“Does More Immigration Lead to More Crime?”

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I. Introduction

As immigration has increased over the past twenty years, there has been a rise in the number of economic studies of the impact of migration on crime, in countries that have been destinations for migrants. This issue is at the forefront of current events; with some arguing that the general public voting in the recent referendum, to leave the EU termed "Brexit" was partly due to fear of immigration, and its effect on crime. Nigel Farage (2013) [1] speaking at the UKIP party conference in September of 2013 claimed that London was in the midst of a “Romanian crime wave” also to accusing the coalition government of welcoming “foreign criminal gangs” from the newly joined EU member states. Therefore, if the general public share these viewpoints on a possible link between immigration and crime, they could vote in so called “right-wing” politicians, leading potentially to serious economic consequences.

II. Literature Review

Mastrobuoni and Pinotti (2011) [2] used an empirical model, to examine whether there is a causal effect between the legal status of a migrant and propensity for criminality. Using data from the wave of immigration that took place in 2007, when Romania and Bulgaria joined the EU, the authors took advantage of the differences in travel policies between countries, to implement a difference-in-difference approach for their estimation strategy. They found that legalization of migrants from Bulgaria and Romania reduced the chance of rearrests from 5.8% to 2.3% for both groups. The explanation of their result relies on the fact that legalisation means greater labour market opportunities for migrants. The findings are consistent with the Becker (1968) model of crime. When rationally behaving immigrants have access to a legal income through labour market opportunities, they decide to commit less crime, as the opportunity cost of crime has increased. However, Freedman *et* *al.* (2014) [3] state the authors estimate reoffending rates only from immigrants returned to prison in Italy. This limits the author's ability to be able to differentiate between the impact of real reductions in criminality from the impact of greater mobility and resettlement of the migrants from Romania and Bulgaria. Freedman *et al*. (2014) concluded in an alternative study that increased mobility of immigrants might cause one to underestimate, not overestimate the effects of increased labour market access. A similar approach to Mastrobuoni and Pinotti (2011) was later taken by Pinotti (2014) [4] in an empirical study on the immigration status of migrants and their propensity for crime in Italy. He used a regression discontinuity as a regression model to test using a sample of the application data for legalization which was provided by recent immigrants and data on major crimes that were carried out by non-natives. He found that when an immigrant gains legalization, the probability of committing crime falls, however, the effect is stronger in locations which presented immigrants with greater labour market access and less strict immigration enforcement. Similarly, to Mastrobuoni and Pinotti (2011), Alonso-Borrego *et al.* (2012) [5] also used an empirical model to test if crime and immigration are linked. They consider the wave of mass immigration into Spain from various locations that took place in a ten-year period beginning in 1999. In their estimation strategy the authors control for different individual characteristics of migrants such as their level of education, language skills and age Moreover they also considering economic characteristics such per capita GDP and the levels of unemployment in the different Spanish provinces. However, as noted by the authors, the use of data at the provincial can cause endogeneity. This is due to differences in economic characteristics of different locations and to the fact that immigrants were seen to cluster in locations that offer them the greatest economic benefits such as access to labour markets. The Spanish Foundation For Science and Technology (2012) [6] in an interview with the authors noted that, to overcome this endogeneity problem, Alonso-Borrego *et al.* (2012) used longitudinal data, allowing them to accurately estimate the effect of immigration on crime, stripping this away from a positive correlation between higher levels of crime in locations with more economic opportunities and the fact that migrants cluster in these areas. They find that there is a positive correlation between immigration and crime; however, this is not a causal effect. This result can be explained by the individual characteristics of the immigrants especially with respect to language skills and educational achievement, since migrants with better language skills and education commit less crime. The Spanish Foundation for Science and Technology (2012) Also point out that the migrant influx consisted of a large proportion of young males, the group that tend to commit most crimes, this being a factor in the positive correlation between crime and immigration, but not being causal. These findings are in line with the famous 'Latino Paradox' that found a decrease in criminality in the population of Mexican immigrants in the USA in the 1970's and 1980's Sampson et al. (1997) [7]. Buonanno *et al.* (2012) [8] also, empirically analyse immigration to Italian provinces from 1999 to 2003 and its impact on crime using Italian law enforcement records. They first show that by using Ordinary Least Squares (OLS) that there is a positive correlation between migrant population size, the number of property crimes and total crime, in particular they find that, a 1% increase in the population of immigrants could lead to a 0.1% rise in the number of total crimes with the impact on property crime being very significant. However, the authors acknowledge that their results could be biased given that differences in geographic locations where the migrants settled can lead to a problem of endogeneity. Bracco and Onnis (2015) [9] explain that the approach taken by the authors with regards to OLS has the potential to suffer from measurement error from the presence of undocumented migrants (non-legalized migrants can't be observed). In order to decrease the possible bias caused by omitted variables Bracco and Onnis (2015) have extended the analysis of Buonanno et al. (2012) by including dummies to account for geographic locations and periods of time. They find that legalizations of migrants have helped to improve OLS coefficient accuracy and this increases substantially the fitting power of their empirical model. Secondly in an attempt to overcome the endogeneity issues faced when taking an OLS approach the authors used instrumental variables, exploiting the difference between immigration to various locations. Specifically, they instrument immigrant flows to Italian provinces versus migrant flows to the rest of the EU. Their subsequent findings show that the impact on total and property crime is not statistically significant but the impact on robberies is significant. In another empirical study, on the effects of immigration and crime, Spenkuch (2013) [10] used fixed effects panel data techniques on data from the county level in USA; this differed to the differences in differences panel data method used by Mastrobuoni and Pinotti (2011). He found that immigration causes a statistically significant increase in property crime. Furthermore Spenkuch (2013) finds that a rise in the population of immigrants of10% leads to a 1.2% rise in property crime, and that immigrants, on average, commit 2.5 times more property crimes as natives. Moreover, he found that when separating immigrants into their respective racial groups, Mexicans were the only group that was found to have a significant impact on property crime, and this can be explained due to Mexicans having poor labour market outcomes. Additionally, Piopiunik and Ruhose (2017) [11] found that in Germany where immigrants were exogenously allocated to various provinces in Germany, a highly statistically significant impact of immigration on all types of crime. However, this result was much stronger in locations that suffered from higher levels of existing crime and unemployment. This can lead to the conclusion that their estimated results may be affected by an endogeneity problem. Bell *et al.* (2013) [12] carried out an empirical study which examined two different waves of migration into the UK and the impact on crime. The first group consisted of Asylum seekers who came to the UK at the end of the 1990's and start of the 2000's, and the second group consisted of economic migrants (A8) that arrived in the UK in search of employment following the enlargement of the EU after 2004. The authors found that the influx of asylum seekers did lead to a small increase in property crime, whereas, for the A8 group they found there was a small negative impact on property crime. Their findings suggest that access to labour market opportunities are the driving factor behind the small increase in criminal activity from the first group. Miles and Cox (2014) [13] examine legalization status of immigrants and its effect on crime by analysing the impact of a US government scheme called "secure communities" on rates of crime. The scheme was implemented in 2008 on a staggered basis across 3000 US counties. The scheme records data on immigrants, arrested at the local level, who have violated immigration laws and may be subsequently deported by federal authorities. Miles and Cox firstly used a difference in difference approach similarly to Mastrobuoni and Pinotti (2011) to estimate the implementation of "Secure Communities" across the US, and the effect on rates of crime. They found that the scheme did not have a statistically significant impact on reducing the rate of crime as measured by the crime rate index of the FBI, or any reduction on crimes of a violent nature. In an interview where they discuss their research [14] they also discovered that the scheme at first focused strongly in Latino districts, questioning whether there might be some bias in the results due to the different economic characteristics of mainly Hispanic neighbourhoods and the fact that one racial group seems to be the focus of the scheme. Legalization status is also analysed by Fasani (2016) [15] which follows on from the work of Mastrobuoni & Pinotti (2011), Pinotti (2014) and Miles and Cox (2014). He looks at the legal status of immigrants and the impact on crime by analysing migrant amnesty data collected over fifteen years, beginning in 1990 in Italy. Fasani's approach takes into account the potential problems due to endogenous factors by using instrumental variables similarly to Buonanno et al. (2012). Fasani instruments the real number of migrants with legal status compared to predicted numbers legalized migrants which is based on previous amnesty data and the geographic locations that legal and illegal migrants have settled. He comes to the conclusion that locations with larger shares of immigrants experience a fall in crime the year after an amnesty takes place. However, Fasani notes that the impact is small, and that Italian natives and other EU migrants do not create a substitution in the market for crime. Furthermore, a German study conducted by Pfeiffer *et al* (2017) [16] found that crimes committed by immigrants were twice as likely to be reported to the police as those committed by Germans. Additionally the research carried at Zurich University of Applied Sciences which analysed asylum seeker data from 2015 and 2016 from Lower Saxony in Germany and found that migrants from Syria, Iraq and Afghanistan, which made up 54% of the migrants in the study committed 34% of the violent crime attributed to asylum seekers, however, they also found that even though migrants from Algeria, Tunisia and Morocco only make up 0.9% of the asylum seekers in their study they are responsible for 17.1% of the share of violent crime, postulate that these groups often have to share cramped living conditions, due to legalization restrictions which could potentially lead to inter-group violence, as they found that 91% of murders and 75% of assault cases were between migrants, moreover, many of the migrants were young-men- the group which commits the most, violent crime, and interestingly they postulate that the male to female ratio of the migrants was a major contributing factor to the situation. In conclusion the current research points towards the fact that immigration may increase some types of property crime, however, this positive correlation is not a causal effect. Therefore, further research is needed to analyse this important question so that the economic effects of increased immigration and a potential link between rising crime levels are fully understood.

