Crime, Refugees and Politics In Sweden

An Econometric Analysis *

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June 9, 2019

Abstract

The aftermath of the recent refugee crisis in Europe has been debated to a great extent across the globe. Yet, little statistical analysis has been done to uncover the impacts of refugee inflows on crime and voting behavior. In this paper, two topics on the effects of the refugee crisis are investigated. We ask: How did the recent increase of refugee inflows affect crime rates and voting behavior in Sweden? The results suggest that the sudden surge of refugees in Sweden caused an increase in crime rates and swayed the voting behavior in favor of Sweden Democrats.

keywords: Swedish politics, immigration, crime, panel data

*This paper is meant as a thesis in fulfillment of the requirements for the degree of Master of Science in Economics at Lund University. Big thanks go to my supervisor and co-supervisor, *Adrian Mehic* and *Joakim Westerlund* Respectively.

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Contents

List of Figures

List of Tables

1 Introduction

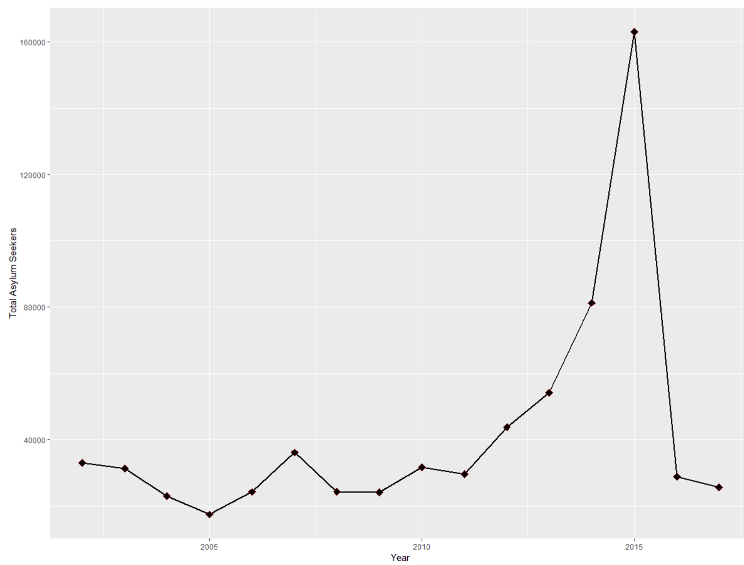
For decades, people have migrated to other countries to seek refuge and safety from life-threatening events. The relation between immigration and crime has been a major question in Europe as a consequence of the recent refugee crisis. It is easy to come to the wrong conclusion by talking to individuals or even listening to the media. Such a sensitive topic requires a statistical analysis to make reasonable inference. A similar question could be asked about the relation between the recent increase of refugee inflows and the change of voting behavior in favor of right wing parties. This paper aims to study these two questions empirically using accessible data from Swedish databases, including Statistics Sweden (SCB), Swedish Migration Agency (Migrationsverket), and Brottsförebyggande rådet (Brå).

In Sweden, the topic on the relation between refugees and crime has been debated increasingly as of the recent refugee crisis, and regardless if refugees are causing crime rates to grow, people might still vote for a far-right party just because they are mentioned together to a great extent. This makes it more interesting to study if it is true that refugees caused crime rates to increase or not, while also tackling the question if the increase in refugees caused the voting behavior to sway in favor of Sweden Democrats (Swedish: Sverigedemokraterna), a radical-right-wing party in Sweden.

Referring to Figure 8, it is apparent that the largest number of refugees was mainly from two nationalities, Syrian and Afghan. The conflict between the Syrian president and other groups erupted around 2012, and according to OCHA (2014) and UNHCR (2015), this led to approximately 4 million individuals escaping the country seeking refuge. Similarly, Afghanistan has been a war zone since 2001, forcing many Afghans to seek refuge in other countries. It is notable that many Syrians were residing various countries as "not awaiting registration" (OCHA, 2014; UNHCR, 2015). This underrates the actual number of refugees because these cases are usually not counted.

According to UNHCR (2014), in Europe, Sweden was one of the few countries to take in many asylum seekers. A few other countries such as Germany took a substantial number as well. It is not important to mention why other major countries did not take a role in helping through these events, but it can be said that Sweden was put in a tight spot that could potentially cause friction. To give a better idea about the immense increase of asylum seekers in Sweden, one can refer to Figure 1. The data used in this plot is the total of asylum seekers over the entire country from 2002 to 2017 and is plotted to give a visual understanding about the timing of the refugee crisis. 162,877 asylum applications were filled in 2015 which was around the Syrian civil war. One can also refer to Figures 6 and 7 for plots on asylum seekers by gender and foreign-born citizens by age respectively.[1] As can be seen, such a large immigration wave has never occurred in Sweden.

Figure 1:
Total asylum seekers in Sweden:
from 2002 till 2017



The journey that refugees face starts from experiencing war in their home country, then traveling with uncertainty on each step of the way. After reaching Sweden and having their asylum application accepted, they might have already been impacted psychologically which could dictate their future behavior. Never mind the difficult experiences they had to face, just the fact that they need to start over in a new country, learn a new language, and try to accept a different culture could cause many psychological issues. The factors that affect the mental health of these individuals differ between adults and children. Some factors that affect adults are the uncertainty about refugee status, underemployment, loss of social status and difficulties in learning the language, whereas the factors that affect children are usually related to acculturation, discrimination, and social exclusion (Kirmayer et al. 2010). Even the large financial support of the United Nations (UN) humanitarian program was not enough to address every refugee's needs (Ostrand 2015). According to Ruist (2015), refugees' salaries in Sweden is on average around 9,000 Swedish kronor per month, which might not be enough to live comfortably. This somewhat asserts the underemployment factor mentioned by Kirmayer et al. (2010) which adds increased stress on a person's day-to-day life.

These mental and financial strains could increase the likelihood of an individual com-

[1] The plot of foreign-born citizens include other immigrants, not just refugees, because data on purely refugees by age is not available in SCB's database

mitting crimes. Nevertheless, many refugees seem to be appreciative of the kindness given to them, and many others refer themselves as Swedes as time passes by, which is a sign of cultural integration. The Swedish government realizes that it could be challenging to find work being a refugee due to the lack of working and language skills in comparison to Swedish born citizens. Because of the nature of this obstacle, the Swedish government has introduced mentoring programs and traineeships that gives them the chance to integrate and feel productive in their society. Again, without a statistical analysis, it is hard to say if an increase in the number of refugees is significantly increasing, decreasing, or not affecting the rate of crime. One purpose of this paper is to statistically explore this question using data collected on most municipalities in Sweden from 2013 to 2017.

In European politics, it is apparent that there is increasing support for far-right-wing parties. Billiet and De Witte (1995) found that having less tolerance to immigrants increases the support for right wing parties. This intolerance could be due to many reasons. One reason, according to Coffé (2002), is when individuals associate themselves with political powerlessness.[2] Another reason could be the thought that refugee immigrants and crime go hand in hand. In fact, many far-right parties argue that refugees lead to an increase in crime rates, which might sway people's voting behavior even if their claims were without any statistical basis. One example would be Vlaams Blok, a Belgian party emphasizing the relation between crime and immigration: "Street crime, drug trafficking, car theft, prostitution, burglaries and homejackings can often be blamed on foreign youngsters and gangs. The number of second-and third-generation Eastern European and Islamic immigrants involved in crime is alarming" (Vlaams Blok, 2003, p.28).

The Sweden Democrats has risen from 5.7% in 2010 to 17.5% in 2018 becoming the third largest party in Sweden. As mentioned before, there could be many reasons for this increase. Dal Bó et al. (2018) suggested that this rise was triggered first already in 2006 when there was a change in the agenda regarding tax cuts and social insurance in order to lower taxes.[3] According to them, over the course of five years, this policy change enlarged the income gap between individuals with fixed jobs and those with unstable employment. However, fast forward to today, the Sweden Democrats continued to increase while unemployment rates fell. This raises a question if this sudden increase of immigration towards Sweden was a cause in the growth of Sweden Democrats. This leads to the other purpose of this paper, which is to study this question statistically and comment on the reasoning behind the change of voting behavior.

[2] Political powerlessness could come from feeling neglected by one's home country. In this case more attention is given to immigrants.

[3] Dal Bó et al. (2018) mention that this implementation was caused when a Center-Right coalition of parties gained power in 2006.

When investigating the relationship between crime rates and immigration, data are collected on the municipality level from 2012 to 2017. Aggregate crime, violence, crimes against the public, theft and sexual assault are considered. It is slightly different for the analysis relating to immigration and the growth of Sweden Democrats because of the nature of Swedish politics. Voting happens every four years, and hence, data are collected for the years 2010, 2014, and 2018. Several other variables , such as education, employment, and disposable income, will be used as control variables when running various regressions. The methodology adopted is panel data using the fixed-effects estimator with extensions of cluster-robust-standard errors and instrumental variables. Several regressions will be run to investigate the proposed questions in order to come up with inference.

The results suggest that the recent increase of refugee immigration towards Sweden caused an increase in crime rates. It is also found that the increase of refugee inflows was one of the reasons that led Sweden Democrats to grow substantially. These findings are discussed thoroughly in the data analysis and results sections. It is important to emphasize that the results do not give any evidence that crime is associated with a certain culture, nor does it provide any proof to the opposite. The topic purely focuses on the relation between crime and immigration regardless of the reasons why they are positively related.

The rest of the paper is structured as follows. Section 2 provides a literature review and positions this paper's contribution. Section 3 discusses the methodology. Section 4 is branched into three subsections. Subsection 4.1 includes information about data collection and variable creation. Subsection 4.2 presents various ways to explore and analyze the data. Subsection 4.3 reports the main empirical findings and robustness checks. The paper concludes with section 5.

2 Literature review and contribution

There have been several research attempts on the topics of immigration and crime and the relation between immigration and the rise of right-wing parties. This section briefly mentions some of the most important papers on both topics and positions the contribution of this paper.

Butcher and Piehl (1998) used the fixed-effects estimator on panel data of various US cities from 1981-1986 and 1986-1990 to study the relation between refugee immigration and crime. They concluded that even though cities with higher immigration rates tend to have higher crime rates, there was no significant relationship between crime and immigration. Bell, Fasani, and Machin (2013) look into two waves of immigration toward the United

Kingdom by testing the empirical connection between refugees and crime.[4] Using the fixed-effects estimator, they found no relation between violent crimes and immigration. By using data on Italian cities, Bianchi et al. (2012) reached the same conclusion. On the other hand, Piopiunik and Ruhose (2017) found a positive relation between crime and immigration using panel data collected on German cities from 1997 to 2006. All of these papers contribute to the literature of crime and immigration, but they do not study recent events that are of interest. One exception is the paper by Gehrsitz and Ungerer (2017), where they use a difference-in-difference model on data of the periods 2014 and 2015 to study the relation between crime and the recent refugee inflows into Germany. Nevertheless, their contribution was based on a different country and a short-term impact.

