ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis [International Economics]

The Impact of Immigration on Crime:

Evidence from Japan and South Korea

Name student: Danian Chen

Student ID number: 425045

Supervisor: Dr. A. Baiardi

Second assessor: Prof. dr. H.D. Webbink

Date: 20-07-2021

Abstract

This thesis examines the impact of immigration on crime for the case of Japan, and South Korea. For each of the two countries, a case study is conducted which decomposes total immigrants by continent to assess the per source continent effect of immigration using panel data and an instrumental variables approach with predicted immigrant shares as instruments. Furthermore, Korea is also investigated by income class using OLS panel regressions. IV results from the Japan study show that, in line with the economic model of crime, Asian immigrants are subject to much worse labour market outcomes relative to Japanese natives, hence resulting in a higher propensity for Asian immigrants to participate in crime for financial gain, i.e., property crime. For Korea, the instruments appear to have a weak first stage, hence its case study is proceeded with OLS whose results reveal that female immigrants from Asia decrease property crimes, whereas male immigrants from Asia appear to increase them. In addition, male immigrants from Europe seem to raise violent crimes. OLS results from Korea income class analysis indicate that female immigrants from low income class tend to induce violent crimes and property crimes, whilst those from upper middle income class reduce property crime. However, as this paper is subject to a number of caveats, these results should be interpreted with caution.

Table of Contents

I. Introduction 1

II. Literature Review 3

2.1 Economics of crime in the context of immigration 3

2.2 Empirical evidence of the effect of immigration on crime 4

2.3 Discussion 7

III. Data and Methodology 8

3.1 Data 8

3.2 Methodology 9

3.3 Descriptive statistics 17

IV. Results 26

V. Conclusion 38

VI. Bibliography 40

VII. Appendices 46

Appendix A: Description of the variables 46

Appendix B: List of countries by continent (based on United Nations Statistics Division) 49

Appendix C: List of countries by income class (based on World Bank Atlas method) 50

Appendix D: Descriptive statistics 51

Appendix E: Regression results 58

I. Introduction

Japan is the world's fastest-ageing nation where 28.7% of the population are 65 or older. By 2036, this group will represent a third of the population (D'Ambrogio, 2020). Moreover, the country has been coping with jaw-droppingly low fertility rate which fell to 1.36 children per woman in 2019. In the same year, death counts reflect 1.376 million, alongside a natural population decline of 512,000, both surpassing their previous records (Jozuka et al., 2019). Historically, Japan had been cautious about accepting immigrants and considers itself ethnically and linguistically homogenous, where its immigrant population accounts for just 2% of the total population (S.B., 2018). Since the demographic squeeze remains to be an inevitable determinant of economic recession, Japan amended its immigration legislation on 1 April 2019 with the objective to welcome 345,000 immigrant workers in the following five years (Denyer, 2018). However, wariness of the influx of immigration has also been present. At the turn of the century, law enforcement in Japan tightened immigration as it perceived immigrants as a rising threat to public safety (Yamamoto, 2010; Yamamoto and Johnson, 2014). More recently, 40% of natives say that immigrants are more responsible for crime occurrences compared to others, according to the Spring 2018 Global Attitudes Survey conducted by the Pew Research Center (Delvin and Stokes, 2018).

South Korea appears to be very similar to Japan in terms of demographics. In fact, it also finds itself in a population conundrum. Having one of the fastest-ageing populations and highest life expectancies in the world, the United Nations forecast that: (1) more than two-fifth of the population will be 65 or older by mid-2060; (2) South Koreans can expect to live to 92 by the end of this century (Quick, 2019). A study by Kontis et al. (2017) published in The Lancet finds that South Korean women are projected to be the world's first to live above 90 on average by 2030, with a 57% chance. Moreover, the country's fertility rate is the lowest in the world at 1.1 children per woman in 2019. This deviates far from the replacement rate, i.e., the fertility rate at which the population is kept constant. Hence, South Korea is not having enough children to stabilise its population without migration (Quick, 2019; Song, 2019). Whilst also being an ethnically homogenous society, Korea gradually learns to accept migrants as it falls victim to the demographic transition (Power, 2019). However, progress has been slow partly due to caution of the immigrant inflow. Shang and Seung (2015) find that South Koreans who think immigrants jeopardise public safety are more likely to develop nationalistic sentiments, based upon the 2010 Korean General Social Survey.

The existing literature has investigated the crime impact of immigration of different immigrant groups, such as Mexicans and non-Mexicans (Spenkuch, 2014; Chalfin, 2014; 2015), asylum-seekers and A8 countries (Bell et al., 2013), by secondary education, Spanish language proficiency, young male age groups, and EU-15 area (Alonso-Borrego et al., 2012), as well as by employment, and gender (Ozden et al., 2018). This research is intended to be the first to estimate the effect of immigration on crime for the case of Japan and South Korea. For each of the two countries, a case study by continent analysis is conducted which decomposes total immigrants by continent to assess the per source continent effect of immigration on crime, which has not been studied before. The limitation of the Japan case study is that there is no investigation possible on the crime impact of immigrants from Oceania and Africa specifically, by gender, and by income class, which to the best of my knowledge have neither been assessed before, except by gender. Hence, Korea is researched by continent which complements by studying immigrants from Oceania and Africa specifically and by gender, whereas it is also investigated in a case study by income class which contributes by examining immigrants by gender and by income class.

Furthermore, this study contributes to making well-informed policy decisions on immigration in both countries. These decisions concern whether to ease immigration to tackle the demographic issues that cause economic stagnation amongst others, or to put a hold on the inflow of immigrants if it appears to be associated with more crimes. To evaluate whether this is actually the case or just stigma, it is of huge social interest, i.e., for the sake of both countries' economy, public safety, and perception of immigrants, to study the following research question:

"What is the impact of immigration on crime?"

In terms of methodology, this paper evaluates the immigration effect on total crimes, violent crimes, and property crimes. Also, demographic, economic, and other factors that are found to be key determinants of crime are controlled for. Therewith, OLS panel regressions with area and time fixed effects are performed to account for unobserved heterogeneity across areas and over time. Moreover, for the assessment by continent, predicted immigrant shares are used as instruments, and IV panel regressions are employed to address endogeneity in immigration. This IV implementation is non-existent in the Korea income class case study as a valid instrument for it has not been found yet.