III. Theoretical Model of Crime

In his seminal model of the economics of crime Becker (1968) [17] states that rational economic agents decide whether or not to commit a criminal act based on the expected utility that they could expect to gain by carrying out the crime, weighted against the probability of being apprehended. Rohling (2010) [18] in a technical analysis of Becker's (1968) Crime and Punishment an Economic Approach states that;

$$Eu_j = p_j U_j(Y_j - f_j) + (1 - p_j) U_j(Y_j)$$

Where Y_j is the financial proceeds of crime, U_j is the utility function; p_j is the likelihood of being arrested and convicted and f_j is the financial equivalent of the punishment if an individual is indeed convicted. Following this logic an individual j carries out a crime if the expected utility from the criminal act is greater than the expected utility that the individual would gain from using their human capital in a legal manner.

The supply of crimes, that individual j commits can be represented by a crime function.

$$O_j = O_j(p_j, f_j, u_j)$$

Where u_j represents all other factors that individual j takes into account when making a decision whether or not to carry out a crime. Furthermore, the market supply of criminal acts is the summation of all the O_j and therefore

$$O = O(p, f, u)$$

Where p, f and u take average values. Thus, an increase in p or f decreases expected utility and thus the supply of offences.

$$O_p > 0 \text{ and } O_f > 0$$

On the other hand, while criminals gain from carrying out criminal acts $G(O)$, society in general is harmed $H(O)$ by crime, and net damage $D(O)$ to society from crime expresses the loss to society from crime $L(O)$.

$$L(O) = D(O) = H(O) = G(O)$$

$$\text{where } H' > 0, H''(O) > 0, G' > 0, \text{ and } G'' < 0$$

The minimization of loss to society from crime is the stated aim of this social policy. The relevant variables are the likelihood of arrest and conviction p and the financial punishment f, as both are directed linked to the quantity of crimes O.

Furthermore, to minimise the loss to society with respect to p and f:

$$D'(O) = 0 \text{ and thus } G'(O) = H'(O)$$

Thus, to set the conditions for optimal policy, p must be equal to 1 and a fine $f = H'(O)$, and this leads to a high deterrence effect, in so forth that the fine f

compensates fully the marginal victim. However, when taking into account the costs of arrest and conviction, a *p* value of 1 cannot be optimal.

Factoring the fore mentioned analysis, the total costs of arrest and conviction *C(p, O)* then are determined by *p* and *O.*

where $C_p > 0$ and $C_O > 0$

Therefore, a rise in the chance of arrest and conviction or the total number of crimes, leads to an increase in the total cost of arrest and conviction.

When total costs of arrest and conviction are factored in to the constrained optimisation problem of minimising social loss and *p* is set to 1, the loss function becomes

$$L(O) = D(O) + C(1,O)$$

Thus, minimising the social loss function from crimes *O* with respect to fines *f* leads to

$$D'(O) + C'(1, O) = 0 \text{ and thus } H'(O) + C'(1,O) = G'(O) = f$$

So that when costs of arrest and conviction are taken into account, convicted criminals compensate the marginal victim optimally, in addition to the marginal cost of their arrest and conviction.

On the other hand, if *f* is held fixed, while *p* is allowed to vary, the optimality condition changes to

$$D'(O) + C'(p, O) + C_p/O_p = 0 \text{ and thus } H'(O) + C'(p, O) > G'(O)$$

This leads to the conclusion that optimisation with respect to p and f is impossible, *f* or *p* must be arbitrarily set and then social loss is minimised by the other variable. The ideal situation is that $p \cong 0$ and $f \to \infty$ (if possible). In this case a deterrent effect is created and total costs to society are low.