Dustmann and Preston (2007) discuss that native-born citizens might worry about how immigration could lead to negative effects on public and social services. While they do not discuss the relationship between immigration and voting behavior, they find that an increased concern about welfare is associated with a change in opinion against immigration by natives. Mayda (2006) suggests a relation between people's tolerance to immigration and economic factors. More specifically, she uses an OLS regression on individual-level-survey data from the United States, Canada, Japan, some Eastern European countries and the Philippines to regress a "pro immigration" dummy on several variables such as income and education. She found a negative relation between the "pro immigration" dummy and income which means the higher the income the fewer people worry about immigration disturbing their welfare. Similar results have been found by Dustman and Fabbri (2005), Hanson, Scheve and Slaughter (2006) and Facchini and Mayda (2006). On the contrary, Steinmayr (2016) finds interesting results on the topic of immigration and its relation to voting behavior. His study was based on state elections in Austria in 2015 regarding the voting behavior towards the far-right Freedom Party of Austria (FPOE), where he found a negative relation between refugee inflows and the support for FPOE. Similarly, Gehrsitz and Ungerer (2017) found that even though there is a rise in the German anti-immigration party, it was not related to the increase of refugee inflows. Also, a recent study by Dal Bó et al. (2018) concluded a robust negative correlation between Sweden Democrats growth and the financial crisis. It appears that when people become more vulnerable economically, they tend to vote for far-right parties (Sweden Democrats, in this case), rather than parties that focus on job-security issues such as Social Democrats. Nevertheless, the data studied upon is from 1989 to 2010 which misses the recent refugee crisis.

This paper adds to the literature of immigration and crime as not much research has been done on the recent refugee crisis (around 2015) and its impacts on crime rates. It also

[4] The first wave was from 1990 to 2000 and the second was after 2004 from EU accession countries.

contributes by adding Sweden to one of the few countries that this topic has been researched upon. In terms of the relation between voting behavior and immigration in Sweden, this paper differs from previous literature as the data analyzed coincide with the recent refugee crisis. Sweden Democrats has grown to become the third largest party in 2018 which makes it even more interesting to study this question on recent data.

3 Methodology

The fixed-effects estimator is used on panel data collected on the municipality level. Panel data could be seen as pooling on a cross-section of municipalities over several time periods. This section will be a brief introduction to the method used and on some benefits and limitations that are associated with it.

According to Hsiao (2003) and Klevmarken (1989), one benefit of panel data is *controlling for individual heterogeneity* which might not be possible to control in time-series or cross-sectional studies. Other benefits are having *less collinearity* between variables and *more degrees of freedom*.[5] Baltagi (2009) explains that panel data are *better suited to measure effects that cannot be identified in cross-section or time-series data*. These are just a few examples of the benefits on using panel data. On the other hand, Baltagi (2009) mentions some limitations in using this method. One relevant limitation is *when having a short-time series dimension*. This limitation occurs in micro panels, which means that the asymptotics will rely mostly on the number of individuals going to "infinite".[6]

In this paper, two topics are focused on, the relationship between crime and immigration and the relation between immigration and voting behavior. Two sets of regressions will be run and are as follows:

$$CR^c_{it} = \mu_i + \lambda_t + \beta_1 Ln(imm)_{it} + \beta_2 Ln(Ed)_{it} + \beta_3 Emp_{it} + \beta_4 DI_{it} + u_{it} \qquad (1)$$

and

$$SD_{it} = \mu_i + \lambda_t + \gamma_1 Ln(imm)_{it} + \gamma_2 Ln(Ed)_{it} + \gamma_3 Emp_{it} + \gamma_4 DI_{it} + u_{it} \qquad (2)$$

where CR^c_{it} is the rate of crime with i, t and c[7] denoting municipalities, time and the type of crime respectively. μ_i are individual-specific effects, λ_t are time-specific effects, $Ln(imm)$ is the natural logarithm of immigration, $Ln(Ed)$ is the natural logarithm of education, Emp is

[5] Having both the time dimension and the cross-sectional dimension increases the degrees of freedom significantly.

[6] A micro panel setting is when $N >> T$, where N is the number of individuals and T is the number of the time periods.

[7] $c \in \{\text{Violence, Arson, Sexual Assult, theft}\}$

employment rate of Swedish born citizens, DI is disposable income rate, and SD is Sweden Democrats' vote rate. β's and γ's are unknown parameters to be estimated. The data collected for each variable is on municipality level from 2012 to 2017.

To find the estimators, it is helpful to rewrite the model in vector form and is as follows:

$$y = \alpha\iota_{NT} + X\beta + u = Z\delta + u \tag{3}$$

where y is $NT \times 1$, α is a scalar, ι_{NT} is a vector of ones ($NT \times 1$), X is $NT \times K$, β is $K \times 1$, $Z = [\iota_{NT}, X]$ and $\delta^T = [\alpha^T, \beta^T]$. u is represented as $u^T = (u_{11}, \dots, u_{1T}, u_{21}, \dots, u_{2T}, \dots, u_{N1}, \dots, u_{NT})$.

In this paper, y denotes crime rates in the first set of regressions and SD's vote shares in the second. N is associated with 290 Swedish municipalities (minus missing data), T with years and K with independent variables. $T = 6$ when running the first set of regressions relating immigration with crime and $T = 3$ when analyzing vote behavior. $K = 4$ with education, disposable income, employment and immigration for both sets of regressions.

The error term (u) for one individual data point is represented as $u_{it} = \lambda_t + \mu_i + \nu_{it}$, where μ_i is unobservable-individual-specific effects and ν_{it} is some stochastic disturbance. i and t represent the individual and time dimensions respectively. u is given as :

$$u = Z_\lambda\lambda + Z_\mu\mu + \nu \tag{4}$$

Where $Z_\lambda = \iota_N \otimes I_T$ and $Z_\mu = I_N \otimes \iota_T$ are matrices containing time dummies and individual dummies respectively. Knowing that $\lambda = (\lambda_1 \dots \lambda_T)$ and $\mu = (\mu_1 \dots \mu_N)$, one can see that $Z_\mu\mu$ and $Z_\lambda\lambda$ will be a $NT \times 1$ vectors, $Z_\mu\mu = (\mu_1, \dots, \mu_1, \mu_2, \dots, \mu_2, \dots, \mu_N, \dots, \mu_N)$ and $Z_\lambda\lambda = (\lambda_1, \lambda_2 \dots, \lambda_T, \lambda_1, \dots, \lambda_T, \dots, \lambda_1, \dots, \lambda_T)$ respectively. Having both time dummies and individual dummies (i.e. including λ_i and μ_i) in the regression is called a two-way model. The intuition behind using the two-way model is to account for the differences between the criminality of various municipalities and the recent years. One can rewrite equation 3 as follows:

$$y = Z\delta + Z_\mu\mu + Z_\lambda\lambda + \nu \tag{5}$$

where Z is the matrix containing the variables, δ is the vector of coefficients and $\nu^T = (\nu_{11}, \dots, \nu_{1T}, \nu_{21}, \dots, \nu_{2T}, \dots, \nu_{N1}, \dots, \nu_{NT})$.

3.1 Fixed effects

In the fixed effects model, μ_i, λ_t and the X variables are conditioned on such as $\mathbb{E}[y_{it}|X, \mu_i, \lambda_t] = x_{it}^T\beta + \mu_i + \lambda_t$. μ_i and λ_T are not constants, but are fixed due to them being conditioned on. Before introducing the fixed effect model, some definitions are necessary. Let J_T and J_N be matrices of ones of dimension $T \times T$ and $N \times N$ respectively. According to Wallace and Hussain (1969), by defining $\bar{J}_T = \frac{1}{T}J$ and $\bar{J}_N = \frac{1}{N}J$, one can introduce the Q matrix to get the fixed effects estimator:

$$Q = E_N \otimes E_T = I_N \otimes I_T - I_N \otimes \bar{J}_T - \bar{J}_N \otimes I_T + \bar{J}_N \otimes \bar{J}_T \tag{6}$$

with $E_N = I_N - \bar{J}_N$ and $E_T = I_T - \bar{J}_T$. Q will eliminate the time and individual effects and have typically elements that look like $(y_{it} - \bar{y}_i - \bar{y}_t + \bar{y})$ with $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}$, $\bar{y}_t = \frac{1}{N}\sum_{t=1}^{T} y_{it}$, $\bar{y} = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} y_{it}$. The fixed effects estimator, also called the *within* estimator, is then produced by running a regression on Qy and QX to get:

$$\beta_{FE} = \left(X^TQX\right)^{-1} X^TQy \tag{7}$$

It is also easy to show that $var(\beta_{FE}) = \sigma^2(X^TQX)^{-1}$ by using the statistical formula of β. σ^2 is usually unknown and is estimated using $s^2 = \frac{u^Tu}{NT-K}$. Assuming the conditions of the law of large numbers holds, the fixed effect model is consistent and converges asymptotically into a normal distribution by the central limit theorem (CLT).

3.2 Poolability and Hausman Test

One consideration when dealing with panel data is the possibility of pooling. When pooling, one runs an OLS regression on the data while treating the data as cross-sectional. The model would then be $y = Z\delta + \nu$. Using the F_{2-way}-statistic, poolability is tested under the null hypothesis that the individual and time effects are equal to zero. The F_{2-way}-statistic is run on some of the regressions, and it is apparent that the null hypothesis is rejected, and hence pooling would not be useful. Now that it is known that pooling the data does not work, the Hausman test is used to determine between if one should use random effects or fixed effects (Hausman, 1978).

3.3 Econometric considerations and limitations

Other econometric considerations briefly mentioned are heteroskedasticity, non-stationarity, endogeneity, and normality. The data is assumed to be heteroskedastic and the regression will be run using cluster-robust-standard errors, which will also deal with any auto-correlation problems. It is also reasonable to assume non-normality in the data, but it is good to have data that are not too skewed from a normal. The empirical distributions of the variables are provided in Figure 11.

To account for possible distributional bias caused by the immigration variable, the IV-fixed effects estimator is considered and is as follows:

$$\beta_{IV} = \left(\widetilde{Z}^T P_{\tilde{X}} \widetilde{Z}\right)^{-1} \widetilde{Z}^T P_{\tilde{X}} \tilde{y} \tag{8}$$

where $\widetilde{y} = Qy$ and $\widetilde{Z} = QZ$. $\widetilde{X} = QX$ is the set of instruments with $P_{\widetilde{X}}$ being a projection matrix on the IV subspace. it is also easy to show using the statistical formula of β_{IV} that $\text{var}\left(\beta_{IV}\right) = \sigma_v^2 \left(\widetilde{Z}^T P_{\tilde{X}} \widetilde{Z}\right)^{-1}$. An argument on the validity and strength of the instruments is mentioned in the data analysis and results section.