IV results from the Japan case study show that immigrants from Asia increase property crimes. Since for Korea, the instruments appear to have a weak first stage, its case study by continent continues with OLS whose results reveal that female immigrants from Asia decrease property crimes, whereas male immigrants from Asia appear to increase them. In addition, male immigrants from Europe seem to raise violent crimes. From the OLS regressions in the Korea income class analysis, it is observable that female immigrants from low income class tend to induce violent crimes and property crimes, whereas those from upper middle income class reduce property crime. However, as this paper is subject to a number of caveats, these results should be interpreted with caution.

This thesis is followed by a literature review, which discusses the economic model of crime in the context of immigration, and the empirical evidence of the impact of immigration on crime. Chapter III gives a thorough description of the data and methodology concerning the OLS and IV regressions. Chapter IV provides an in-depth analysis of the OLS and IV estimates. Lastly, Chapter V concludes and discusses the limitations of this paper alongside recommendations for future research.

II. Literature Review

In this section, I will first discuss the economic theory of crime with respect to immigration. This is followed by empirical evidence of the effect of immigration on crime. At last, I will provide a discussion of the review and elaborate on how this study relates to the literature.

2.1 Economics of crime in the context of immigration

The economic model of crime formulated by Becker (1968) and advanced by Ehrlich (1973) is the standard framework that is used to examine crime in economics. It assumes that individuals are rational and that their decision-making between illicit and licit activity is based upon the expected utility from those activities. That is, people will engage in crime if the expected utility from doing so outweighs that from a legitimate alternative, which is often employment in the formal labour market (Freeman, 1999).

Mathematically, the individual intends to participate in criminal activity if:

$$(1-p)U(W_c) - pU(S) > U(W) \tag{1}$$

Where *W* is wage from legitimate work, W_c is the returns from successful crime (i.e., when not caught), *U(.)* is the utility, *p* is the probability of being caught, and *S* is the monetary equivalent of sanctions when caught (Freeman, 1999). Apparently, people who are jobless and those with a job paying formal wages lower than the returns to crime, are more likely to engage in crime.

Examining this model with the inclusion of immigrants provides answers to the variation in crime occurrence between immigrants and natives. It stems from the difference in the relative returns from legal and illegal activities between both agents. Immigrants on average have worse labour market opportunities, thus lower income *W* as compared to natives, which implies a higher propensity to participate in crime amongst immigrants, *ceteris paribus*. This holds true for undocumented immigrants in particular, who are not employed in the formal labour market (Caponi and Plesca, 2014; Mastrobuoni and Pinotti, 2015; Pinotti, 2016). Since formal labour market participation is a legitimate alternative concerning crimes for financial gain, rather than "crimes for pleasure", immigrants are expected to raise property crimes but not necessarily violent crimes (Spenkuch, 2014). On the other hand, immigrants face higher expected costs *S* relative to natives. That is, they are subject to additional sanctions such as losing their work permit, or being deported from the host country, which reduces their incentive to commit offences as compared to natives, *ceteris paribus* (Spenkuch, 2014; Baker, 2015; Mastrobuoni and Pinotti, 2015; Pinotti, 2017). Hence, there are reasonable arguments in support of the view that immigration affects crime. However, in which direction it does so considering the contrasting effects is theoretically ambiguous, and thus remains an empirical question.

2.2 Empirical evidence of the effect of immigration on crime

The economic literature on the crime effect of immigration is centrally focused on adopting an instrumental variables (IV) approach to obtain causal inference, following the same methodology that is used to evaluate the labour market impact of immigration. It aims to find a valid instrument that captures an exogenous change in the immigrant population in an area, and then assess whether crime patterns change. There is an extensive literature built upon Altonji and Card (1991) and Card (2001) on the utilisation of the prior settlement pattern of immigrants from the same national or ethnic group as an instrument, which appears to be a strong predictor of prospective immigrants' choice of destination.

Spenkuch (2014) uses decadal panel data on US counties from 1980-2000 and opts to assess the elasticity of crime with respect to immigration by measuring them in logs. In constructing the instrument, he follows Altonji and Card (1991) and Card (2001) and aggregates a set of source countries into nine groups of which some are continents. The IV estimates show that a 10% rise in immigrant share leads to a rise in the property crime rate of about 1.2%, which is significant. Violent crime rates remain unaffected. The author then decomposes total immigrant share into Mexicans and non-Mexicans to examine whether the economic model of crime can provide an explanation for his estimates. Since Mexicans on average have relatively worse labour market opportunities than other ethnicities, the property crime regression shows estimates that are in line with the model. That is, Mexican immigrants seem to significantly increase property crime, whereas non-Mexicans lead to a reduction which is not significant.

Additional investigation on the finding on Mexican immigrants, however, shows contrary results. Chalfin (2015) uses decadal panel data on US metropolitan statistical areas (MSAs) over the same time period as in Spenkuch (2014) to assess the effect of Mexican immigration on crime. Violent and property crime are disaggregated into subtypes and measured in log of crimes per capita. He uses variation in Mexican fertility rates as his IV, i.e., number of Mexican births that are predicted to end up in each MSA in a certain year given that the entire cohort migrates, deflated by MSA. The 2SLS estimates show that a 1 percentage point increase in Mexican immigrant share leads to a significant 13% fall in rape and 20% rise in assault, both falling under violent crime. A similar increase in immigrant share is, in contrast to Spenkuch (2014), associated with a significant 11% reduction in larceny, falling under property crime.

Furthermore, another study by Chalfin (2014) on the Mexican immigration impact on crime across US MSAs, uses rainfall shocks in network-linked Mexican states to instrument for immigrant share. The 2SLS estimates indicate that Mexican immigration leads to no appreciable change in either violent or property crime. The fact that the three studies show completely different findings might be due the possibility that the three different instruments estimate different local average treatment effects (LATEs) that are based upon different samples of compliers.