Other costs imposed on society are caused by the cost of punishing criminals; these costs can be modelled as total social cost of punishment *bpfO,* which is the summation of costs to criminals, in addition to costs to society, this can be split into the following categories *pO*: the quantity of convicted criminals, *f*: the punishment per crime and *b*: the coefficient, which transforms the punishment to criminals into costs for society. The value of the coefficient *b*: is linked to the type of punishment. Firstly: fines. These impose no costs to society as they are a transfer payment from criminal to victim so $b \cong 0$, and secondly: a prison term. This does impose costs to the criminal in terms of loss of earnings and on society in terms of the cost of housing the prisoner so b > 1 in this case.

Consequently, Becker's general social loss function from committed crimes *L(O)* can be given by

$$L(O) = D(O) + C(p, O) + bpfO$$

Where D(O) is societal damages from *O* crimes, *C(p, O)* are total costs from arrests and convictions, and *pbfO* are societal total losses arising from punishment, where b > 0 is the coefficient that transforms the punishment to criminals into costs for society.

From the preceding analysis we can put forward a model for optimal social policy as follows. Social loss *L(O)* minimised with respect to *p* and *f* leads to

$$D_O + C_O = -bpf(a-1/\varepsilon_f) \quad (1)$$

$$\text{Where } \varepsilon_f = -(p/O)(O_p) > 0$$

$$DO + CO + Cp/Op = -bfp(1-1/\varepsilon_p) \quad (2)$$

$$\text{Where } \varepsilon_p = -(p/O)(O_p) > 0$$

These two equations determine the optimal values of *p* and *f.* The left-hand side of the two equations represents the marginal costs from an increase in *O* or conversely a fall in *f* or *p*. whereas; the right-hand side represents the marginal revenue of crime.

In previous empirical studies into a possible link between immigration and crime, the theoretical model first put forward by Becker (1968) has been widely used to try and ascertain why immigrants may commit crimes at different rates to natives. This paper will also make use of this theoretical framework to examine the impact of migration on crime.

When making use of this theoretical framework, this empirical study will take into account that the levels of human capital that migrants have in terms of

their language skills, years of education and work experience may be significantly less than natives in the countries that they migrate to, therefore the ability to earn a wage in the employment market could potentially be severely curtailed and so the utility migrants gain from committing crime could be much higher than the average native because the proceeds of crime are far greater than the marginal wage they are able to earn legally, or in some cases they might not be entitled to participate in the employment market at all.
With regards to the costs of committing crime for migrants versus natives, another factor to consider is that immigrants run the risk of being deported to their country of origin for breaking immigration laws not just the punishment a native would suffer, thus the expected costs of committing a criminal act are likely higher for non-natives.

III. Data Sources and Summary Statistics

In the paper I use an annual panel dataset at the country level, featuring fifteen European countries (Belgium, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Netherlands, Austria, Portugal, Finland, Sweden, United Kingdom, Norway and Switzerland) over the period 1993 - 2007.
The data for total population in the respective countries has been sourced from the World Bank total population database, which is assembled from various different sources including the UN population division, Census reports and other data from statistical offices, Eurostat - (Demographic statistics and the UN Statistical Division). Limitations of these data are that total population is defined as all residents of a country, disregarding their citizenship or legal status, thus, there may-be some overlap between immigration statistics and population data, in addition the respective statistical agencies in individual countries use different techniques to collect and define population data, therefore, there is likely no homogeneity across various geographical areas.
The total population data is a midyear estimate. The female fraction of a population is a demographic indictor because it gives information about the age of a countries population; for example, Institut National D'Etudes Demographiques (2015) [19] using information from the UN, World Population Prospects (2017) states that in 2015 the gender balance in France was 50.4% male and 49.6% female. Explaining that one hundred and seven males are born for every-one hundred females, however, males suffer from higher rates of mortality. But at a certain age the totals for males and females converge. In France this is at age twenty five, and after this age, females begin to outnumber males, therefore populations with a larger share of females are

older, moreover, Ulmer and Steffensmeier (2014) [20] state that the age group that commits the most crime is those 25 and younger according to the FBI, so the age of a population can give information on the stability of a nation. The data for female fraction of the total population is sourced from the World Bank database of population indicators and is based on the World Bank staff estimates, which have been calculated via age/sex distributions from the UN population division.

The data on criminal activity was sourced from the Eurostat Crime and Criminal Justice Database, where police statistics are the number of criminal acts recorded by the police and the number of suspected offenders and offenders brought into formal contact with law enforcement agencies.
The crime data is measured as offence per one hundred thousand inhabitants. In this paper crime has been divided into two distinct categories; firstly, violent crime which includes intentional homicide, acts causing harm such as assault and sexual offences, and secondly property crimes which includes robbery and burglary. Total crime; the summation of all crimes is also given.
Threats to the accuracy of the crime data, include the fact that not all criminal acts committed are reported to or detected by law enforcement agencies, and furthermore the way that police record the details of crimes maybe different across countries in the dataset. Missing data has been an issue particularly affecting the data on Belgium, Ireland, France, Austria and Finland.
The United Nations Department of Economic and Social Affairs provided data on immigration to destination countries within Europe and the source countries that were migrated from. This information was collated from various sources including the United Nations Statistical Department Demographic Yearbook. The data has the potential for inaccuracies, especially because the database is compiled from various sources, therefore discrepancies between inputs may occur. Statistics on economic indicators, including average wages in each country in the dataset has been collected from the database at the OECD, who calculated their results by dividing the total salary data from the national accounts in the respective countries by the total number of workers in those locations, which they weighted depending on whether the employee was full or part time. Average wages are measured in US dollars with 2016 = 100 being the base year. An additional economic indicator is GDP per capita measured in current US dollars and is sourced from the World Bank Economic Indicators database, which made use of statistics from the World Bank national accounts and OECD National Accounts data. This figure is the summation of gross value created by all economic agents in a country minus any taxes or subsidies; they have calculated this data without making any reductions for depreciation. Data

on unemployment has been collected from the World Bank database of economic indicators and is defined as the share of the work force that is not in employment but available for work and actively searching for a job. The World Bank has compiled the database from the International Labour Organisation and the ILOSTAT database. A limitation of the data is that it does not give any indication of age or underemployment.

Data relating to government spending on public order and safety as a percentage of GDP is sourced from the Eurostat Annual government finance statistics data and is an all-encompassing figure of spending on public protection, the measure contains the following categories 'police services', 'fire protection services', 'law courts', 'prisons', 'R&D related to public order and safety' as well as expenditure not elsewhere classified. Due to the limitation of the data, information solely on police spending was not available. Table 1 shows summary statistics for the variables described in this section, these values are unweighted and raw.