One limitation when undergoing the tests reported in this paper is the lack of time periods, $T = 6$ and $T = 3$. More precisely, $N >> T$, which makes it difficult to test for stationarity or cointegration. When having non-stationary data, the results could end up spurious and irrelevant. Nevertheless, according to Baltagi (2009), when dealing with micro-panels, one depends on N being "large enough". In this paper $N = 289$ is assumed to be sufficient as previous papers dealing with micro-panels assumed so as well, e.g. Cornwell and Trumbull (1994).

4 Data analysis and results

4.1 Data and variables

The data was collected from three sources, Migrationsverket (Swedish Migration Agency), SCB (Statistics Sweden) and The Swedish National Council for Crime Prevention (Brottsförebyggande rådet, Brå for short). For the regressions run on the relation between crime and immigration, data on 287 municipalities out of 290 is collected because Lekeberg, Skurup, and Öckerö did not provide all the needed data for 2012-2014. The sexual crime rate variable and crimes against the public had more missing data with $N = 280$ and $N = 266$ respectively. As for data concerning the regressions on the relation between SD and immigration, Askersund, Grums, Karlsborg, Laxå, Stenungsund, Sunne, Älvdalen had missing data points in 2010 which reduces N to 280. When running the regression, $N = 253$ because other data points were not available in the years 2014 and 2018.

Data for the immigration variable is collected on the municipality level from 2012 to 2017 from SCB's database. This variable accounts for all foreign born citizens in each municipality and acts as a proxy for refugee immigration. A distributional bias might arise from the Swedish refugee allocation system which could cause an endogeneity problem.[8] To account for the potential endogeneity, the natural logarithm of the sum of "quota refugee" (kvotflykting) and "persons from asylum accommodation" (person från anläggningsboende (ABO)) is used as an instrumental variable (IV_1). As a robustness check, the lag of the natural logarithm of immigration ($Ln(imm_{t-1})$) is used as a second instrumental variable (IV_2).

On the municipality level, data of various crime types is collected from Brå's database. The types include aggregate crime (*Totalt antal brott*), violence (*Brott mot liv och hälsa*), theft (*Stöld, rån m.m.*), sexual assault (*Sexual brott*) and crimes against the public (*Allmänfarliga brott*), where the names in the parenthesis are the Swedish translations listed in the database. Crimes included in each type are mentioned in Table 6. Crime rates are generated by dividing each crime type by the population of each municipality to form the dependent variables of the first set of regressions. Data on SD is collected from SCB's database under "Election to the Riksdag" for 2010, 2014, and 2018 form the dependent variable for the second set of regressions.

Other independent variables that are thought to affect the rate of crime and SD are disposable income, education, and employment. The education variable is constructed for each municipality by taking the natural logarithm of the sum of post secondary education (less than 3 years), post-secondary education (3 years or more), and post-graduate education. Employment and disposable income could be found under "gainful employment" and "disposable income for households" respectively, given as percentages. When running the regression on SD and immigration, data on the year of 2018 are required, but are not available on disposable income and employment. It is reasonable to proxy the data of 2018 by the data of 2017 because these variables are approximately unchanged in a one year gap. The data for each of these control variables are collected from SCB's database and are reorganized to fit a typical-panel-data setting.

4.2 Validity and strength of instruments

The immigration variable is assumed to be endogenous because of the nature of the placement program in Sweden. Refugees can reallocate from the municipality that they were admitted to at anytime which causes a distribution bias. This is mostly typical in family reunification cases, where newly admitted refugees reallocate to be around their relatives. Because of this bias, a valid and exogenous instrument is needed. The main instrument (IV_1)

[8] Refugees can easily reallocate regardless of which municipality they are allocated to. This is explained further in the validity and strength of instruments subsection

considered is the natural logarithm of the sum of "quota refugee" and "persons from asylum accommodation". This variable accounts for the potential bias because these two categories are under an allocation scheme that disperses immigrants to municipalities exogenously. IV_1 is considered as a strong instrument as it is significantly correlated with immigration and is assumed exogenous as explained. A paper by Mehic (2019) considers the same placement program as an instrument for immigration, but on cross-sectional data. The instrument in this paper has a slightly different structure as it is constructed from 2012 to 2017. This placement program has also been used as an instrument in various papers to tackle different questions (Edin et al. 2003; Dahlberg and Edmark 2008; Dahlberg et al. 2012). The instrument used for the robustness check (IV_2) is the lag of natural logarithm of immigration ($Ln(imm_{t-1})$) which is less likely to be affected by current shocks. The results of the OLS, IV_1, and IV_2 estimators are very similar which gives confidence in the robustness of the results. When running the regression concerning the relation between SD and immigration, IV_2 will not be used as a robustness check because taking the lag of immigration would lead to the loss of significant information. This is discussed further in the empirical findings subsection.

4.3 Preliminary data analysis

Before discussing the results, it is beneficial to explore the data from different angles. One issue that should be looked into when working with data is outliers. Outliers should not be removed unless there is a valid reason for doing so. Figure 9 and 10 include boxplots of all the variables and are also given for each year to investigate how the data behaves in a panel setting. It can be depicted from Figure 9 and 10 that outliers do not cause any alarm for most of the variables. The only two variables that appear to be skewed are disposable income and sexual crime rates. Even though not reported, the regressions are run with and without outliers, giving similar results. Because similar results are obtained, outliers of the two variables are not excluded. As mentioned before, it is reasonable to assume non-normality in the data, but having data that are close to a normal is favorable. It can be depicted from Figure 11 that the data for most of the variables do not look very skewed.

In Table 1, the descriptive statics are reported to give a more concise idea about how the data behaves. It is hard to see the dispersion of data in the sexual crime rates variable because of how small the ratios are, but it is noticeable that the maximum is very far from the minimum, the 25% quantile, and the 75% quantile which gives a hint on the possibility of extreme outliers in the data. When comparing between the variables, note that $Ln(imm)$ and $Ln(Ed)$ are logged, while other variables are ratios. It is also observed that theft rates are higher than that of sexual crime rates, violence, and crimes against the public. Because crimes against the public and sexual crime rates had missing data points, one could refer to Tables 7 and 8 for the descriptive statistics provided for each, but it is not very important as it is approximately the same as in Table 1. It could be more interesting to discuss the descriptive statistics of SD provided in Table 9, but it is also similar.

Table 1: Descriptive statistics

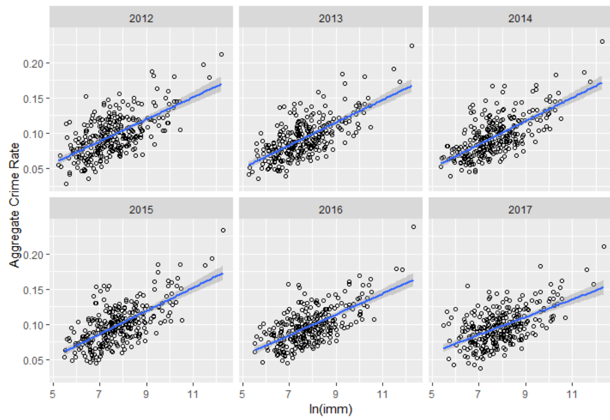
$Variable$	NT	Mean	Std. dev.	Min.	25 %	Median	75 %	Max.
Aggregate Crime rate	1,722	0.096	0.028	0.028	0.077	0.094	0.112	0.239
theft rates	1,722	0.036	0.013	0.011	0.027	0.034	0.043	0.099
Violence rates	1,722	0.008	0.003	0.001	0.006	0.007	0.009	0.021
Sex crime rates	1,680	0.001	0.001	0.000	0.001	0.001	0.002	0.031
Crimes against the public	1,596	0.001	0.000	0.000	0.000	0.000	0.001	0.002
Emp	1,722	0.831	0.030	0.719	0.812	0.832	0.852	0.907
DI	1,722	0.009	0.002	0.007	0.008	0.009	0.010	0.029
$Ln(imm)$	1,722	7.741	1.164	5.226	6.931	7.611	8.384	12.366
$Ln(Ed)$	1,722	8.231	1.183	5.814	7.365	8.049	9.007	12.894
SD	759	0.139	0.073	0.017	0.070	0.139	0.193	0.392

Tables 10 and 11 in the appendix provide information about the correlations between all the variables studied. It is seen that the rate of most crime types has a positive correlation with immigration, except for crimes against the public with a negative correlation. It is also notable that the correlation between SD and immigration is positive. This does not give any indication to causality, but it is useful to view the correlation matrix between the variables before looking at the empirical results.

A matter that is investigated by previous researchers is the cross-sectional relation of crime rates and immigration. Exploring the data from this angle would give an insight into if cities with a higher number of immigrants tend to have higher crime rates or vice versa. By looking at Figure 2, it is expected to have higher crime rates in cities with more immigrants. One can also refer to Figure 15 for similar scatter plots of other types of crime rates. It is harder to read the scatter plot of sexual crime rates as it is affected by outliers. OLS regressions for each type of crime rates across the years are reported in Tables 13, 14, 15, 16, and 17, suggesting that cities with a higher number of immigrants have higher crime rates. Housing in Sweden is usually based on a queuing system which makes it reasonable to assume that refugees are usually admitted to areas that are poor and more criminal. However, this does not give an insight about the relation between the recent increase of refugee immigration and crime rates.

One should differentiate between regressing crime rates $\left(\frac{Crime}{population\ of\ municipality}\right)$ and regressing crime as a whole. Using crime as a whole without transforming it into a ratio over

Figure 2:
Scatter plot of aggregate crime rate
against the natural logarithm of immigration across the years



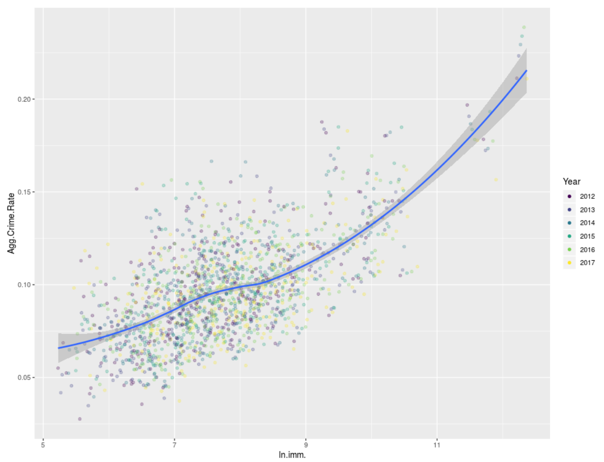
the population of each municipality would answer: "what happens to crime when the population increases?". One would expect an increase in all crime types (as a whole) when the population increases, as shown in Figure 13, but that would not answer if immigrants are causing crime rates to increase. This association stays the same across all the years, which can be depicted from Figure 12. It is not very important to study this further, as it does not provide an insight into the questions studied, but is mentioned for the sake of clarity.