Bell et al. (2013) focuses on England and Wales in 2002-2009 and examines the impact on property and violent crime of two large waves of UK immigration. The first concerns the substantial inflow of asylum-seekers in late 1990s and early 2000s due to dislocations of numerous countries. The second is about the post-2004 rise from the A8 countries. They evaluate the effect using the immigrants share and the crime rate as measurements, i.e., number of immigrants and number of reported crimes, each relative to the total population. Regarding IV construction, the authors consider the dispersal policy that was enacted in 2001 to instrument for the asylum-seekers. For the A8 countries, they follow Altonji and Card (1991) and Card (2001) in adopting the prior settlement pattern of A8 immigrants as their instrument. The IV estimates show that a 1 percentage point rise in the fraction of asylum-seekers (A8 immigrants) leads to a 1.09% increase (0.39% decrease) in property crime rate. No effect on violent crime was observable for either wave. As in Spenkuch (2014), Bell and co-authors also make use of the economic model of crime to interpret their results, which were consistent therewith. Since A8 immigrants' reason for immigration was to seek better labour market opportunities, there is not much of an incentive to commit property crime for financial gains. The asylum-seekers, however, were prevented from seeking formal work, and the welfare benefits that they were entitled to were little compared to the unemployment benefits that the natives received. This likely means that they are subject to the attraction of committing property crime for financial gains as a result of having bad or no labour market opportunities.

Alonso-Borrego et al. (2012) uses Spanish province-level panel data to investigate the immigration effect on total crime rates, felony rates, property crime rates, and misdemeanour rates. They study the impact of various immigrant groups, i.e., by secondary education, Spanish language proficiency, young male age groups, and EU-15 area. The authors utilise the lagged values of each of these immigrant variables as IVs to instrument for the respective immigrant variable, assuming that the past realisations of these explanatory variables of interest are exogenous. They provide generalised method of moments (GMM) estimates which show that immigrants from Latin America who finished at least secondary education appear to reduce crime rates in Spain. This is consistent with the finding of Chalfin (2015) on Mexican immigrants known as the Latino Paradox. On the other hand, other immigrant groups with lower education levels are associated with a rise in crimes.

Bianchi et al. (2012) focuses on Italy and uses province-level data covering 1990-2003 to study the effect of immigration on total, violent, and property crime, as well as decompositions of property crime. They measure the immigration variable as the log of immigrant share, and the crime variables as the log of crime rate. Concerning the instrument, the authors employ a variant of the prior settlement pattern of immigrants from the same nationality. They argue that it is not feasible to differentiate the push and pull factors on the basis of total influx of immigrants by nationality, in case all immigrants from a particular source country were to settle in the same province. Hence, the authors measure the supply push factors based upon the bilateral migration flows towards destination countries other than Italy. The IV estimates show no significant impact of immigration on any crime type, except for a rise in robberies, which only account for a tiny fraction of all crimes. This paper does not investigate additional mechanisms in different subsets of total immigrants to possibly interpret the results in relation to the labour market opportunities in the economic model of crime.

Ozden et al. (2018) researches the crime impact of immigration using Malaysian state-level data covering 2003-2010 for total, violent, and property crime. They examine the elasticity of crime with respect to immigration by measuring them in logs. In addition, total immigrants are disaggregated by employment, and by gender to investigate those who are employed, and those who are male. In constructing the instrument, they use population changes and different age groups of source countries over the years. The IV estimates indicate that overall immigrants as well as those who are employed, and male, significantly decrease violent and property crime.

2.3 Discussion

Notwithstanding the state-of-the-art empirical papers in this field of study that are discussed above, there seems to be no consensus regarding the crime impact of immigration. This could partially be explained by the difficulty of identifying causal effect, which originates from the speculation of exogeneity of the IVs in some studies. On the other hand, it could also be the case that different instruments estimate different LATEs that are based upon different samples of compliers. Other explanations may be that different analyses use different operationalisations of variables, are conducted at different levels of aggregation and/or different increments of time periods. Nevertheless, the results of most studies that are discussed do provide insights such as the importance of labour market opportunities by focusing on not only the overall effect of immigration, but also that of different subsets of immigrants.

This thesis is the first to assess the effect of immigration on crime for the case of Japan, and South Korea. The case studies by continent analysis follow Altonji and Card (1991) and Card (2001) in utilising prior settlement pattern of immigrants from the same national or ethnic group as instruments. They are in line with Spenkuch (2014) in that they use past immigrants by continent in constructing the IV to instrument for the overall immigrants. However, the motivation behind adopting this analysis is that they contribute to the existing literature by decomposing total immigrants by continent to assess the per source continent effect of immigration on crime, which has not been studied before. The limitation of the Japan case study is that there is no investigation possible on the crime impact of immigrants from Oceania and Africa specifically, by gender, and by income class, which to the best of my knowledge have also not been studied before, except by gender. Hence, the motivation behind researching

Korea is that its case study by continent complements by studying immigrants from Oceania and Africa specifically and by gender, whereas its case study by income class contributes by examining immigrants by gender and by income class.

III. Data and Methodology

This chapter provides an in-depth discussion of the data, methodology and descriptive statistics of each of the three case studies. This paper follows the existing literature which often analyses the impact of immigration on different types of crimes, i.e., total crimes, violent crimes, and property crimes. In addition, demographic, economic and other factors that are found to be key determinants of crime are controlled for. Therewith, OLS panel regressions with area and time fixed effects are performed to account for unobserved heterogeneity across areas and over time. Moreover, for the assessment by continent, predicted immigrant shares are used as instruments, and IV panel regressions are employed to address endogeneity in immigration. This IV implementation is non-existent in the Korea income class study as a valid instrument for it has not been found yet.

3.1 Data

3.1.1 Case study: Japan

Data on all variables are from the Statistics Bureau of Japan (with e-Stat as its Portal Site of Official Statistics of Japan) (2021). Its database "System of Social and Demographic Statistics" provides prefectural and annual data on all variables that are considered in this case study. It already aggregated immigrants from all source countries by their respective continent whose data are therefore readily usable. However, what source countries are considered and what classification the country assignment is based upon, remain untraceable. The period of study is from 2012 up until 2018 and includes all 47 prefectures of Japan, which provides us with 329 observations to work with. The year 2000 data on immigrants from various source continents is used for IV construction because when these past immigrants have settled at first, it allows for a sufficiently long timespan for the new immigrants to be aware of these ethnic clusters and settle therein. The founders of the IV, Altonji and Card (1991), use the year 1970 to predict the fraction of immigrants over the following decade, which implies that the timespan considered in this case study would suffice.