IV. Econometric Strategy

OLS and Fixed Effects Regression

In an attempt to provide an answer to the question "Does more immigration lead to more crime?" I will start analysing whether there is a positive relationship between levels of inwards migration. Then I will try and isolate a causal relationship of immigration on crime.

In the empirical analysis I will focus, separately on violent and property crimes. I will use a panel dataset constructed from data with the following countries: Belgium, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Netherlands, Austria, Portugal, Finland, Sweden, the United Kingdom, Norway and Switzerland over a fourteen-year period (1993 to 2007). The worldwide source countries that the migrants originally came from have been grouped by continent. (Africa, Asia, Europe, Oceania, North America and those from unknown locations)

I will use fixed effects estimation strategy as in Spenkuch (2012). In the regression model below, η, the parameter of interest represents the elasticity of the crime rate, with respect to the immigrant population share from Africa, Asia, Oceania, Europe, North America and unknown locations. The model will be regressed using weighted least squares, with the weights being represented by the destination country population.

$$\ln(crime_{c,t}) = \eta \ln(immigrants_{c,t}) + \beta \ln(population_{c,t}) + X'_{c,t}\, \gamma + \mu_c + \tau_t + \varepsilon_{c,t},$$

Where the subscripts c and t are, respectively, the country of destination and year. The variable crime $_{c,t}$ is the crime rate. Additionally $immigrants_{c,t}$ and $population_{c,t}$ are the total numbers of immigrants and the population respectively. In this paper a set of country level covariates represented by $X'_{c,t}$. This vector of covariates controls for various factors. Demographics of a country are controlled for by log fraction female, whereas, economic conditions are controlled for via the log of average wages, unemployment and GDP per capita respectively, additionally log of law enforcement spending as a percentage of GDP attempts to control for changes in police expenditure. , μ_c are country level fixed effects that control for country unobserved heterogeneity that does not change over time. τ_t are year fixed effects that capture the influence of aggregate (time series) trends. Finally $\varepsilon_{c,t}$, is the error term.

Spenkuch (2012) notes that endogenous factors such as age race and income should not be controlled for, as natives and migrants do differ, and if these factors were fully controlled for then, our estimate η would not give any information on the impact of migration on levels of criminal activity. To conclude, the fixed effect strategy, by making use of the country and year fixed effects, holds constant unobserved characteristics, which would normally vary over time, leading to an econometric model that potentially gives an unbiased estimate of η.

Results from OLS and Fixed Effects Regressions

Property Crime

Table 2 shows the findings for OLS and fixed effects regressions, property crime rates are the dependent variable. (This log, log model can be interpreted as $\%\Delta y = \beta i \%\Delta x$). The OLS results in column (1) and (2) shows there is a statistically significant positive correlation between African migration and increasing levels of the property crime rate. There is a negative correlation for European immigration and the property crime rate. In both cases when year and country fixed effects are controlled, the results are no longer significant. Bell *et al.* (2013) [21] found that Asylum seekers, including migrants from

Somalia, who came to the UK at the end of the 1990's, caused a significant increase in the property crime rate. A8 EU enlargement immigrants conversely caused a small significant fall in the property crime rate, but their significant findings did control for fixed effects, whereas the significant results in this paper only occur with OLS and heteroscedasticity robust standard errors. Bell *et al.* (2013) [22] noted that the Asylum seeker group in the UK had severely restricted access to official labour markets, with long periods of time before Asylum seekers could legally work. Asylum seekers waiting for their cases to be heard received substantially lower benefits which made them more likely to turn to crime. This effect may explain the findings of this paper, because this paper, and Bell *et al.* (2013) cover the same time period, as they both include the A8 EU enlargement in 2004.

The fraction female of a population also provides a significant correlational result in column (1) using OLS and is negatively correlated. However, the impact is no longer significant in column (2) when heteroskedastic standard errors are applied. This is also the case in columns (3) to (6) once fixed effects for year and country are applied. Campeniello *et al.* (2017) [23] in their research into the gender crime gap, found that only 30% of property crimes in the United States were carried out by females. It is likely the same effect is present in the European findings of this paper and may explain why the fraction female of a population is significant and has a large negative coefficient. Once again small dataset size could be an issue.

Economic indicators, which have a statistically significant effect on crime rates are average wage, and GDP per capita, although these results are only significant in columns (1) and (2) for both indicators. Buonanno *et al.* (2010) [24] found a correlation between increasing income, immigration and property crimes in the North of Italy. In their research, property crime made-up for 83% of all the crimes in their sample. But, correlation is not causation and, there could be other unseen factors driving the result in their findings, and the results of this research paper in terms of the positive correlation between average wage, GDP per capita and property crime rates. Furthermore, they discovered when they controlled for GDP at the provincial level, their estimates of the impact of immigration on property crime fell. They surmised this effect could be due to an increase in GDP, which may be a driver of rising crime and immigration, especially property offences. On the other hand, Piopiunik and Ruhose (2017) [25] did not find evidence to suggest that the effects of crime were different in German counties with unequal levels of GDP per capita. Therefore, the impact of economic factors such as increasing GDP and its effect on immigration and property crime is somewhat ambiguous in the literature, and thus this paper. As mentioned previously the major limitation of these findings is that we do not have enough variation in the data, due to the small sample size. Ideally, if more information was available, we might see a different outcome. It might be possible with more data; the results would be similar to those found in the literature (a positive correlation for immigrants without access to labour markets) with respect to immigration and property crime when fixed effects are implemented.

Violent Crime

Table 3 shows the findings for OLS and fixed effects regressions with property crime rates as the dependent variable. (This log, log model can be interpreted as $\%\Delta y=\beta i\%\Delta x$). The OLS regressions in columns (1) and (2) of this paper show a negative correlation between increasing immigration from Africa and violent crime rates. These results hold in columns (3) and (4) when controlling for year and year fixed effects. However, in column (6) this effect becomes positive, but not significant, once year and country fixed effects are applied. While, in the second row of table 3, the results of increasing Asian immigration on violent crime rates shows a significant positive correlation in columns (1) and (2) with OLS and heteroscedasticity robust standard errors. These results hold in columns (3) and (4), however the sign changes in columns (5) and (6). Moreover, the results for increasing immigration from the USA, and its effect on violent crime rates, shows that there is a negative significant correlation, which holds even when controlling for year and country fixed effects. In common with these findings, the majority of the existing literature fails to find a significant relationship between rising immigration and increasing violent crime rates, once year and country fixed effects are applied. However, an exception is research which has been quoted by the BBC (2018) [26] of an empirical paper by Pfeiffer *et al.* (2017). These factors could potentially explain the findings of this paper in column (6) when year and country fixed effects are applied i.e. those with little or no hope of asylum or work have no incentive to obey the law and may turn to crime be it property or violent. For the African group we see a positive coefficient, whereas a negative coefficient for the Asian group which fits with the findings of Pfeiffer *et al.* (2017). However, possibility due to a lack of variation caused by small sample size the coefficients on both groups are not significant in column (6) with both year and country fixed effects, so the findings are ambiguous.