Again, the crime rate variables are constructed by dividing each crime type over the population of each municipality. Intuitively, if immigrants caused no crimes for example, it is likely to have a negative correlation because the denominator would increase while the numerator would stay the same, leading to a decrease in crime rates. Observing Figures 3 and 14, one would expect a positive relation between most crime types (as rates) and immigration.

One could also consider the same topic, but by separating the data based on gender. The reason why this is not interesting in this particular study is because the considered time span is limited to the refugee crisis. This means that the number of male and female asylum seekers will increase approximately in the same fashion, which makes it difficult to separate the effect. One can refer to Figure 6, where it is apparent that the data of male and female refugees behave similarly. This just says that regardless if the regression is run on the entire-data set, the male-data set, or the female-data set, the same conclusion will be intact.[9] It would be more interesting to look into the relation between gender immigration and crime using a time period that would not force both genders to immigrate together, but

[9] The regressions run with or without separating the data by gender give similar results.

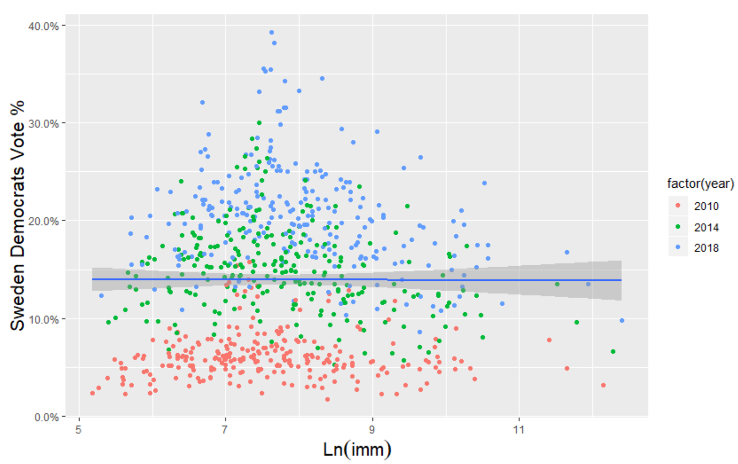
Figure 3:
Polynomial pooled scatter plot of aggregate crime rate
against the natural logarithm of immigration



nevertheless, that is not what is investigated.

As for the topic on the relation between SD and refugee immigration, one can refer to Figure 4, where not much can be depicted on the relation between the variables. One thing that can be depicted from this figure is that the highest support that Sweden Democrats ever received was in 2018. Again, these plots of the pooled data do not indicate causality, but are important to analyze for a better understanding of the data and what to expect from the regressions.

Figure 4:
Scatter plot of SD against the natural logarithm of immigration



4.4 Main empirical results and robustness checks

In this subsection, the main findings and their corresponding robustness tests are reported and discussed. The first topic of interest is the relation between the recent increase of refugee immigration and crime rates in Sweden. The H_0 of the Hausman test is always rejected which indicates that the fixed effects estimator should be used. In Table 2, the $FE - IV_1$ coefficients are retrieved by regressing all crime types on the natural logarithm of immigration ($Ln(imm)$), employment rate (Emp) , disposable income (DI) and the natural logarithm of education ($Ln(Ed)$), while using IV_1 as an instrumental variable. According to the results, it can be said that the recent increase of refugee immigration led to an increase in aggregate crime rates between 2012 and 2017. More specifically, a 1% increase in immigration caused an increase of 0.035 in the ratio of aggregate crime to population in Sweden. The only crime type studied that has a significant relation with the recent increase of refugee immigration is violence. These results coincide with a paper by Piopiunik and Ruhose (2017), where they found that immigration caused crime rates to increase using data collected on German cities between 1997 and 2006. Nevertheless, their study does not take the recent refugee crisis into account. Gehrsitz and Ungerer (2017) studied this relation using data that coincide with the recent refugee crisis in 2015. Surprisingly, their results differ from what is found in this paper and from the findings by Piopiunik and Ruhose (2017), where they conclude no significant relation between crime and immigration. This raises an interesting question of why the refugee crisis increased crime rates in Sweden, while it was insignificant in Germany. It is also notable that Emp has a negative relation with aggregate crime rates and theft rates, which is intuitive, because having a higher employment rate should lower crime rates of some types, as people have less reasons to steal and commit other crimes of a similar nature (included in aggregate crime rates). The same can be said about the relation between crime and education, as a higher level of education leads to less aggregate crimes, violence, and sexual crimes. One can also notice that there is no relation between all types of crime rates and DI. The $FE - OLS$ results are very similar to that of the $FE - IV_1$, and are reported in table 12 in the appendix.

In Table 3, a robustness check is implemented by using the lag of the natural logarithm of immigration (IV_2) as another instrument. It can be seen That the coefficient of aggregate crime rate is approximately the same in both regressions. Also, both Emp and education have a negative correlation with aggregate crime rates and sexual crime rates. One could also notice that the estimated coefficient of immigration is significant in the regressions of theft rate and crimes against the public. Even though this is the case, the same conclusion is preserved.

Table 2:
$FE - IV_1$ regressions of all crime types (as rates) and immigration

Aggregate crime rate, violence rate, theft rate, Sexual crimes rate, and crimes against the public are regressed, using the IV-fixed effect estimator, on the natural logarithm of immigration ($Ln(imm)$), employment rate (Emp), disposable income rate (DI), and the natural logarithm of education ($Ln(Ed)$). The coefficients reported are computed using the $FE - IV_1$ estimator given in the methodology section. Municipality-Clustered robust-standard errors are reported between the parenthesis. The last three rows represent, the goodness of fit (R^2), the number of municipalities, and the number of time periods respectively. Some observation were not included in sexual crimes rate and crimes against the public due to missing values. Significant values are represented using $*, **$ & $***$.

Variable	Aggregate crime rate	Violence rate	Theft rate	Sex crime rate	Crimes against the public
$Ln(imm)$	0.035*	0.005*	0.010	0.001	0.0004
	(0.021)	(0.002)	(0.009)	(0.001)	(0.0004)
Emp	-0.37***	-0.015	-0.100***	-0.002	-0.00046
	(0.088)	(0.009)	(0.033)	(0.005)	(0.0016)
DI	0.02	-0.0003	0.005	-0.001	0.0003
	(0.016)	(0.002)	(0.007)	(0.001)	(0.0003)
$Ln(Ed)$	-0.116***	-0.003	-0.024*	-0.003*	-0.0003
	(0.04)	(0.004)	(0.013)	(0.002)	(0.0005)
Observations	1722	1722	1722	1680	1596
Model	$FE - IV_1$	$FE - IV_1$	$FE - IV_1$	$FE - IV_1$	$FE - IV_1$
R^2	0.13	0.29	0.12	0.0021	0.0033
N	287	287	287	280	266
T	6	6	6	6	6

$*p < 0.1$; $**p < 0.05$; $***p < 0.01$

Table 3:
Robustness Check: $FE - IV_2$ regressions of crime rates and immigration

Aggregate crime rate, violence rate, theft rate, Sex crimes rate, and crimes against the public are regressed on the natural logarithm of immigration ($Ln(imm)$), employment rate (Emp), disposable income rate (DI), and the natural logarithm of education ($Ln(Ed)$). The regressions were done for each year between 2012 and 2017 ($T = 6$). The coefficients reported are computed using the $FE - IV_2$ estimator given in the methodology section. Municipality-Clustered robust-standard errors are reported between the parenthesis. The last three rows represent, the goodness of fit (R^2), the number of municipalities, and the number of time periods respectively. Some observation were not included in sex crimes rate and crimes against the public due to missing values. Significant values are represented using $*, **$ & $***$.

Variable	Aggregate crime rate	Violence rate	Theft rate	Sex crime rate	Crimes against the public
$Ln(imm)$	0.029***	0.003***	0.010***	0.0004	0.0004***
	(0.010)	0.001	(0.004)	(0.001)	(0.0002)
Emp	-0.409***	-0.014	-0.090***	-0.001	-0.001
	(0.090)	(0.009)	(0.027)	(0.007)	(0.001)
DI	0.008	-0.001	0.001	-0.002	0.0004
	(0.590)	(0.002)	(0.006)	(0.002)	(0.001)
$Ln(Ed)$	-0.115***	-0.002	-0.011	-0.004***	-0.0005
	(0.027)	(0.003)	(0.009)	(0.002)	(0.0005)
Observations	1435	1435	1435	1400	1330
Model	$FE - IV_2$	$FE - IV_2$	$FE - IV_2$	$FE - IV_2$	$FE - IV_2$
R^2	0.062	0.034	0.014	0.004	0.004
N	287	287	287	280	266
T	5	5	5	5	5

$*p < 0.1$;$**p < 0.05$; $***p < 0.01$

The second topic discussed is the relation between immigration and the sudden rise of Sweden Democrats. Table 4 reports the $FE - OLS$ and $FE - IV_1$ estimators with SD regressed on the natural logarithm of immigration ($Ln(imm)$), employment rate (Emp), disposable income rate (DI), and the natural logarithm of education ($Ln(Ed)$), while using

IV_1 as an instrumental variable. The results of the $FE - IV_1$ regression suggest that the increase of refugee immigration caused an increase in Sweden Democrats votes. This means that the sudden increase of refugee inflows in Sweden swayed the voting behavior in favor of Sweden Democrats. These results match the findings of Mehic (2019), where he found a positive relation between immigration and the change of voting behavior in favor of Sweden Democrats. Other papers such as Steinmayr (2016) and Gehrsitz and Ungerer (2017) studied the relation between the rise of anti-immigration parties and refugees in Austria and Germany respectively. The paper by Steinmayr (2016) suggested a negative correlation between refugee inflows and the far-right Free Party of Austria (FPOE), and the paper by Gehrsitz and Ungerer (2017) found no relation between the far-right party in Germany and refugees. This is also interesting, where it seems that the voting behavior swayed in favor of Sweden Democrats because of the increase in refugees, while that was not the case in other countries such as Germany and Austria. In line with the findings of Mayda (2006), it is notable that an increase in disposable income (DI) leads to less votes for Sweden Democrats. This relation is reasonable, as people with a low level of disposable income might feel neglected in a government that provides extra funding and attention to newly admitted refugees.