3.1.2 Case study: South Korea

Data on all variables are from Statistics Korea (with KOSIS as its Portal Site of Official Statistics of Korea) (2021). Its database provides provincial and annual data on all variables that are considered in both case studies. For the analysis by continent, immigrants from 187 source countries are aggregated by their respective continent, following the list of geographic regions from the United Nations Statistics Division (2021). In classifying the countries by income class, the GNI per capita data on any source country are used and taken from the World Bank (2021a; 2021b), except for Taiwan, which is obtained from National Statistics, Republic of China (Taiwan) (2021). The period of study is from 2013 up until 2019 and includes all 17 provinces of Korea. Due to some missing values, this provides us with 113 observations to work with. The year 2012 is used for IV construction as this is the earliest year available that contains data on the number of immigrants from the 187 source countries.

3.2 Methodology

3.2.1 Case study: Japan

I perform an OLS panel regression with prefecture and year fixed effects to control for unobserved heterogeneity across prefectures and years. The baseline model specification is the following:

$$crimerate_{it} = \beta_0 + \beta_1 immigrantshare_{it} + \beta_2 \ln(totalpopulation_{it}) + \beta_3 youngmaleshare_{it} + \beta_4 marriagerate_{it} + \beta_5 unemploymentrate_{it} + \beta_6 \ln(realincomepc_{it}) + \beta_7 clearancerate_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{2}$$

Where i indicates prefecture and t indicates year. $crimerate_{it}$ is the outcome variable which gives the crime rate in number of reported total crimes, violent crimes, or property crimes per 100,000 persons. $immigrantshare_{it}$ is the variable of interest that specifies the total share of immigrants in percentages. This is followed by three demographic confounders: $\ln(totalpopulation_{it})$ is the log of total population. As the model includes prefecture fixed effects, it indirectly accounts for population density which is amongst the main factors of crime (Glaeser and Sacerdote, 1999); $youngmaleshare_{it}$ is the share of male aged 15-29 relative to the total population in percentages who appear to be most prone to engaging in criminal activities (Gottfredson and Hirschi, 1983; Farrington, 1986; Grogger, 1998; Freeman, 1999; Levitt, 2002; Dills et al., 2010); $marriagerate_{it}$ is the crude marriage rate in number of marriages per 1,000 persons. Two economic indicators based upon the economic model of crime (Becker, 1968; Ehrlich, 1973) include: *unemploymentrate*$_{it}$ represents the unemployment rate in percentages and proxies the employment opportunities (Raphael and Winter-Ember, 2001; Fougere et al., 2009; Bianchi et al., 2012; Spenkuch, 2014); ln*(realincomepc*$_{it}$*)* is the log of real income per capita expressed in JPY which proxies the income opportunities (Grogger, 1998; Gould et al., 2002; Machin and Meghir, 2004). Moreover, *clearancerate*$_{it}$ gives the clearance rate for total crimes, violent crimes, or property crimes in percentages, which is defined as the number of crimes cleared by police relative to the number of reported crimes. In the criminology literature, this variable is known as a measurement for how effective and strict the justice system is and proxies the expected costs of committing a crime (Wolpin, 1978; Ehrlich, 1996). Lastly, α_i is the prefecture fixed effects and λ_t is the year fixed effects with ε_{it} as the idiosyncratic error term. A detailed description of the variables is provided in Appendix A.

To study the relationship of interest from a geographical perspective, I disaggregate the total immigrant share into share of immigrants from various source continents and employ the following decomposed specification:

$$crimerate_{it} = \beta_0 + \beta_1 immigrantshare_{it}^{Asia} + \beta_2 immigrantshare_{it}^{Europe} + \beta_3 immigrantshare_{it}^{NA} + \beta_4 immigrantshare_{it}^{SA} + \beta_5 immigrantshare_{it}^{Other} + \boldsymbol{X_{it}\beta} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{3}$$

Where *immigrantshare*$^{Asia}_{it}$, *immigrantshare*$^{Europe}_{it}$, *immigrantshare*$^{NA}_{it}$, *immigrantshare*$^{SA}_{it}$, *immigrantshare*$^{Other}_{it}$ are share of immigrants from Asia, Europe, North America, South America, and other, respectively. $\boldsymbol{X_{it}}$ is a vector of the aforementioned control variables.

Up to this point, the explanatory variable of interest is assumed to be exogenous, i.e., Cov(*immigrantshare*$_{it}$, ε_{it}) = 0. However, there are several reasons as to why immigrant share is likely to be endogenous and hence a threat to identification of a causal effect on crime rate. There can be measurement error in counting the number of immigrants by the census which biases the estimates of the share of immigrants. Additionally, omitted variable bias (OVB) can still be an issue after accounting for several factors of crime and fixed effects. For instance, this paper does not contain data on poverty and education. The Gini-coefficient can be added to account for income inequality (Chiu and Madden, 1998; Kelly, 2000). An education level covariate is also an important candidate as there is evidence of its crime-reducing impact (Lochner and Moretti, 2004; Machin et al., 2011). Lastly, endogeneity in the settlement pattern of immigrants is another matter of concern. If immigrants settle in areas with low crime rates, e.g., because of attractive employment opportunities that are present there, this will bias estimates downwards. In contrast, if immigrants move to areas where crime is on the rise, e.g., because they are attracted by lower housing prices that are available there, this will lead to an upward bias.

To avoid the abovementioned threats to identification and obtain a causal interpretation of the impact of immigration on crime, I perform an instrumental variables regression. Along with Bartel's (1989) finding that immigrants tend to settle in ethnic clusters, this thesis follows Altonji and Card (1991) and Card (2001) in that it uses the past immigrant inflow to construct the predicted number of immigrants. For the baseline specification, this is done as follows:

$$\widehat{immigrants}_{it} = \sum_{c=1}^{5}\left(\frac{immigrants_{ci2000}}{immigrants_{c2000}} \times immigrants_{ct}\right) \tag{4}$$

Where $\widehat{immigrants}_{it}$ is the predicted total number of immigrants in prefecture i in year t. $immigrants_{ci2000}$ is the number of immigrants from continent c residing in prefecture i in 2000. $immigrants_{c2000}$ indicates the number of immigrants from continent c residing in Japan in 2000. $immigrants_{ct}$ gives the number of immigrants from continent c residing in Japan in year t.

