel	Lr 3D unsafefeel
	= = = = = = = = = = = = = = = = = = = =						
$\log(\mathrm{IMM/POP})$	0.011**	0.004	0.000	0.008	0.008	0.043*	0.051**
	(0.005)	(0.007)	(0.005)	(0.009)	(0.000)	(0.024)	(0.020)
(tvcat1==1)*IMMVAR	-0.000	-0.004	-0.001	-0.011**	*600.0-	-0.013***	-0.011**
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
(tvcat1==3)*IMMVAR	-0.006	-0.002	-0.001	0.013**	0.012**	0.014**	0.009
	(0.004)	(0.005)	(0.004)	(0.005)	(0.000)	(0.006)	(0.000)
tvcat1 == 1	-0.013**	-0.005	-0.013*	0.001	-0.047**	0.016	0.005
	(0.006)	(0.011)	(0.008)	(0.007)	(0.020)	(0.011)	(0.008)
tvcat1==3	0.036***	0.034***	0.032***	0.012	0.075***	-0.001	0.015
	(0.006)	(0.010)	(0.006)	(0.009)	(0.021)	(0.014)	(0.011)
(edulvl==0)*IMMVAR	0.010	0.021	0.016	0.006	-0.000	0.014	0.010
	(0.011)	(0.014)	(0.013)	(0.008)	(0.008)	(0.013)	(0.010)
(edulvl == 1)*IMMVAR	0.006	0.014**	0.017***	0.025***	0.026***	0.022***	0.025***
	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)	(0.007)	(0.000)
(edulvl == 2)*IMMVAR	0.006	0.010*	0.019***	0.008**	0.011	0.007	0.013***
	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)
(edulvl == 4)*IMMVAR	-0.005	-0.000	0.004	-0.017*	-0.018**	-0.020*	-0.005
	(0.007)	(0.008)	(0.007)	(0.009)	(0.008)	(0.011)	(0.011)
(edulvl==5)*IMMVAR	-0.015***	-0.022***	-0.016***	-0.006	-0.006	-0.012**	-0.011*
	(0.004)	(0.005)	(0.005)	(0.006)	(0.000)	(0.006)	(0.000)
(edulvl == 6)*IMMVAR	-0.007	-0.017	-0.028**	-0.008	-0.016	-0.012	-0.016
	(0.009)	(0.012)	(0.011)	(0.012)	(0.011)	(0.014)	(0.013)
Observations	97539	101417	100938	90534	90534	82909	82909
R-squared	0.133	0.133	0.133	0.133	0.133	0.133	0.133
Regional FE	YES	YES	YES	YES	YES	YES	YES
Country X Year FE	YES	YES	YES	YES	YES	YES	YES
Clustered SE	YES	$\overline{\text{YES}}$	YES	$\overline{\text{YES}}$	$\overline{\text{YES}}$	$\overline{\text{YES}}$	YES
		Robust standard		errors in parentheses			

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

3: Upper secondary, 4: Post secondary, non-tertiary, 5: First stage of tertiary, 6: Second stage of tertiary). Controls include degree of Dependent variable is whether respondent feels unsafe or very unsafe when walking alone after dark. Immigration definitions and regional definitions as in previous tables. Change in immigration is interacted with categorical variables on TV consumption per day and level of education.  $Tvcat1=(1: TV \le 1h, 2: 1 < TV \le 3h, 3: TV > 3h)$ . edulvl=(0: Not completed primary, 1: Primary, 2: Lower secondary, 2: Lower secondary, 3: TV > 3h)urbanization of local area, gender, age, age squared, if main source of income is financial. Standard errors are clustered by regions.

Table 11: Linear probability models of crime perception using alternative definitions of presence of immigrants by regions	obability model	s of crime perce	ption using alte	ernative definiti	ons of presence	of immigrants	by regions
	(1)	(2)	(3)	(4)	(5)	(9)	(7)
	${ m ESSn}$	$\mathrm{ESSp}$	$\mathrm{ESSp}$	${ m LFSn}$	${ m LFSn}$	$ ext{LFSb}$	$\Gamma ESb$
VARIABLES	veryunsafefeel	veryunsafefeel	veryunsafefeel	veryunsafefeel	veryunsafefeel	veryunsafefeel	veryunsafefeel
$\log(\mathrm{IMM/POP})$	0.005	-0.002	-0.005*	0.003	0.000	0.043**	0.035**
	(0.003)	(0.004)	(0.002)	(0.006)	(0.005)	(0.020)	(0.015)
(tvcat1==1)*IMMVAR	-0.000	0.001	0.001	0.000	0.001	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
(tvcat1==3)*IMMVAR	0.002	0.007**	0.005	0.006	0.006	0.007**	0.007**
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
tvcat1 == 1	0.004**	0.002	0.003	0.004	0.008	*600.0	0.006*
	(0.002)	(0.003)	(0.002)	(0.003)	(0.008)	(0.005)	(0.003)
tvcat1==3	0.023***	0.011*	0.017***	0.016**	0.047***	0.009	0.012*
	(0.004)	(0.006)	(0.005)	(0.000)	(0.015)	(0.008)	(0.007)
(edulvl==0)*IMMVAR	-0.010	-0.005	-0.008	-0.003	-0.005	-0.004	-0.007
	(0.008)	(0.000)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
(edulvl == 1)*IMMVAR	0.003	0.009**	0.007	0.009**	0.009**	0.010***	0.009**
	(0.003)	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
(edulvl == 2)*IMMVAR	0.002	0.008**	0.010***	0.004	**200.0	0.005	*900.0
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
(edulvl == 4)*IMMVAR	-0.005	0.001	0.003	0.001	-0.001	0.004	0.006
	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)
(edulvl==5)*IMMVAR	0.001	0.000	-0.000	-0.001	-0.003	0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
(edulvl == 6)*IMMVAR	0.001	-0.005	-0.008	-0.003	-0.004	-0.006	-0.007
	(0.005)	(0.007)	(0.005)	(0.006)	(0.006)	(0.007)	(0.000)
Observations	97539	101417	100938	90534	90534	82909	82909
R-squared	0.058	0.057	0.057	0.059	0.059	0.059	0.059
Regional FE	YES	YES	YES	YES	YES	YES	YES
Country X Year FE	YES	YES	YES	YES	YES	YES	YES
Clustered SE	m YES	YES	YES	$\overline{ m AES}$	YES	$\overline{ m AES}$	m YES
		Robust	Robust standard errors in parentheses	in parentheses			