Table 4:
$FE - OLS$ and $FE - IV_1$ regressions of SD and Immigration

The Sweden Democrats variable (SD) is regressed using the OLS and 2SLS-fixed effect methods on the natural logarithm of immigration ($Ln(imm)$), employment rate (Emp), disposable income rate (DI), and the natural logarithm of education ($Ln(Ed)$). The regressions were done for each Swedish political election of 2010, 2014, and 2018 ($T = 3$). The coefficients reported are computed using the FE-OLS and FE-2SLS estimators discussed in the methodology section. Municipality-Clustered robust-standard errors are reported between the parenthesis. The last three rows represent, the goodness of fit (R^2), the number of municipalities, and the number of time periods respectively. Some observation were not included due to missing values. Significant values are represented using $*, **$ & $***$.

$Variable$	SD $(FE - OLS)$	SD $(FE - IV_1)$
$Ln(imm)$	0.025***	0.293***
	(0.012)	(0.094)
Emp	0.268***	-0.038
	(0.103)	(0.179)
DI	-0.201***	-0.168***
	(0.047)	(0.065)
$Ln(Ed)$	0.065***	0.044
	(0.037)	(0.052)
Observations	759	759
R^2	0.29	0.03
N	253	253
T	3	3

$*p < 0.1; **p < 0.05; ***p < 0.01$

When running a robustness check on the regression of SD and immigration, using the lag is not advisable. Using the lag of immigration as another instrument was not a problem in the previous regressions, as not much "valuable" information is lost when conducting the test. When using it in this case, the information of the year 2010 would be lost. This means that even though the data set is sufficiently big, one would lose information of events that occurred before the refugee crisis. Another way to check for robustness is by partitioning the data cross sectionally (i.e. cutting the data by a certain percentage). By using this method, one would still lose data points, but without the loss of important information. In Table 5, the pooled data set is cut by approximately 10%, 25%, 35% and 50% in partitions (1), (2), (3) and (4) respectively, explained further below. In order to replicate these partitions, it is noted that municipalities are rearranged alphabetically. If the panel becomes unbalanced when partitioning, one should add or remove a data point to re-balance the panel. For example, in partition (1), $759 \times 0.1 \approx 76$ data points are excluded,but because one municipality had a missing data point (that of 2010), it is added back to keep the panel balanced. Removing the data arbitrary might be useful, but is not always a strong robustness test, which is why it could be more interesting to partition the data based on a different criteria. In partition (5), extreme outliers of the disposable income variable are excluded, which can be depicted from Figure 5. As expected, similar results can be seen from the robustness tests reported in Table 5.

Figure 5: Data transformation of disposable income

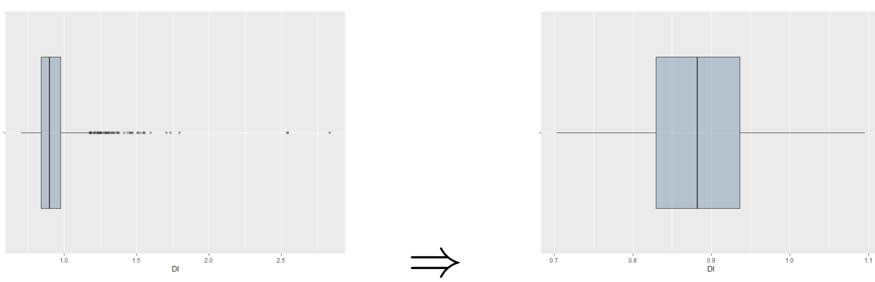


Table 5:
Robustness Check: $FE - IV_1$ regressions of SD and immigration with partitioned data

The Sweden Democrats variable (SD) is regressed on the natural logarithm of immigration ($Ln(imm)$), employment rate (Emp), disposable income rate (DI), and the natural logarithm of education ($Ln(Ed)$). The regressions were done for each Swedish political election of 2010, 2014, and 2018 ($T = 3$). The coefficients reported are computed using the $FE - IV_1$ estimator discussed in the methodology section. Municipality-Clustered robust-standard errors are reported between the parenthesis. The last three rows represent, the goodness of fit (R^2), the number of municipalities, and the number of time periods respectively. the data is cut by approximately 10%, 25%, 35% and 50% in partitions (1), (2), (3) and (4) respectively. In partition (5), extreme outliers of disposable income are excluded from the data set. Significant values are represented using $*, **$ & $***$.

$Variable$	(1)	(2)	(3)	(4)	(5)
$Ln(imm)$	0.324***	0.275***	0.282***	0.276***	0.298***
	(0.120)	(0.106)	(0.106)	(0.128)	(0.108)
Emp	-0.082	-0.103	-0.029	-0.152	-0.057
	(0.218)	(0.201)	(0.211)	(0.245)	(0.184)
DI	-0.216***	-0.211***	-0.196***	-0.225***	-0.217***
	(0.076)	(0.076)	(0.077)	(0.082)	(0.096)
$Ln(Ed)$	0.025	0.030	0.015	0.007	0.050
	(0.058)	(0.058)	(0.063)	(0.071)	(0.060)
Observations	684	570	495	381	654
R^2	0.024	0.029	0.027	0.022	0.015
N	228	190	165	127	218
T	3	3	3	3	3

$*p < 0.1; **p < 0.05; ***p < 0.01$

5 Conclusion

In this paper, two topics are studied using data collected from SCB, Brå, and Migrationsverket. The first topic concerns the relation between the rise in refugee immigration and crime. Specifically, studying if the recent surge of refugees towards Sweden has increased crime rates. Violence, theft, sexual assault and crimes against the public are various crime types that have been studied using data from 2012 to 2017. The second topic of interest is the relation between the rise in immigration and the change of voting behavior in favor of Sweden Democrats. The data used for this study was gathered for the years of 2010, 2014, and 2018.[10] Both topics were studied empirically using the $FE - IV_1$ estimator with education, disposable income, and employment being used as control variables in the regressions.

According to the analysis in this paper, it is suggested that the recent increase of refugee inflows towards Sweden caused an increase in crime rates (mainly, violence crimes). It is also notable that higher education and employment rates led to lower crime rates. Similar results are reported when using $Ln(imm_{t-1})$ as another instrument to test for robustness.

It is also suggested that the sudden surge of refugees swayed the voting behavior in favor of Sweden Democrats. Another factor that lead to the growth of Sweden Democrats is

[10] Swedish elections take place every 4 years.

having relatively less disposable income. One might think when the income gap is enlarged, individuals would tend to vote for parties that focus on job security, but this is not the case. Similar results are yielded from the robustness test run on the regressions regarding this topic.

As mentioned previously, a paper by Gehrsitz and Ungerer (2017) found that the recent increase of refugee inflows was not a cause in increasing crime rates, nor it had any relation with the rise of the far-right party in Germany. This raises an interesting question: why did the refugee crisis in 2015 lead to an increase in crime rates and to a change in voting behavior in favor of the far-right party in Sweden, while that was not the case in Germany?

It is hard to say why these relations came to be, and the only insight that this paper provides is on the relation between these recent events. More precisely, the results do not give any indication on why the sudden increase in refugees caused an increase in crime rates, and there is no evidence that it is of cultural reasons. Most studies linked it to psychological and financial reasons. One could refer to the medical paper by Kirmayer et al. (2010) that discusses some psychological reasons on why this is the case. One could also refer to an economic paper by Ruist (2015) that mentions the financial strains put on newly admitted refugees.

Finally, the results in this paper are purely academic and add to the literature that could help further the understanding on how to allocate resources in order to increase integration.

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Appendix

Figure 6: Refugee seeking by gender: from 2010 to 2018

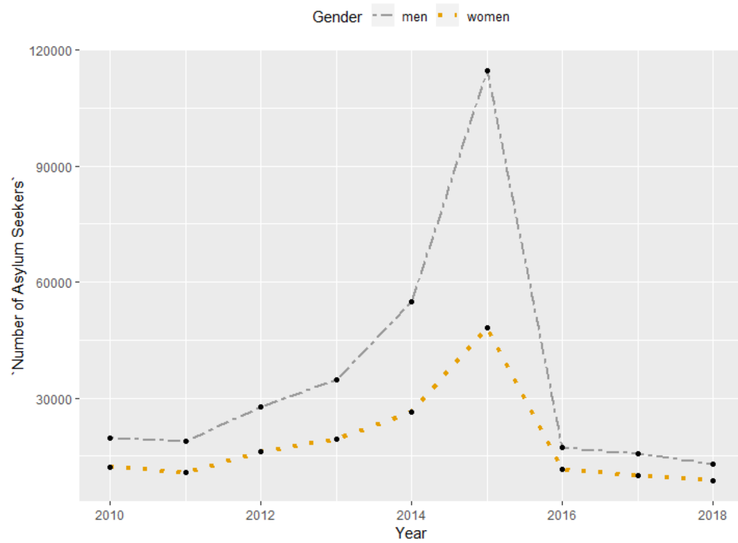


Figure 7: Foreign born citizens by age: from 2010 to 2018

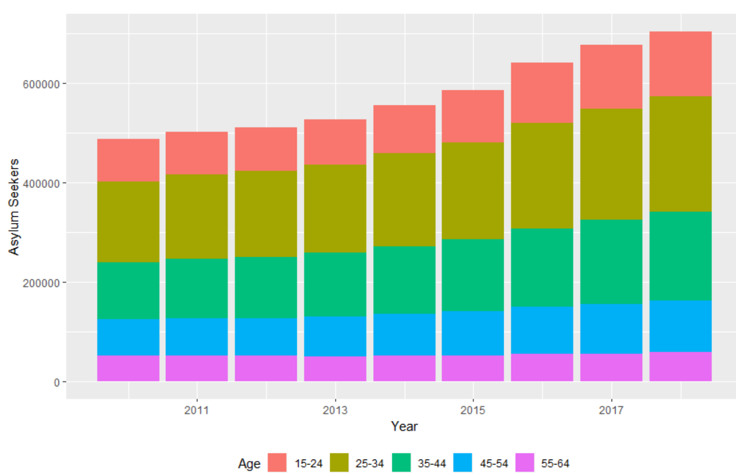


Figure 8: Mean of refugees by country: from 2010 to 2017

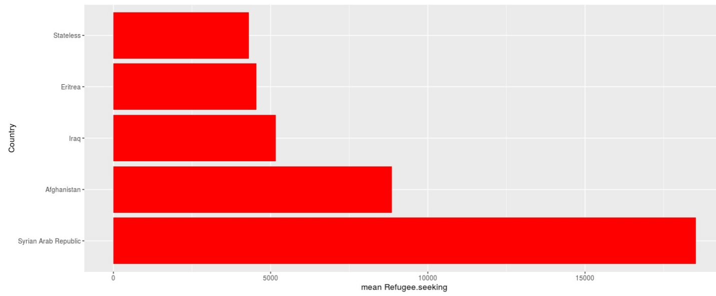


Table 6:
Included crimes in each type

Crime Type	Included Crimes
Violence (3 chap.)	Attempted murder or murder Abuse Manslaughter Causing injury / illness Acting as a danger for others
theft (8 chap.)	Grand theft auto Burglary and theft (not of firearms) Theft (including burglary) of firearms Other theft Robbery
Sexual assault (6 chap.)	Rape Sexual abuse Sexual coercion, utilization Incompetent sexual abuse Intercourse with offspring or siblings Contact with children for sexual purposes Utilization of children under 18 years Buying sexual actions from children Purchase of sexual service
Crimes against the public (13 chap.)	Public Destruction Public carelessness Arson Other common hazardous negligence Spreading of poison / contagious destruction

Figure 9: Variables box plot

On the left, box plots are represented for each year and on the right, box plots are represented for the pooled set of data of each control variable. From top to bottom, box plots of data of the natural log of immigration, employment rate, natural log of education, disposable income and SD's shares are plotted.