For the decomposed specification, the predicted number of immigrants from each source continent c in prefecture i in year t is then implicitly obtained via the inner-sum operation:

$$\widehat{immigrants}_{it}^{c} = \frac{immigrants_{ci2000}}{immigrants_{c2000}} \times immigrants_{ct} \tag{5}$$

Similar to how the endogenous immigrant share variables are defined, the predicted number of immigrants variables are then divided by the total population and multiplied by 100 to obtain the predicted share of immigrants in percentages which serve as our IVs. Therewith, the following first stage regressions are performed, respectively:

$$immigrantshare_{it} = \gamma_0 + \gamma_1 \widehat{immigrantshare}_{it} + \boldsymbol{X_{it}\gamma} + \alpha_i + \lambda_t + u_{it} \tag{6}$$

$$immigrantshare_{it}^{c} = \gamma_0 + \gamma_1 \widehat{immigrantshare}_{it}^{c} + \boldsymbol{X_{it}\gamma} + \alpha_i + \lambda_t + u_{it} \tag{7}$$

Subsequently, the following second stage regressions of the baseline and decomposed specifications are performed, respectively:

$$crimerate_{it} = \delta_0 + \delta_1 \widetilde{immigrantshare}_{it} + \boldsymbol{X_{it}\delta} + \alpha_i + \lambda_t + \nu_{it} \tag{8}$$

$$crimerate_{it} = \delta_0 + \delta_1 \widetilde{immigrantshare}_{it}^{Asia} + \delta_2 \widetilde{immigrantshare}_{it}^{Europe} + \delta_3 \widetilde{immigrantshare}_{it}^{NA} + \delta_4 \widetilde{immigrantshare}_{it}^{SA} + \delta_5 \widetilde{immigrantshare}_{it}^{Other} + \boldsymbol{X_{it}\delta} + \alpha_i + \lambda_t + \nu_{it} \tag{9}$$

Where $\widetilde{immigrantshare}_{it}$ and $\widetilde{immigrantshare}_{it}^{c}$ indicate the total and per source continent share of immigrants that is instrumented for, respectively.

For an IV to be valid, it should satisfy the instrument relevance and exclusion restriction (Stock and Watson, 2015). The first condition is met when the IV is a strong predictor of the endogenous variable, i.e., Cov($\widehat{immigrantshare}_{it}$, $immigrantshare_{it}$) ≠ 0. As a rule-of-thumb, this is the case when the F-statistic > 10 in the first stage (Stock and Watson, 2015). Thus, for each of the constructed IVs this will be announced in the results section of this paper. For the second condition to be met, the instrument should be exogenous, i.e., Cov($\widehat{immigrantshare}_{it}$, ε_{it}) = 0. Since in this thesis, coefficients are exactly identified, that is, there are as many IVs as endogenous variables (in this case study: 1 in baseline and 5 in decomposed specification), it is impossible to test the exclusion restriction statistically via the Sargan-Hansen test for overidentifying restrictions. Instead, judgement would have to be based upon expert opinion and personal knowledge of the IV application (Stock and Watson, 2015). In constructing the predicted number of immigrants as instrument as it is done in equation (4), Card (2001) argues the exogeneity of the IV by assuming that the total number of immigrants from a given source country who enter the US is independent of occupation-specific demand conditions in any city. Hence, following one of the founders of the instrument, I assume in this paper that the total number of immigrants from a given source country who enter Japan is independent of shocks to current crime rates in any prefecture. Nonetheless, this instrument exogeneity is debatable.

3.2.2 Case study: South Korea (by continent)

This case study is conducted in a similar fashion. I perform an OLS panel regression with province and year fixed effects to control for unobserved heterogeneity across provinces and years. The baseline model specification is, identical to equation (2), as follows:

$$crimerate_{it} = \varphi_0 + \varphi_1 immigrantshare_{it} + \varphi_2 \ln(totalpopulation_{it}) + \varphi_3 youngmaleshare_{it} + \varphi_4 marriagerate_{it} + \varphi_5 unemploymentrate_{it} + \varphi_6 \ln(realincomepc_{it}) + \varphi_7 clearancerate_{it} + \theta_i + \mu_t + \varepsilon_{it} \quad (10)$$

Where i indicates province and t indicates year. $crimerate_{it}$ is the outcome variable which gives the crime rate in number of reported total crimes, violent crimes, or property crimes per 100,000 persons. $immigrantshare_{it}$ is the variable of interest that specifies the total share of immigrants in percentages. This is followed by three demographic covariates: $\ln(totalpopulation_{it})$ is the log of total population; $youngmaleshare_{it}$ is the share of male aged 15-29 relative to the total population in percentages; $marriagerate_{it}$ is the crude marriage rate in number of marriages per 1,000 persons. Two economic factors include: $unemploymentrate_{it}$ represents the unemployment rate in percentages; $\ln(realincomepc_{it})$ is the log of real income per capita expressed in KRW. Moreover, $clearancerate_{it}$ gives the clearance rate for total crimes, violent crimes, or property crimes in percentages, which is defined as the number of crimes cleared by police relative to the number of reported crimes. Lastly, θ_i is the province fixed effects and μ_t is the year fixed effects with ε_{it} as the idiosyncratic error term. A detailed description of the variables is provided in Appendix A.

To study the relationship of interest from a geographical perspective, I aggregate immigrants from 187 source countries by their respective continent: Asia, Europe, North America, South America, Oceania, or Africa. Aggregation has the advantage of lessening measurement error, which is almost certainly present in the number of immigrants from any single country (Spenkuch, 2014). The assignment of countries follows the list of geographic regions of the United Nations Statistics Division (2021), i.e., based upon the standard country or area codes for statistical use (M49). A list of the 187 countries by continent is provided in Appendix B.

Then, I perform the following decomposed specification by continent:

$$crimerate_{it} = \varphi_0 + \varphi_1 immigrantshare_{it}^{Asia} + \varphi_2 immigrantshare_{it}^{Europe} + \varphi_3 immigrantshare_{it}^{NA} + \varphi_4 immigrantshare_{it}^{SA} + \varphi_5 immigrantshare_{it}^{Oceania} + \varphi_6 immigrantshare_{it}^{Africa} + \boldsymbol{X_{it}\varphi} + \theta_i + \mu_t + \varepsilon_{it} \quad (11)$$

Where $immigrantshare^{Asia}{}_{it}$, $immigrantshare^{Europe}{}_{it}$, $immigrantshare^{NA}{}_{it}$, $immigrantshare^{SA}{}_{it}$, $immigrantshare^{Oceania}{}_{it}$, $immigrantshare^{Africa}{}_{it}$ are share of immigrants from Asia, Europe, North

America, South America, Oceania, and Africa, respectively. $\boldsymbol{X_{it}}$ is a vector of the aforementioned control variables.