In this paper fraction female has a strong negative correlational effect on violent crime rates. This effect possibly could be explained by the findings of Campeniello *et al.* (2017). Their research into the gender crime gap found that only 30% of property crimes in the United States were carried out by females, however, it is not certain whether, this effect holds for violent crime. In the regressions for law and order spending, in columns (5) and (6) when country fixed effects, and year and country fixed effects are controlled for, then this variable becomes positive and significant. A potential economic explanation is the likelihood of an increase in spending on law enforcement results in greater crime detection. A limitation of the data is that we don't have police spending data, but rather a total figure for law and order spending.

V. Instrumental Variables Approach

Methodology

The OLS strategy with fixed effects provides an estimation of the relationship between migration and crime rates. A requirement of a causal relationship between immigration and crime is that the residual not be correlated with the log (real) number of migrants. There are three principal reasons why this may occur (i) there may be an error measuring the quantity of migrants (ii) omitted variable bias (iii) endogeneity in the location patterns of migrants (rational migrants would locate to low crime areas). In my analysis I will replicate the approach taken by Spenkuch (2012) to overcome these issues. He uses a supply-push (theses are events in the immigrant's home country that induce outwards migration) instrumental variables approach which was developed by Card (2001). This strategy instrumented the findings of Bartel (1989) who found that migrants tend to locate to certain locations. Spenkuch (2012) recognises that for the first differences estimator to be consistent the instrument must have a correlation with the variation in the numbers of migrants in location *c* at time *t*, but, has no effect on the period *t* change in rates of crime in country c apart from changes in the quantity of migrants.

Formally: an instrument $Z_{c,t}$ will be valid if:

$$\mathrm{Cov}[Z^*_{c,t}, \Delta\log(\mathit{immigrants}_{c,t})^*] \neq 0 \text{ and } \mathrm{Cov}[z^*_{c,t}, \Delta\varepsilon_{c,t}] = 0,$$

Where * represents the variability of the residual, in the respective variable.

Spenkuch (2012) uses the observation that migrants will settle in the same location as previous immigrants of the same nationality to calculate the predicted change in the log number of migrants from year *t* -10 to *t* which is then used to instrument for the real change in migration patterns.

The following equation represents location *c*'s estimated total quantity of migrants in year *t.*

$$\widehat{immigrants}_{c,t} = \sum_{g} [(\sum_{c} immigrants_{c,g,t})(immigrants_{c,g,t-10}/\sum_{c} immigrants_{c,g,t-10})]$$

The instrument that will be used in my paper is as follows:

$$\Delta\log(\widehat{immigrants}_{c,t}) = \log(\widehat{immigrants}_{c,t}) - \log(\widehat{immigrants}_{c,t-10})$$

Which is the real change in the log of the quantity of migrants. From year *t* – 10 to *t.*

Where, t denotes year, g is the country that was migrated from.

However, due to limitations caused by missing data, this paper will only carry out an instrumental variables approach on immigration and crime for migrants from Africa and Europe respectively.

Testing for Exogeneity and Relevance

The conditions needed for a variable, z to be valid instrument for x, is that, firstly the instrument z must be relevant i.e. be correlated with x: Cov(z, x) ≠ 0 and secondly the instrument z must be exogenous i.e. uncorrelated with u Cov(z, u) = 0.

The first assumption, that the instrument is relevant i.e. Cov(z, x) ≠ 0, means that our model contains instruments that are not weak. The consequences of weak instruments are that they do not have much ability to explain the variation of the predicted value of the exogenous variable we are trying to estimate. Additionally, weak instruments can be biased and not normally distributed, thus inference testing will not be possible.

Testing Excluded Instruments Separately

To check whether, the proposed model satisfies the above criteria for both the instruments separately we can examine the F-test results from the first stage regression for the coefficients on the excluded instruments to ascertain whether F > 10. However, simply analysing the F-statistics in panel 1 of table 5.A and 6.A is not sufficient, because the excluded instruments do not give enough information to simultaneously identify the coefficients on the endogenous variables. Spenkuch (2012) [27] notes some of the issues that might arise from including weak instruments are that firstly the instrumental variables estimates can be asymptotically inefficient, which may lead to biased results and secondly the issue of finite-sample bias. Bloom *el al.* [28], state that finite sample bias can firstly bias point estimates and secondly lead to incorrect statistical inferences. Therefore, to ascertain whether both the coefficients on are identified we need to examine the weakly identified Sanderson-Wind -Meijer (2015) [29] F-statistic: which are shown in panel 2 of 5.A and 6.A and compare it to the Stock-Yogo (2005) [30] critical values below in 5.A and 6.A respectively. As in both 5.A and 6.A the Sanderson-Wind Meijer F-statistics are greater than the Stock-Yogo critical values, we can claim that both the coefficients are separately relevant.

Testing Excluded Instruments Jointly

Furthermore, we can also test the instruments together for the presence of weak instruments, to do this we need to analyse X_i: an exogenous regressor.

$$X_i = \pi_0 + \pi_1 Z_{1i} + \ldots + \pi_m Z_{mi} + \pi_{m+1} W_{1i} + \ldots + \pi_{m+r} W_{mi} + vi$$

And carry-out an F-test on the coefficients of the set of instruments $Z_{1i},\ldots,Z_{mi}$ to determine whether, they are jointly equal to zero, this will show if the set of instruments are weak. The results of this test are shown in 4.B and 5.B respectively. When the errors are assumed to be i.i.d then the Cragg-Donald Wald F statistic (1993) [31] is compared to the Stock-Yogo (2005) critical values. As the Cragg-Donald Wald F Statistic F-statistic is greater than the Stock-Yogo critical values, we can reject the null hypothesis that the equation is weakly identified and conclude that the set of instruments are relevant.

Instrumental Variables Results

Due to the constraints imposed by the presence of missing data, the instrumental variables strategy can only be applied to empirically testing if a link between immigration and crime exists, when considering migrants from European and Asian sources.