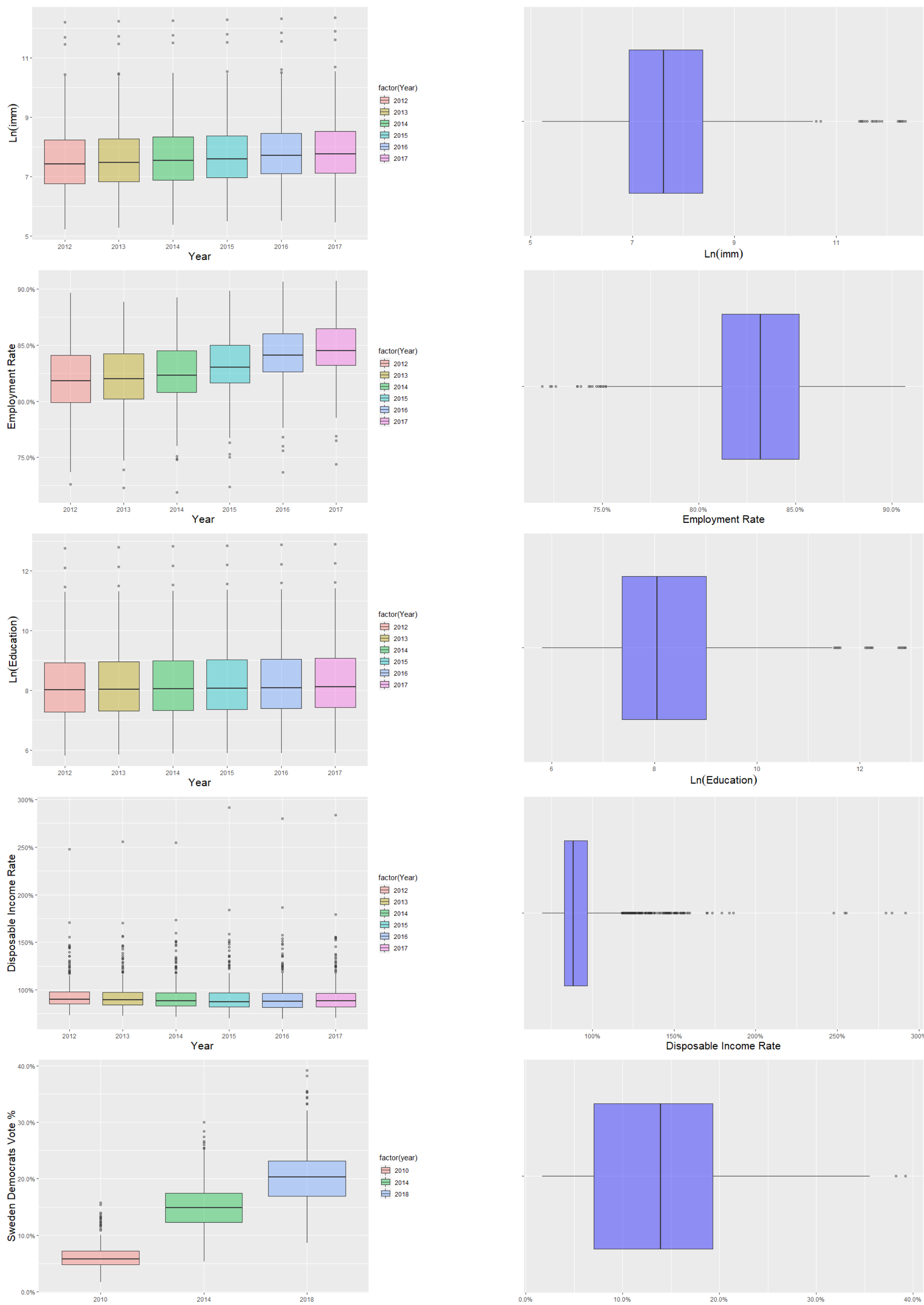
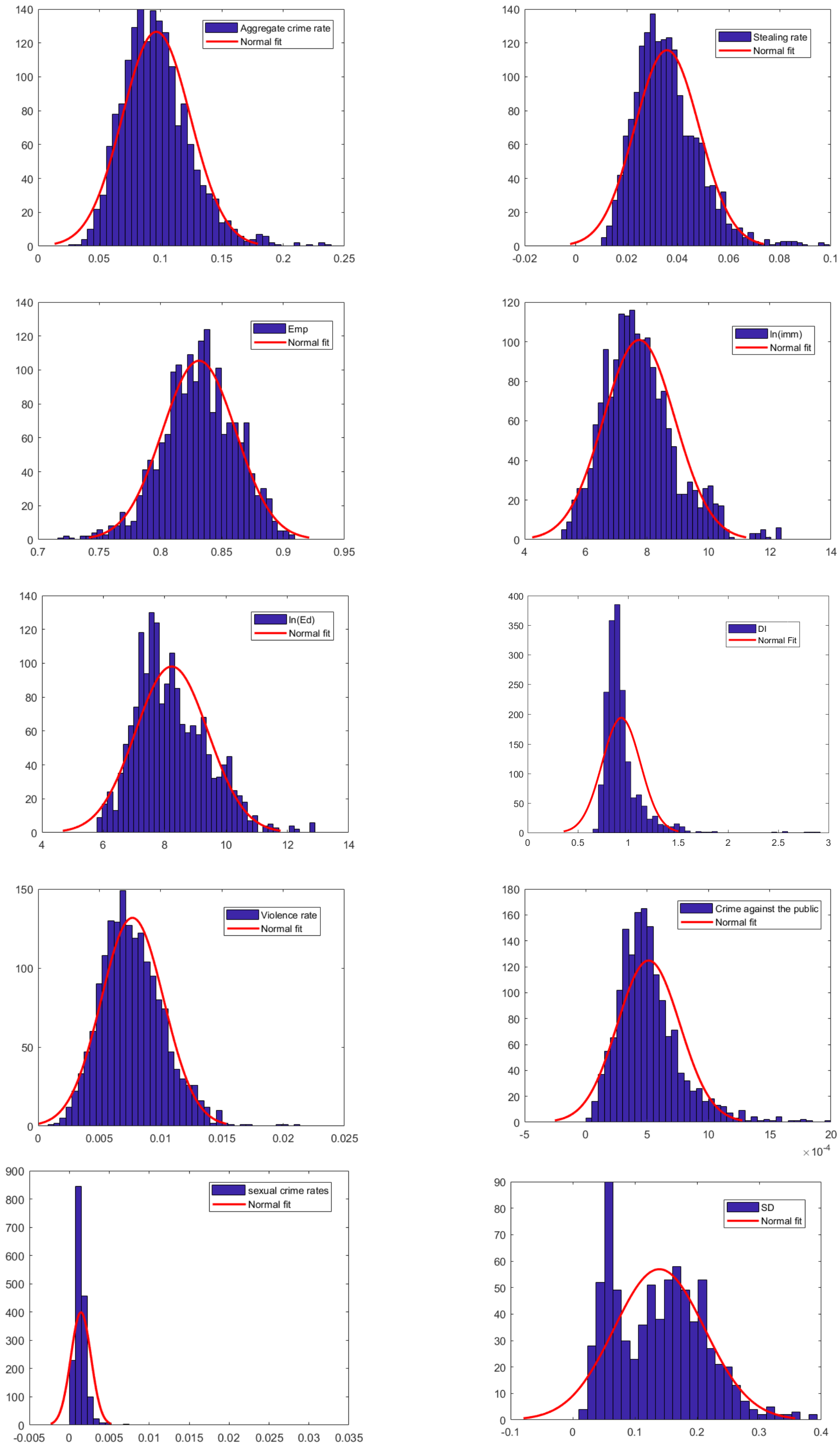


Figure 10: Crime types box plots

On the left, box plots are represented for each year and on the right, box plots are represented for the pooled set of data of each control variable. From top to bottom, box plots of Aggregate crime, Violent crimes, theft,crimes against the public and Sex crimes are plotted.

Figure 11: Histograms of variables

Histograms are plotted for each variable while fitting a normal distribution for comparison. Histogram plotted for the sex crime variable is post-treatment.



Descriptive statistics

Table 7: Descriptive statistics for crimes against the public

This table provides the descriptive statistics for the data concerning the regression of crime against the public.

Variable	N	Mean	Std. dev.	Min.	25 %	Median	75 %	Max.
Crime agains the public	1,596	0.001	0.000	0.000	0.000	0.000	0.001	0.002
$Ln(imm)$	1,596	7.854	1.124	5.226	7.090	7.718	8.463	12.366
Emp	1,596	0.831	0.030	0.719	0.812	0.832	0.851	0.906
DI	1,596	0.941	0.195	0.695	0.837	0.893	0.976	2.916
$Ln(Ed)$	1,596	8.342	1.147	6.073	7.498	8.180	9.093	12.894

Table 8: Descriptive statistics for sexual crime rates

This table provides the descriptive statistics for the data concerning the regression of sexual crime rates.