To evaluate the crime impact of immigration from a different viewpoint, I disaggregate the total immigrant share by gender and employ the following decomposed specification:

$$crimerate_{it} = \varphi_0 + \varphi_1 immigrantshare_{it}^{m} + \varphi_2 immigrantshare_{it}^{f} + \boldsymbol{X_{it}\varphi} + \theta_i + \mu_t + \varepsilon_{it} \qquad (12)$$

Where $immigrantshare^{m}_{it}$, $immigrantshare^{f}_{it}$ are total share of male immigrants and total share of female immigrants, respectively.

To analyse the effect of interest at the most disaggregated level given the data's possibilities, I decompose total immigrant share by gender and continent, which allows me to run the following decomposed specification:

$$crimerate_{it} = \varphi_0 + \varphi_1 immigrantshare_{it}^{m,Asia} + \varphi_2 immigrantshare_{it}^{m,Europe} + \varphi_3 immigrantshare_{it}^{m,NA} + \varphi_4 immigrantshare_{it}^{m,SA} + \varphi_5 immigrantshare_{it}^{m,Oceania} + \varphi_6 immigrantshare_{it}^{m,Africa} + \varphi_7 immigrantshare_{it}^{f,Asia} + \varphi_8 immigrantshare_{it}^{f,Europe} + \varphi_9 immigrantshare_{it}^{f,NA} + \varphi_{10} immigrantshare_{it}^{f,SA} + \varphi_{11} immigrantshare_{it}^{f,Oceania} + \varphi_{12} immigrantshare_{it}^{f,Africa} + \boldsymbol{X_{it}\varphi} + \theta_i + \mu_t + \varepsilon_{it} \qquad (13)$$

Where $immigrantshare^{g,c}_{it}$, are share of immigrants who are gender g from continent c, where g = male, female, and c = Asia, Europe, North America, South America, Oceania, and Africa.

Similarly, due to endogeneity in the explanatory variable of interest, I perform an IV regression. Following Altonji and Card (1991) and Card (2001), I use the past immigrant inflow to construct the predicted number of immigrants for both genders together (as in Japan case study) and by gender. For the equations (10) and (12), this is done as follows:

$$\widehat{immigrants}_{it}^{g} = \sum_{c=1}^{6} \left(\frac{immigrants_{ci2012}^{g}}{immigrants_{c2012}^{g}} \times immigrants_{ct}^{g} \right) \qquad (14)$$

Where g = both genders, male, female. $\widehat{immigrants}_{it}^{g}$ is the predicted number of immigrants g in province i in year t. $immigrants^{g}_{ci2012}$ is the number of immigrants g from continent c residing in province i in 2012. $immigrants^{g}_{c2012}$ indicates the number of immigrants g from continent c residing in Korea in 2012. *immigrants*$^{g}_{ct}$ gives the number of immigrants g from continent c residing in Korea in year t.

For equations (11) and (13), the predicted number of immigrants g from each continent c in province i in year t is then implicitly obtained via the inner-sum operation:

$$\widehat{immigrants}_{it}^{g,c} = \frac{immigrants_{ci2012}^{g}}{immigrants_{c2012}^{g}} \times immigrants_{ct}^{g} \quad (15)$$

The predicted number of immigrants variables are then divided by the total population and multiplied by 100 to obtain the predicted share of immigrants in percentages which serve as our IVs. Therewith, the following first stage regressions are performed, respectively:

$$immigrantshare_{it}^{g} = \pi_0 + \pi_1 \widehat{immigrantshare}_{it}^{g} + \boldsymbol{X_{it}\pi} + \theta_i + \mu_t + u_{it} \quad (16)$$

$$immigrantshare_{it}^{g,c} = \pi_0 + \pi_1 \widehat{immigrantshare}_{it}^{g,c} + \boldsymbol{X_{it}\pi} + \theta_i + \mu_t + u_{it} \quad (17)$$

Subsequently, the following second stage regressions of the baseline and the three decomposed specifications are performed, respectively:

$$crimerate_{it} = \psi_0 + \psi_1 \widetilde{immigrantshare}_{it} + \boldsymbol{X_{it}\psi} + \theta_i + \mu_t + \nu_{it} \quad (18)$$

$$crimerate_{it} = \psi_0 + \psi_1 \widetilde{immigrantshare}_{it}^{Asia} + \psi_2 \widetilde{immigrantshare}_{it}^{Europe} + \psi_3 \widetilde{immigrantshare}_{it}^{NA} + \psi_4 \widetilde{immigrantshare}_{it}^{SA} + \psi_5 \widetilde{immigrantshare}_{it}^{Oceania} + \psi_6 \widetilde{immigrantshare}_{it}^{Africa} + \boldsymbol{X_{it}\psi} + \theta_i + \mu_t + \nu_{it} \quad (19)$$

$$crimerate_{it} = \psi_0 + \psi_1 \widetilde{immigrantshare}_{it}^{m} + \psi_2 \widetilde{immigrantshare}_{it}^{f} + \boldsymbol{X_{it}\psi} + \theta_i + \mu_t + \nu_{it} \quad (20)$$

$$crimerate_{it} = \psi_0 + \psi_1 \widetilde{immigrantshare}_{it}^{m,Asia} + \psi_2 \widetilde{immigrantshare}_{it}^{m,Europe} + \psi_3 \widetilde{immigrantshare}_{it}^{m,NA} + \psi_4 \widetilde{immigrantshare}_{it}^{m,SA} + \psi_5 \widetilde{immigrantshare}_{it}^{m,Oceania} + \psi_6 \widetilde{immigrantshare}_{it}^{m,Africa} + \psi_7 \widetilde{immigrantshare}_{it}^{f,Asia} + \psi_8 \widetilde{immigrantshare}_{it}^{f,Europe} + \psi_9 \widetilde{immigrantshare}_{it}^{f,NA} + \psi_{10} \widetilde{immigrantshare}_{it}^{f,SA} + \psi_{11} \widetilde{immigrantshare}_{it}^{f,Oceania} + \psi_{12} \widetilde{immigrantshare}_{it}^{f,Africa} + \boldsymbol{X_{it}\psi} + \theta_i + \mu_t + \nu_{it} \quad (21)$$

Where $\widetilde{immigrantshare}_{it}^{g}$ and $\widetilde{immigrantshare}_{it}^{g,c}$ indicate the total and per source continent immigrant share g that is instrumented for, respectively, where g = both genders, male, female.