Property Crime

The left-hand column of table 4 displays the results for the Instrumental variables strategy, with the log of property crime rates as the dependent variable. (This log, log model can be interpreted as $\%\Delta y=\beta i\%\Delta x$). Spenkuch (2012) [32] notes that an estimate of the causal relationship is valid provided, there is no heterogeneity in effects, and the observational error is classical, and these conditions are not violated in this paper. The first row of table 4 shows the estimate of the impact of Asian immigration on property crime rates; however, this is not significant. Whereas, the estimate for European immigrants and their effect on property crime rates does show a significant negative causal relationship exists. Bell *et al.* (2010) [33] also discovered that the A8 European immigrants in their study caused a negative causal decrease in property crimes, although in their study they found that Asylum seekers did cause a statistically significant causal increase in property crime, but only amongst those Asylum seekers who were prohibited from legal employment. Furthermore, as the European immigrants in this paper were also part of the A8 wave, and had full employment opportunities, and thus little reason to commit incentive driven crime, this provides an economic explanation to why they have a negative significant causal relationship with the property crime rate. A limitation of this paper is that due to dataset size, many of the various immigrant source groups such as Africa, were dropped to make the instrument relevant. Therefore, we need remember this when comparing the IV to the OLS findings, as we are not comparing the same set of independent variables. This may explain differences due to interactional effects in the different immigrant source groups. As in the instrumental variables case, there is only a subset of the original variables in the OLS, and fixed effects regressions. However, for the impact of increased Asian and European immigration and its effect on property crime rates, the OLS and IV do display the same signs, with the later source group being statistically significant in both OLS and IV, with the instrumental variables coefficient being smaller than the OLS.

Spenkuch (2012) [34] found that Mexicans (a group with poor labour market opportunities) were the only group who had a statistically significant causal effect on property crime rates in his US study, and it would be interesting to examine whether the same effect holds in this empirical research with respect to immigrants with poor labour market outcomes. Ideally, we would like to carry out a sensitivity analysis, to try and ascertain whether, sub-setting migrants from Afghanistan, Syria and Iraq from the rest of the Asian group would change the results with respect to the property crime rate, as the majority of these immigrants were asylum seekers with poor employment prospects and an incentive to commit property crime, it is possible we would see a positive significant causal relationship. Whereas the majority of Asians from locations such as China or Hong-Kong might have good labour market access, and this could be the reason the result is insignificant.

Buonanno *et al.* (2010) [35] only found a significant causal effect between immigration and robberies, and no causal relationship between other types of property crimes. Ideally it would be beneficial to examine the various types of property crime separately, to examine whether either burglaries or robberies provided any different results. Additionally, law and order spending is statistically significant. The intuition is that because this measure is total spending on law and order, thus increased spending is likely to lead to higher detection rates.

Violent Crime

The right-hand column of table 4 gives the results for the instrumental variables estimation with violent crime rates as the dependent variable. (This log, log model can be interpreted as $\%\Delta y=\beta i\%\Delta x$). There is an insignificant positive causal effect between Asian immigration and violent crime, unlike the OLS and fixed effects results which are significant. There is an insignificant positive causal effect between Asian immigration and violent crime, unlike the OLS and fixed effects results which are significant. The BBC [26] has highlighted that asylum seekers from Afghanistan, Syria and Iraq, may have a propensity for violent crime. A sensitivity analysis, which could subset these migrants, from other Asian immigrants, would be beneficial to ascertain whether there is a positive significant causal effect from increasing migration from Afghanistan, Syria and Iraq and increasing violent crime rates. The findings show there is a significant negative causal effect between European immigration and violent crime rates.

In terms of the instrumental variables results, the results for European immigration are contrary to the findings of Bell *et al.* (2010) [36] who found no significant causal link between European economic migrants, and violent crime in their UK study, once instrumental variables had been used. An explanation could be that the study focused on one country at a particular time period, whereas this paper, examines many countries over a longer time frame and thus captures more of the variation in the data. Moreover, as the period covered by the study saw an influx of economic migrants from the EU enlargement in 2004, these migrants enjoyed on the whole full labour market access. They risked deportation if they committed violent crime, so had an incentive to obey the law in the countries they migrated to. This could explain why European migrants have a negative causal impact on violent crime rates.

Buonanno *et al.* (2010) [37] also confirm no significant causal relationship between violent crime and immigration, however, their results only rely on data from the year 2001, while this paper studies a longer time frame, which could make comparisons difficult. Furthermore Spenkuch (2012) [38] in his IV results found inconclusive evidence when examining immigration and its impact on violent crime in the USA, although whether findings from North America can be compared to those in Europe is debatable, therefore the findings of this paper, with respect to European immigration having a negative causal effect on violent crime goes against the majority of the findings of the literature. There is a statistically significant causal link between GDP per capita and the rate of violent crime but could possibly be explained by the fact that the majority of migrants are young men, and this age group commit the most violent crime. Furthermore, they tend to locate to countries with more economic opportunities. Additionally, law and order spending provides a positive significant causal effect. The intuition is that because this measure is total spending on law and order, increased spending leads to higher detection rates. However, on the last two points the literature is ambiguous.

Conclusion

After examining the various findings of the empirical project, the conclusion is that immigrants with good employment prospects, such as European immigrants, who came to the European Union in 2004 and 2007 respectively, have a negative causal impact on both property and violent crime rates. These findings agree with the majority of the literature for property crime, but conversely are different in terms of violent crime. However, this paper did not find that immigrants cause crime, conversely the results suggest that in the right conditions immigration actually reduces crime, although only if the migrants have good job prospects.

Table 1

Variable	Obs.	Mean.	Std. Dev.	Min.	Max.
Crimes					
Total Crime Rate	232	.0678125	.0287851	.0192569	.1427974
Violent Crime Rate	220	.0044196	.0035374	.0005436	.0176453
Murder Rate	226	.0000139	5.07e-06	5.42e-06	.000031
Assault Rate	224	.0043669	.0035195	.00053	.0176278
Property Crime Rate	209	.0050867	.0027483	0	.0133247
Burglary Rate	230	.0040029	.0025045	.00014	.012033
Robbery Rate	209	.0010429	.0006808	.0001196	.0029313
Immigration					
Total Immigration	204	259692.2	323566.3	6226	1795992
Fraction Immigrants	204	.0127396	.0082509	.0006159	.0637073
Caribbean Total	150	18696.45	51815.66	131	294212
Africa Total	152	15627.91	22101.73	381	110832
Asia Total	152	31353.71	57562.27	73	286581
European Total	166	86586.65	132126.9	2036	667456
Oceana Total	125	1111.016	1465.174	6	10392
Population					
Fraction Female	240	50.93246	.4619511	50.0504	32702
Total Population	240	2.45e+07	2.54e+07	3576261	8.25e+07
Economics					
GDP Per Capita	240	30051.55	12197.09	9535.595	85170.86
Average Wages	238	39171.11	6980.405	22939	56839
Jobless Rate	240	7.826667	3.856934	2.1	24.2
Public Order Spending					
Law Enforcement Spending	200	1.507	.3361786	.9	2.4

See data appendix for descriptions of variables and methods of how the variables have been calculated.