Variable	N	Mean	Std. dev.	Min.	25 %	Median	75 %	Max.
Sexual Crime rates	1,680	0.001	0.001	0.000	0.001	0.001	0.002	0.031
$Ln(imm)$	1,680	7.782	1.147	5.226	7.009	7.646	8.417	12.366
Emp	1,680	0.831	0.030	0.719	0.812	0.832	0.851	0.906
DI	1,680	0.937	0.193	0.695	0.832	0.890	0.972	2.916
$Ln(Ed)$	1,680	8.276	1.161	5.852	7.429	8.085	9.031	12.894

Table 9: Descriptive statistics: SD

This table provides the descriptive statistics for the data concerning the regression of SD

Variable	N	Mean	Std. dev.	Min.	25 %	Median	75 %	Max.
SD	759	0.139	0.073	0.017	0.070	0.139	0.193	0.392
DI	759	0.941	0.188	0.703	0.841	0.899	0.974	2.834
Emp	759	0.828	0.032	0.719	0.806	0.830	0.851	0.907
$Ln(Ed)$	759	8.153	1.153	5.753	7.316	7.973	8.938	12.894
$Ln(imm)$	759	7.786	1.210	5.182	6.983	7.659	8.484	12.398

Table 10: Correlation table of aggregate crime rate

In this table, correlations are provided between aggregate crime rate, natural log of immigration, employment rate, disposable income rate, natural log of education and natural log of the instrumental variable. Only significant correlations are provided.

Variable	Aggregate Crime Rate	$Ln(imm)$	Emp	DI	$ln(Ed)$	$Ln(IV)$
Aggregate Crime Rate	1.00					
$Ln(imm)$	0.64	1.00				
Emp	-0.31		1.00			
DI		0.34	0.43	1.00		
$Ln(Ed)$	0.48		0.08	0.47	1.00	
$Ln(IV)$	0.23	0.45	0.01		0.45	1.00

Table 11: Correlation table of other crime types and SD

In this table, correlations are provided between sexual crime rates, crimes against the public, violence and theft and the natural log of immigration, employment rate, disposable income rate, natural log of education and natural log of the instrumental variable. Only significant correlations are provided.

Variable	Sex Crimes	Crimes against the public	Violence	theft	SD
$Ln(imm)$	0.0804	-0.1112	0.3355	0.6442	0.3748
Emp	-0.0691	-0.2172	-0.3407	-0.3091	0.2970
DI	-0.0954	-0.2721	-0.2643	0.1674	-0.2147
$Ln(Ed)$		-0.2285	0.1519	0.5471	0.1193
$Ln(IV)$	0.0723	-0.1052	0.1409	0.1639	

Figure 12: Scatter plot of all type of crimes (as a whole) across the Years

These figures are plots of all the natural logarithm of all crime types (as a whole) against the natural logarithm of immigration across the years. The 95% confidence interval is visualized as the shaded area.

Figure 13:
polynomial pooled scatter plot of crime as a whole against The natural logarithm of immigration

The scatter plots in this figure represent all crime types (as a whole) against the natural logarithm of immigration. In order, natural logarithm sexual crimes, violence, theft, crimes against the public and aggregate crimes are included. The coloring represents each year across the pooled data. The 95% confidence interval is visualized as the shaded area.

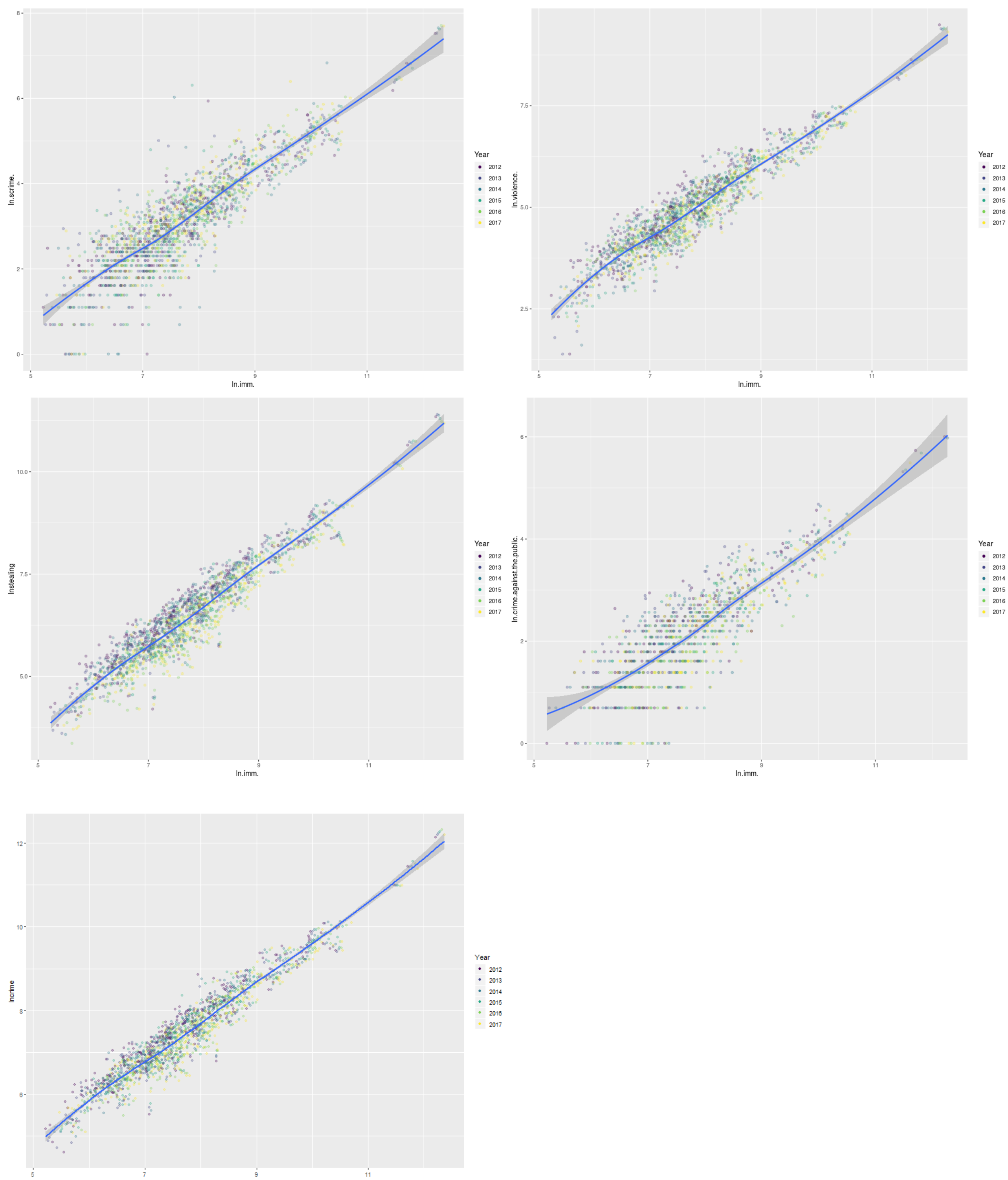


Table 12:
FE-OLS regressions of crime and immigration

Aggregate crime rate, violence rate, theft rate, Sex crimes rate, and crimes against the public are regressed using the fixed effect method on the natural logarithm of immigration ($Ln(imm)$), employment rate (Emp), disposable income rate (DI), and the natural logarithm of education ($Ln(Ed)$). The regressions were done for each year between 2012 and 2017 ($T = 6$). The coefficients reported are computed using the fixed effects estimator given in the methodology section. Municipality-Clustered robust-standard errors are reported between the parenthesis. The last three rows represent, the goodness of fit (R^2), the number of municipalities, and the number of time periods respectively. Some observation were not included in sex crimes rate and crimes against the public due to missing values. Significant values are represented using $*, **$ & $***$.

Variable	Agg. crime rate	Violence rate	theft rate	Sex crime rate	Crimes against the public
$Ln(imm)$	0.017***	0.004***	0.002	0.00057	0.0001631
	(0.005)	(0.001)	(0.002)	(0.001)	(0.0001)
Emp	-0.327***	-0.014*	-0.076***	0.000	0.000
	(0.050)	(0.008)	(0.026)	(0.006)	(0.001)
DI	0.012	-0.0004	0.002	-0.002	0.0001721
	(0.014)	(0.002)	(0.005)	(0.002)	(0.0002)
$Ln(Ed)$	-0.098***	-0.002	-0.016	-0.002***	-0.0000612
	(0.027)	(0.003)	(0.010)	(0.002)	(0.0005)
Observations	1,722	1,722	1,722	1680	1,596
Model	$FE - OLS$	$FE - OLS$	$FE - OLS$	$FE - OLS$	$FE - OLS$
R^2	0.048	0.032	0.009	0.002	0.0063
N	287	287	287	280	266
T	6	6	6	6	6

$*p < 0.1; **p < 0.05; ***p < 0.01$

Table 13:
OLS regression of aggregate crime rate and immigration across The Years

The aggregate crime rate variable is regressed using the OLS method on the natural logarithm of immigration ($Ln(imm)$), employment rate (Emp), disposable income rate (DI), and the natural logarithm of education ($Ln(Ed)$) for each year between 2012 and 2017. The coefficients reported are computed using the OLS estimator, $\beta_{OLS} = (X^TX)^{-1}X^Ty$ with robust-standard errors reported between the parenthesis. The last row represents the goodness of fit (R^2). Significant values are represented using $*, **$ & $***$.

	Dependent Variable						
	Agg. Crime Rate						
	Full Sample	2012	2013	2014	2015	2016	2017
$Ln(imm)$	0.028***	0.031***	0.029***	0.029***	0.030***	0.026***	0.022***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Emp	-0.227***	-0.238***	-0.226***	-0.265***	-0.224***	-0.205***	-0.250***
	(0.017)	(0.046)	(0.043)	(0.043)	(0.047)	(0.046)	(0.052)
DI	0.001	-0.005	0.002	0.005	0.006	-0.0002	-0.002
	(0.003)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
$Ln(Ed)$	-0.014***	-0.016***	-0.014***	-0.014***	-0.015***	-0.012***	-0.010***
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.181***	0.196***	0.172***	0.201***	0.171***	0.166***	0.220***
	(0.014)	(0.036)	(0.034)	(0.035)	(0.039)	(0.039)	(0.044)
Estimator	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*
Fixed effects	None	None	None	None	None	None	None
Observations	1,722	287	287	287	287	287	287
R^2	0.554	0.583	0.609	0.619	0.562	0.532	0.437

$*p < 0.1; **p < 0.05; ***p < 0.01$

Table 14:
OLS regression of violence rates and immigration across the years

The violence crime rate variable is regressed using the OLS method on the natural logarithm of immigration ($Ln(imm)$), employment rate (Emp), disposable income rate (DI), and the natural logarithm of education ($Ln(Ed)$) for each year between 2012 and 2017. The coefficients reported are computed using the OLS estimator, $\beta_{OLS} = (X^T X)^{-1} X^T y$ with robust-standard errors reported between the parenthesis. The last row represents the goodness of fit (R^2). Significant values are represented using $*, **$ & $***$.