Robust standard errors in parentheses  $^{***}$  p<0.01,  $^{**}$  p<0.05,  $^{*}$  p<0.1

Dependent variable is whether respondent feels unsafe or very unsafe when walking alone after dark. Immigration definitions and regional definitions as in previous tables. Change in immigration is interacted with categorical variables on TV consumption per day and level 3: Upper secondary, 4: Post secondary, non-tertiary, 5: First stage of tertiary, 6: Second stage of tertiary). Controls include degree of of education. Tvcat1=(1:  $TV \le 1h$ , 2:  $1 < TV \le 3h$ , 3: TV > 3h). edulvl=(0: Not completed primary, 1: Primary, 2: Lower secondary, urbanization of local area, gender, age, age squared, if main source of income is financial. Standard errors are clustered by regions. Table 12: Crime Perception and Attitudes Towards Immigration

	(1)	(2)	(2)	
	(1)	(2)	(3)	(4)
VARIABLES	IMMWORSE	ALLOWIMM	IMMWORSE	ALLOWIMM
(mean) crimevictim	0.017***	0.008	-0.206	0.110
	(0.005)	(0.005)	(0.133)	(0.130)
(mean) unsafefeel	0.124***	-0.077***	0.408***	-0.306***
	(0.006)	(0.005)	(0.124)	(0.076)
Observations	111423	111539	517	517
R-squared	0.111	0.133	0.843	0.859
Regional FE	YES	YES	YES	YES
Country X Year FE	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Columns (1) and (2) are linear probability models of attitude towards immigration on individual data, controlling for regional fixed effects, country-specific time dummies and the usual set of controls. Columns (3) and (4) are regional fixed effects regressions on collapsed data at NUTSII level. The dependent variable IMMWORSE in columns (1) and (3) is whether immigrants make country worse (i.e. respondents who answer less than or equal 4, on a scale from 0 to 10, from worse to better). The dependent variable ALLOWIMM in columns (2) and (4) indicates whether many or some few immigrants from poorer countries outside Europe should be allowed to come and live in the country (as opposed to few and none). Standard errors are clustered by country.

	Table 13:	OLS and IV di	ifference regres	Table 13: OLS and IV difference regressions of crime victimization	ation
	(1)	(2)	(3)	(4)	(5)
	OLS	$\overline{\text{IV}}$	$\overline{N}$	IV first stage $col.(2)$	IV first stage col.(2) IV first stage col.(3)
VARIABLES	dlogCRIME	dlogCRIME dlogCRIME dlogCRIME	dlogCRIME	DlogIMMVAR	DlogIMMVAR
log change IMMVAR	0.010	-0.938	-0.380		
	(0.106)	(0.659)	(0.325)		
Supply Push IV (country)				0.647***	
				(0.230)	
Supply Push IV (region)					1.111***
					(0.219)
Observations	207	207	207	207	207
R-squared	0.063			0.135	0.204
		Standard erro	Standard errors in parentheses	es	

All regressions include analogous controls as in previous fixed effects estimations. Immigrants are defined as born abroad in non-European countries using ESS data. The instrument is defined as the sum of the log changes of immigration in other European Columns (1) and (2) include an instrument defined at country level, column (3) at NUTSI regional level. Columns (4) and (5) are countries (or regions) weighted by the share of continental areas of origin of immigrants in 2000 provided by OECD DIOC database. first stage regressions of, respectively, columns (2) and (3).

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

	Table 14: (	OLS and IV diffe	rence regressions	Table 14: OLS and IV difference regressions of unsafety feeling	
	(1)	(2)	(3)	(4)	(2)
	STO	IV	IV	IV first stage col.(2) IV first stage col.(3)	IV first stage $col.(3)$
VARIABLES	DlogUNSAFE	DlogUNSAFE	DlogUNSAFE	DlogIMMVAR	DlogIMMVAR
log change IMMVAR	-0.122	-0.197	-0.018		
	(0.087)	(0.458)	(0.258)		
Supply Push IV (country)				0.647***	
				(0.236)	
Supply Push IV (region)					1.111***
					(0.219)
Observations	207	207	207	207	207
R-squared	0.069			0.135	0.204
		Standard errors	Standard errors in parentheses		
		*** p<0.01, ** ]	*** p<0.01, ** p<0.05, * p<0.1		

All regressions include analogous controls as in previous fixed effects estimations. Immigrants are defined as born abroad in non-European countries using ESS data. The instrument is defined as the sum of the log changes of immigration in other European Columns (1) and (2) include an instrument defined at country level, column (3) at NUTSI regional level. Columns (4) and (5) are countries (or regions) weighted by the share of continental areas of origin of immigrants in 2000 provided by OECD DIOC database. first stage regressions of, respectively, columns (2) and (3).