Table2			Fixed Effects			
Log Variables	(1) Property crime Rate	(2) Property crime Rate	(3) Property crime Rate	(4) Property crime Rate	(5) Property crime Rate	(6) Property crime Rate
% Africa	0.225**	0.225*	0.177	0.146	0.0356	0.0914
	(0.0838)	(0.0948)	(0.182)	(0.216)	(0.0974)	(0.114)
% Asia	-0.0768	-0.0768	-0.110	-0.0193	-0.147	-0.293
	(0.0788)	(0.0988)	(0.143)	(0.178)	(0.141)	(0.145)
% Oceania	-0.0386	-0.0386	-0.117	-0.0729	-0.247	-0.167
	(0.0989)	(0.129)	(0.199)	(0.217)	(0.219)	(0.217)
% Europe	-0.364**	-0.364**	-0.172	-0.130	0.127	0.132
	(0.122)	(0.120)	(0.250)	(0.296)	(0.121)	(0.157)
% USA	0.235*	0.235	0.238	0.149	0.0304	-0.0120
	(0.112)	(0.133)	(0.205)	(0.206)	(0.0753)	(0.0716)
% Unknown	0.0403	0.0403	0.0128	-0.000920	0.0178	0.0220
	(0.0466)	(0.0406)	(0.0287)	(0.0322)	(0.0167)	(0.0194)
% Female	-19.07*	-19.07	-24.11	-26.94	-35.45	-38.51
	(8.914)	(10.86)	(19.33)	(23.05)	(33.78)	(30.69)
Average wage	1.300**	1.300***	1.403	1.404	0.635	0.950
	(0.400)	(0.340)	(0.655)	(0.699)	(0.761)	(0.915)
GDP per cap.	-0.471*	-0.471*	-0.235	-0.847	-0.0548	1.417
	(0.221)	(0.208)	(0.507)	(0.937)	(0.271)	(1.037)
Unemp. rate	-0.157	-0.157	-0.237	-0.327	-0.0420	0.0420
	(0.111)	(0.103)	(0.180)	(0.175)	(0.137)	(0.160)
Law/order $	0.278	0.278	0.515	0.235	0.160	0.00119
	(0.256)	(0.276)	(0.551)	(0.621)	(0.589)	(0.596)
year			-0.0415		-0.0299	
			(0.0317)		(0.0249)	
OLS	Yes	Yes	Yes	Yes	Yes	Yes
OLS(robust)	No	Yes	Yes	Yes	Yes	Yes
Controlling for year	No	No	Yes	No	No	No
Controlling for year FE	No	No	No	Yes	No	Yes
Controlling for country FE	No	No	No	No	Yes	Yes
Controlling for year and country FE	No	No	No	No	No	Yes
N	102	102	102	102	102	102

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

See data appendix for descriptions of variables and methods of how the variables have been calculated.

Table 3			Fixed Effects			
Log Variables	(1) Violent crime Rate	(2) Violent crime Rate	(3) Violent crime Rate	(4) Violent crime Rate	(5) Violent crime Rate	(6) Violent crime Rate
% Africa	-0.461***	-0.461***	-0.438**	-0.434**	-0.00516	0.0209
	(0.0685)	(0.0585)	(0.123)	(0.136)	(0.0404)	(0.0390)
% Asia	0.456***	0.456***	0.493***	0.430**	-0.0337	-0.102
	(0.0656)	(0.0724)	(0.105)	(0.124)	(0.0569)	(0.0713)
% Oceania	0.0335	0.0335	0.0985	0.0864	0.0265	-0.0142
	(0.0812)	(0.141)	(0.185)	(0.191)	(0.0331)	(0.0441)
% Europe	-0.0791	-0.0791	-0.229	-0.240	-0.00822	0.0191
	(0.102)	(0.115)	(0.200)	(0.236)	(0.0522)	(0.0756)
% USA	-0.606***	-0.606**	-0.614*	-0.564	-0.0548*	-0.0698*
	(0.0905)	(0.188)	(0.276)	(0.287)	(0.0244)	(0.0268)
% Unknown	0.0139	0.0139	0.0369	0.0437	-0.0319*	-0.0415**
	(0.0388)	(0.0464)	(0.0628)	(0.0640)	(0.0122)	(0.0110)
% Female	-55.12***	-55.12***	-50.89**	-49.26*	-14.58	-20.18
	(7.447)	(7.271)	(15.52)	(17.16)	(16.03)	(15.11)
Average wage	-0.128	-0.128	-0.227	-0.210	0.472	0.413
	(0.333)	(0.292)	(0.510)	(0.564)	(0.435)	(0.565)
GDP per cap.	-0.0645	-0.0645	-0.280	0.0496	0.0340	0.654
	(0.185)	(0.213)	(0.306)	(0.450)	(0.112)	(0.340)
Unemp. rate	-0.118	-0.118	-0.0341	-0.00466	-0.115*	-0.132
	(0.0916)	(0.107)	(0.148)	(0.167)	(0.0394)	(0.0974)
Law/order $	-0.396	-0.396	-0.601	-0.401	0.626*	0.608*
	(0.210)	(0.301)	(0.618)	(0.671)	(0.246)	(0.243)
year			0.0358*		0.0129	
			(0.0131)		(0.00998)	
OLS	Yes	Yes	Yes	Yes	Yes	Yes
OLS(robust)	No	Yes	Yes	Yes	Yes	Yes
Controlling for year	No	No	Yes	No	No	No
Controlling for year FE	No	No	No	Yes	No	Yes
Controlling for country FE	No	No	No	No	Yes	Yes
Controlling for year and country FE	No	No	No	No	No	Yes
N	107	107	107	107	107	107

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

See data appendix for descriptions of variables and methods of how the variables have been calculated.

Table 4 Log Variables	(1) Property Crime Rate	(2) Violent Crime Rate
% Asia	-0.169	0.0511
	(0.104)	(0.0635)
% Europe	-0.212*	-0.465**
	(0.0951)	(0.164)
% Female	-29.97***	-17.87*
	(6.953)	(8.767)
Average Wage	1.365	-0.449
	(0.763)	(0.559)
GDP per cap.	-0.114	1.223***
	(0.175)	(0.230)
Unemp. Rate	-0.242	-0.229
	(0.203)	(0.187)
Law/order $	1.187***	1.140***
	(0.273)	(0.279)
Instrumental Variables	Yes	Yes
N	80	81

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

See data appendix for descriptions of variables and methods of how the variables have been calculated.