Identically, concerning the validity of the IVs, the first stage F-statistic of each of the constructed IVs will be announced in the results section of this paper. Also, the coefficients in this case study are exactly identified as well. Hence, following Card (2001), the instruments used in this study are assumed exogenous.

3.2.3 Case study: South Korea (by income class)

Similarly, I perform an OLS panel regression with province and year fixed effects to control for unobserved heterogeneity across provinces and years. The baseline model specification is also equation (10).

To study the relationship of interest from an income perspective, I aggregate immigrants from 187 source countries by their respective income class: high income, upper middle income, lower middle income, or low income. The classification of the income classes follows the World Bank Atlas method of exchange rates, i.e., based on the source country's GNI per capita converted to current USD[1]: high-income economies are those with a GNI per capita of $12,536 or more; upper middle-income economies are those with a GNI per capita between $4,046 and $12,535; lower middle-income economies are those with a GNI per capita between $1,036 and $4,045; low-income economies are defined as those with a GNI per capita $1,035 or less (World Bank, 2021a; 2021b). The 187 countries by income class are listed in Appendix C.

Then, I perform the following decomposed specification by income class:

$$crimerate_{it} = \omega_0 + \omega_1 immigrantshare_{it}^{H} + \omega_2 immigrantshare_{it}^{UM} + \omega_3 immigrantshare_{it}^{LM} + \omega_4 immigrantshare_{it}^{L} + \boldsymbol{X_{it}\omega} + \theta_i + \mu_t + \varepsilon_{it} \quad (22)$$

Where $immigrantshare^{H}_{it}$, $immigrantshare^{UM}_{it}$, $immigrantshare^{LM}_{it}$, $immigrantshare^{L}_{it}$ are share of immigrants from high income, upper middle income, lower middle income, and low income, respectively. The same covariates and fixed effects are used as in analysis by continent.

[1] The Atlas method smooths exchange rate fluctuations by using a three year moving average, price-adjusted conversion factor. For more details, see World Bank (2021c).

For a gender impact assessment of immigration on crime, I disaggregate the total immigrant share by gender and employ the decomposed specification from equation (12).

To also analyse the effect of interest at the most disaggregated level given these data's possibilities, I decompose total immigrant share by gender and income class, which allows me to run the following decomposed specification:

$$crimerate_{it} = \omega_0 + \omega_1 immigrantshare_{it}^{m,H} + \omega_2 immigrantshare_{it}^{m,UM} + \omega_3 immigrantshare_{it}^{m,LM} + \omega_4 immigrantshare_{it}^{m,L} + \omega_5 immigrantshare_{it}^{f,H} + \omega_6 immigrantshare_{it}^{f,UM} + \omega_7 immigrantshare_{it}^{f,LM} + \omega_8 immigrantshare_{it}^{f,L} + \boldsymbol{X_{it}\omega} + \theta_i + \mu_t + \varepsilon_{it} \quad (23)$$

Where $immigrantshare^{g,c}{}_{it}$, is immigrant share who are gender g from income class c, where g = male, female, and c = high income, upper middle income, lower middle income, low income.

3.3 Descriptive statistics

3.3.1 Case study: Japan

Figure 1 shows the average crime rate over the years 2012-2018 by crime type. It appears that in this period of study, the average number of reported total crimes per 100,000 persons falls on a yearly basis. Looking at its decompositions, this mainly comes from the decrease in property crime. Reduction in other crime accounts for less, whereas violent crime remains relatively stagnant. In addition, property crime makes up the largest fraction of total crime, followed by other crime, whilst violent crime accounts for the smallest portion.

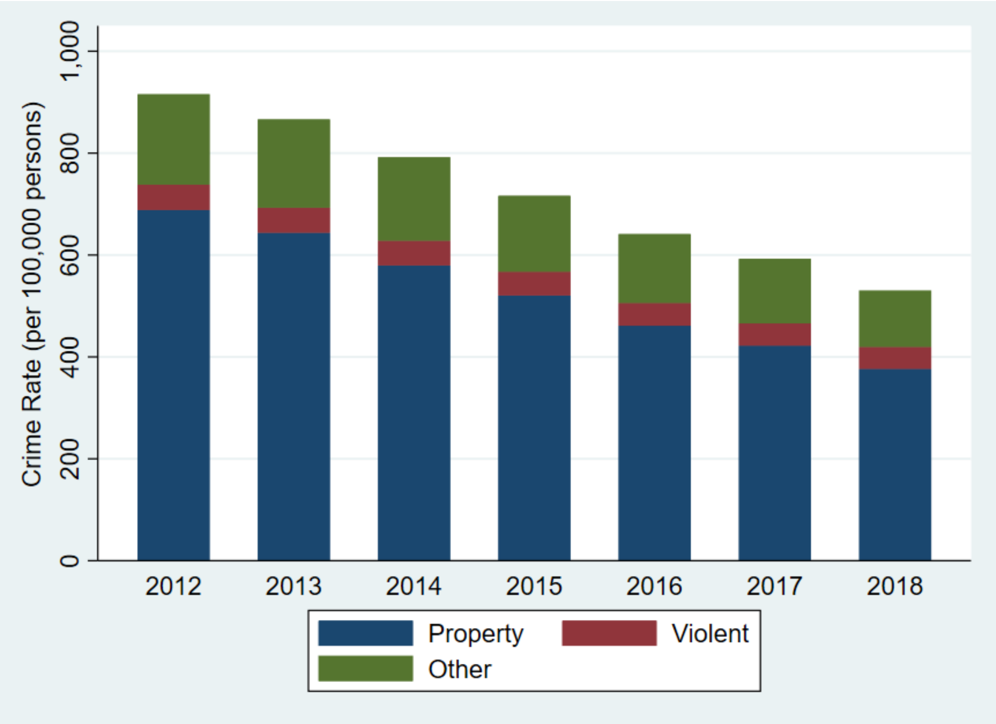

Figure 1: Average crime rate per year by crime type

Figure 2 in Appendix D exhibits the average crime rate per prefecture by crime type. In terms of total crime, it is noticeable that Osaka is characterised with the highest rate, followed by Tokyo, Hyogo, and Fukuoka. On the other hand, Akita, Iwate, and Nagasaki have the lowest crime rates. Also when evaluated per prefecture, property crime seems to be the main driver behind the differences amongst prefectures, followed by other crime, then violent crime.