	Dependent Variable						
	Violence Rate						
	Full Sample	2012	2013	2014	2015	2016	2017
$Ln(imm)$	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.0001)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Emp	-0.014***	-0.018***	-0.010**	-0.019***	-0.020***	-0.018***	-0.017***
	(0.002)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
DI	-0.003***	-0.004***	-0.003***	-0.002***	-0.002**	-0.003***	-0.002***
	(0.0003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Ln(Ed)$	-0.002***	-0.001***	-0.001***	-0.002***	-0.002***	-0.002***	-0.001***
	(0.0001)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Constant	0.017***	0.019***	0.012***	0.020***	0.021***	0.023***	0.020***
	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Estimator	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*
Fixed effects	None	None	None	None	None	None	None
Observations	1,722	287	287	287	287	287	287
R^2	0.367	0.380	0.389	0.407	0.365	0.390	0.352

$*p < 0.1; **p < 0.05; ***p < 0.01$

Table 15:
OLS regression of theft rate and immigration across the years

The theft rate variable is regressed using the OLS method on the natural logarithm of immigration ($Ln(imm)$), employment rate (Emp), disposable income rate (DI), and the natural logarithm of education ($Ln(Ed)$) for each year between 2012 and 2017. The coefficients reported are computed using the OLS estimator, $\beta_{OLS} = (X^T X)^{-1} X^T y$ with robust-standard errors reported between the parenthesis. The last row represents the goodness of fit (R^2). Significant values are represented using $*, **$ & $***$.

	Dependent Variable						
	theft Rate						
	Full Sample	2012	2013	2014	2015	2016	2017
$Ln(imm)$	0.009***	0.013***	0.011***	0.010***	0.010***	0.008***	0.007***
	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Emp	-0.143***	-0.108***	-0.123***	-0.128***	-0.106***	-0.099***	-0.133***
	(0.008)	(0.022)	(0.021)	(0.021)	(0.023)	(0.021)	(0.021)
DI	0.010***	0.006	0.010**	0.007*	0.007*	0.007**	0.009***
	(0.001)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
$Ln(Ed)$	-0.003***	-0.006***	-0.004***	-0.003**	-0.004***	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.099***	0.078***	0.079***	0.084***	0.069***	0.059***	0.094***
	(0.007)	(0.017)	(0.017)	(0.017)	(0.019)	(0.018)	(0.018)
Estimator	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*
Fixed effects	None	None	None	None	None	None	None
Observations	1,722	287	287	287	287	287	287
R^2	0.520	0.522	0.562	0.563	0.497	0.533	0.499

$*p < 0.1; **p < 0.05; ***p < 0.01$

Table 16:
OLS Regression of sexual crime rates and immigration across the years

The Sexual crime rate variable is regressed using the OLS method on the natural logarithm of immigration ($Ln(imm)$), employment rate (Emp rate), disposable income rate (DI rate), and the natural logarithm of education ($Ln(Ed)$) for each year between 2012 and 2017. The coefficients reported are computed using the OLS estimator, $\beta_{OLS} = (X^TX)^{-1}X^Ty$ with robust-standard errors reported between the parenthesis. The last row represents the goodness of fit (R^2). Significant values are represented using $*, **$ & $***$.

	Dependent Variable						
	Sex crime rate						
	Full Sample	2012	2013	2014	2015	2016	2017
$Ln(imm)$	0.0003***	0.0001	0.0004**	0.0002	0.0002	0.0002	0.0002*
	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0001)	(0.0001)
Emp	-0.0001	-0.004***	0.0004	-0.006	0.002	-0.007***	0.0005
	(0.001)	(0.002)	(0.003)	(0.005)	(0.004)	(0.002)	(0.003)
DI	-0.001***	-0.0003	-0.0005	-0.0004	-0.001	-0.0003	-0.001*
	(0.0002)	(0.0003)	(0.0005)	(0.001)	(0.001)	(0.0003)	(0.0004)
$Ln(Ed)$	-0.0002**	0.00005	-0.0003*	-0.0002	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0001)	(0.0001)
Constant	0.001	0.004***	0.001	0.006	-0.0002	0.007***	0.001
	(0.001)	(0.001)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)
Estimator	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*
Fixed effects	None	None	None	None	None	None	None
Observations	1,680	280	280	280	280	280	280
R^2	0.026	0.112	0.032	0.020	0.015	0.081	0.034

$*p < 0.1$;$**p < 0.05$; $***p < 0.01$

Table 17:
OLS regression of crimes against the public and immigration across the years

The crimes against the public variable is regressed using the OLS method on the natural logarithm of immigration ($Ln(imm)$), employment rate (Emp), disposable income rate (DI), and the natural logarithm of education ($Ln(Ed)$) for each year between 2012 and 2017. The coefficients reported are computed using the OLS estimator, $\beta_{OLS} = (X^T X)^{-1} X^T y$ with robust-standard errors reported between the parenthesis. The last row represents the goodness of fit (R^2). Significant values are represented using $*, **$ & $***$.

	Dependent Variable						
	Crimes against the public						
	Full Sample	2012	2013	2014	2015	2016	2017
$Ln(imm)$	0.0001***	0.0001***	0.0001**	0.0002***	0.0001***	0.0001***	0.0001
	(0.00001)	(0.00003)	(0.00004)	(0.00003)	(0.00003)	(0.00003)	(0.00004)
Emp	-0.001***	-0.001*	-0.001*	-0.0004	-0.001	-0.0004	-0.0004
	(0.0002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
DI	-0.0001***	-0.0001	-0.0001	-0.0002**	-0.0001	-0.0001	-0.0002*
	(0.00004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Ln(Ed)$	-0.0001***	-0.0002***	-0.0001***	-0.0002***	-0.0001***	-0.0002***	-0.0001**
	(0.00001)	(0.00004)	(0.00004)	(0.00003)	(0.00003)	(0.00003)	(0.00004)
Constant	0.002***	0.002***	0.002***	0.001***	0.002***	0.001**	0.001**
	(0.0002)	(0.0005)	(0.001)	(0.0005)	(0.0005)	(0.001)	(0.001)
Estimator	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*
Fixed effects	None	None	None	None	None	None	None
Observations	1,596	266	266	266	266	266	266
R^2	0.138	0.151	0.118	0.191	0.151	0.155	0.106

$*p < 0.1$;$**p < 0.05$; $***p < 0.01$

Figure 14:
Polynomial pooled scatter plots of types of crime rates
against the natural logarithm of immigration

The scatter plots in this figure represent all crime types (as ratios) against the natural logarithm of immigration. In order, natural logarithm sexual crimes, violence, theft and crimes against the public. The coloring represents each year across the pooled data. The 95% confidence interval is visualized as the shaded area.

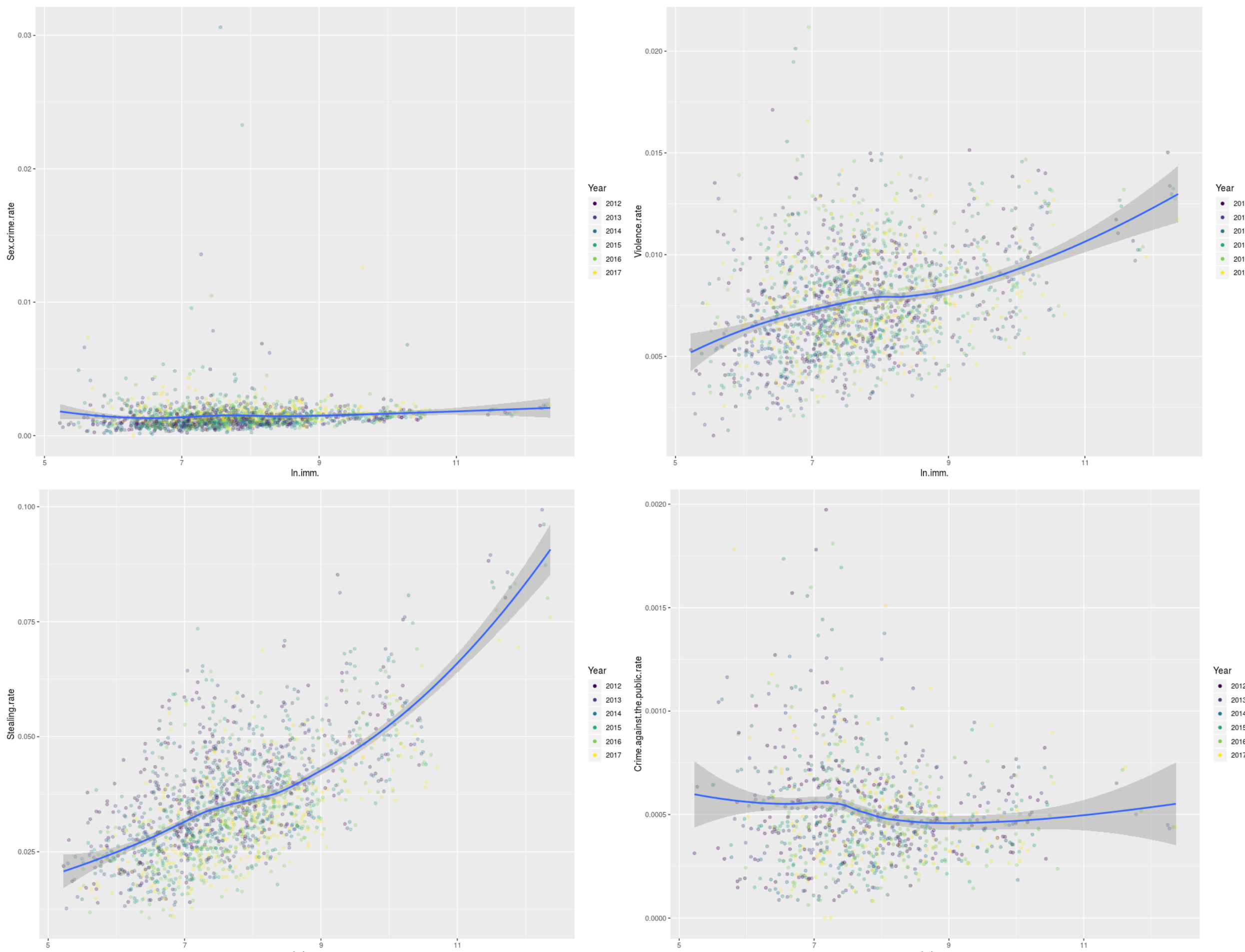


Figure 15: Scatter plots of all type of crimes across the Years

These figures are plots of all the natural logarithm of all crime types (as a whole) against the natural logarithm of immigration across the years. The 95% confidence interval is visualized as the shaded area.