Table 5

Summary Results for First-Stage Regressions for Property Crime

A

Variable	Panel 1 F(2, 72)	P-val	Panel 2 SW F test for Weak identification SW F(1, 72)
Log Fraction Asia	16.78	0.0000	39.50
Log Fraction Europe	72.89	0.0000	185.93

NB: first-stage test statistics heteroskedasticity-robust

Stock-Yogo weak ID F test critical values for single endogenous regressor:

10% maximal IV size	19.93
15% maximal IV size	11.59
20% maximal IV size	8.75
25% maximal IV size	7.25

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for i.i.d. errors only.

B

Weak identification test	
Ho: equation is weakly identified	
Cragg-Donald Wald F statistic	40.25
Kleibergen-Paap Wald rk F statistic	25.30

Stock-Yogo weak ID test critical values for K1=2 and L1=2:

10% maximal IV size	7.03
15% maximal IV size	4.58
20% maximal IV size	3.95
25% maximal IV size	3.63

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Table 6

Summary Results for First-Stage Regressions for Violent Crime

A	Panel 1		Panel 2 SW F test for Weak identification
Variable	| F(2, 73)	P-val |	SW F(1, 73)
Log Fraction Asia |	16.89	0.0000|	40.30
Log Fraction Euro |	74.84	0.0000|	191.30
NB: first-stage test statistics heteroscedasticity-robust			
Stock-Yogo weak ID F test critical values for single endogenous regressor:			
	10% maximal IV size	19.93	
	15% maximal IV size	11.59	
	20% maximal IV size	8.75	
	25% maximal IV size	7.25	
Source: Stock-Yogo (2005). Reproduced by permission.			
NB: Critical values are for i.i.d. errors only.			

B		
	Weak identification test	
Ho: equation is weakly identified		
Cragg-Donald Wald F statistic		40.06
Kleibergen-Paap Wald rk F statistic		26.22
Stock-Yogo weak ID test critical values for K1=2 and L1=2:		
	10% maximal IV size	7.03
	15% maximal IV size	4.58
	20% maximal IV size	3.95
	25% maximal IV size	3.63
Source: Stock-Yogo (2005). Reproduced by permission.		
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.		

Data Appendix

% Africa is the logarithm of total immigrants from Africa divided by the total population in the respective destination countries.

% Asia is the logarithm of total immigrants from Asia divided by the total population in the respective destination countries.

% Europe is the logarithm of total immigrants from Europe divided by the total population in the respective destination countries.

% Oceania is the logarithm of total immigrants from Oceania divided by the total population in the respective destination countries.

% USA is the logarithm of total immigrants from North America divided by the total population in the respective destination countries.

% Unknown is the logarithm of total immigrants from unknown source countries divided by the total population in the respective destination countries.

% Female is the logarithm of the fraction of a total population that is female in a destination country.

Average wage is the logarithm of average wage as per the description in the data and summary statistics section.

GDP per cap. is the logarithm of GDP per capita as per the description in the data and summary statistics section.

Unemp. Rate is the logarithm of the unemployment rate as per the description in the data and summary statistics section.

Law/order $ is the logarithm of law and order spending as per the description in the data and summary statistics section.

Austrian migration data is collated from population registers. Immigration being defined as those persons who register to stay in the country. The data the statistics on migration in Belgium is collected via the population register. Immigration is defined as those foreigners who legally enter the country and stay for at least three months. Immigration data on Denmark is derived from the central population register, with immigration being defined as EEA/Swiss nationals who stay for six months or more, and those persons from outside the Nordic region, EEA and Switzerland if they plan to stay three or more months. Data collated on migration in Finland is collected through the population register and includes all people that change their permanent residence country to Finnish. Immigration in Finland is defined as those foreigners who have gained a residency permit and Fins who have returned from residing abroad. In France migration data is calculated via the quantity of residence permits that are issued for at least a year. In Germany data on migration is sourced from the population register. Immigration is defined as those arriving from abroad who register their home abode in Germany as being their main place of living. Greek migration statistics are derived from information on residence permits. Immigration statistics are calculated from the quantity of residence permits that have been issued to foreigners. The data collected on migration in Ireland is collated from a quarterly national household survey and various other sources. Immigration is defined as people who are usually residents of Ireland and that did not reside in there a year ago. In Italy the data on migration is calculated via information from the population register, immigration is seen as those Italians who reside domestically after residing abroad, those from the EEA if they stay in Italy for twelve months or more, and those from non-EEA countries holding a residence permit intending to stay for twelve months or greater.In the Netherlands migration data is sourced from the municipal population register. Immigration is seen as people who stay in the country for four months or more. Norwegian migration statistics are collated through the population register, where immigration refers to all people that intend to stay in Norway for six or more months. Data on immigration in Portugal is collected from permit data, and immigration data is measured as foreigners who have made an application of a residence permit in a given year. The statistics on migration to Spain is derived from the municipal population register. Immigration is defined as foreigners and citizens intending to remain in Spain. In Sweden migration statistics are collated from the population register. Immigration is seen as foreigners and citizens coming from abroad and intending to remain in the country for twelve months or more. The data for migration in Switzerland is collated via the population and foreigner register. Immigration is defined as all persons coming to the country from abroad to permanently or temporarily reside in this country.In the UK flows of migrants are measured via the International Passenger Survey (IPS) and immigration includes all persons who have remained abroad for twelve months or more and now intend to remain in the UK for a year or more.

Statistics on economic indicators, including average wages in individual countries has been collected from the database at the OECD, who calculated their results by dividing the total salary data from the national accounts in the respective countries by the total number of workers in those locations, which they then proceeded to multiply this figure by the ratio of the usual hours worked by an average full-time worker to the average hours worked per week by all workers (including part-time). Average wages are measured in US dollars and are an index with 2016 being the base year. An additional economic indicator is GDP per capita measured in current US dollars and is sourced from the World Bank Economic Indicators database, which made use of statistics from the World Bank national accounts and OECD National Accounts data. This figure is the summation of gross value created by all economic agents within a respective country minus any taxes or subsidies; they have calculated this data without making any reductions for depreciation. Data on unemployment has been collected from the World Bank database of economic indicators and is defined as the share of the work force that is not in employment but available for work and actively searching for a job. The World Bank has compiled the database from the international labour organisation and the ILOSTAT database.

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