Figure 3 presents the average immigrant share for the years 2012-2018 by source continent. It is apparent that total immigrant share increases on an annual basis, which especially comes from the rise in share of immigrants from Asia. Immigrant shares from the four remaining source continents increase slightly. Furthermore, Asian immigrants make up the largest fraction of all immigrants, followed by South Americans, whilst immigrants from other continent account for the smallest portion.

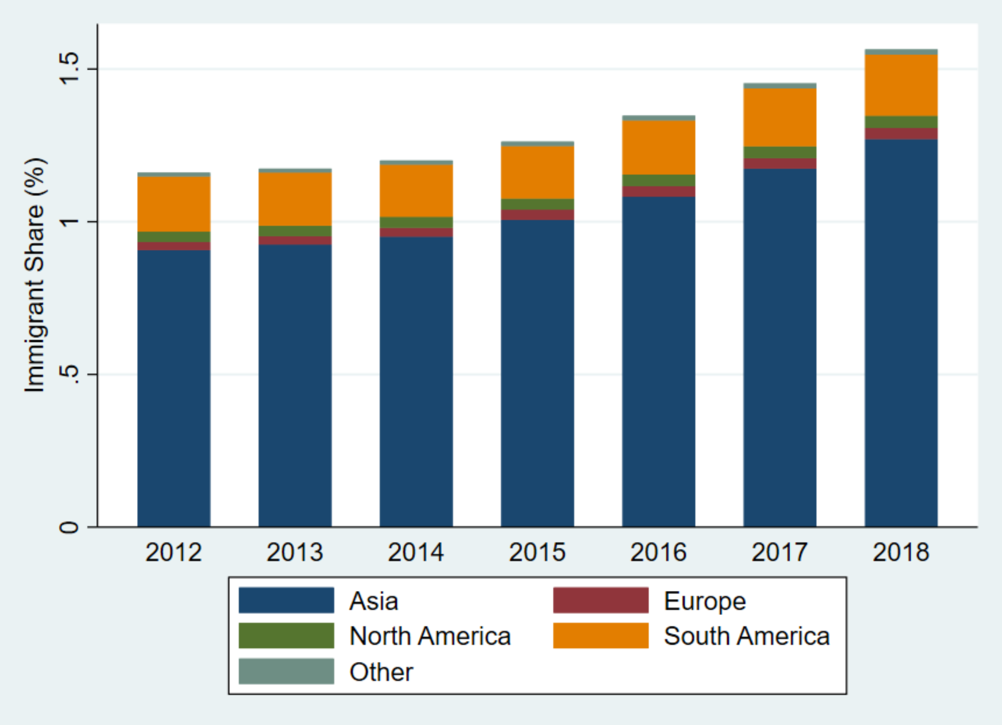

Figure 3: Average immigrant share per year by source continent

Figure 4 in Appendix D presents the average immigrant share per prefecture by source continent. In terms of total immigrant share, Tokyo has the highest percentage, followed by Aichi, Mie, and Osaka. On the other hand, Aomori, Akita, and Miyazaki have the lowest share of immigrants. Similarly, when observed per prefecture, Asian immigrant share is the main determinant for differences across prefectures, followed by South American immigrant share, then those of the remaining source continents.

Table 1 provides the descriptive statistics of the variables used in this case study. It shows that Japan's total number of reported crimes is 721.89 per 100,000 persons on average, where property crime constitutes the most and violent crime the least, consistent with what is seen from the aforementioned figures. The average total share of immigrants in Japan is around 1.31%, which as indicated in the introduction, appears to be tiny. Asian immigrants represent circa 80% of all immigrants, followed by South Americans, whilst North Americans, Europeans and other-continental immigrants make up the slightest share. This is also in line with the discussed figures. Concerning the demographics, what is interesting is that the share of young male in the total population is also small, at 7.18% on average. This is likely largely explained by Japan's prolonged period of low fertility rates and its fast-ageing group, as stressed in the introduction as well. Regarding the economic indicators, Japan's average unemployment rate is 3.06%, which is lower than half of that of the OECD average at 6.91%

over this period of study (OECD, 2021). Lastly, less than half of total and property crimes but more than 80% of violent crimes are cleared by the police, on average.

Table 1: Descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Total crime rate (per 100,000 persons)	329	721.892	270.907	243.775	1896.084
Violent crime rate (per 100,000 persons)	329	46.518	14.967	18.211	86.470
Property crime rate (per 100,000 persons)	329	527.565	214.773	174.124	1496.705
Immigrant share total (%)	329	1.309	0.784	0.291	4.108
Immigrant share Asia (%)	329	1.045	0.603	0.248	3.583
Immigrant share Europe (%)	329	0.032	0.031	0.009	0.235
Immigrant share North America (%)	329	0.037	0.030	0.014	0.188
Immigrant share South America (%)	329	0.181	0.274	0.001	1.014
Immigrant share other (%)	329	0.014	0.009	0.004	0.062
Total population (1,000 persons)	329	2703.400	2704.235	560.000	13822.000
Young male (%)	329	7.178	0.662	5.403	8.705
Marriage rate (%)	329	4.621	0.533	3.110	6.750
Unemployment rate (%)	329	3.056	0.860	1.100	6.800
Real income per capita (1,000 JPY)	329	3465.125	338.977	2850.958	4670.303
Total crime clearance rate (%)	329	41.480	11.007	17.024	78.418
Violent crime clearance rate (%)	329	83.892	8.519	54.263	102.513
Property crime clearance rate (%)	329	38.593	11.970	11.770	77.790

Table 2 in Appendix D exhibits the correlation between the variables in this case study. As expected, the correlations between the three types of crime rate are substantial and positive, even close to 1 between total crime and property crime. The correlations between the six immigrant shares are also of considerable values and positive, except for those between Europe and South America, and between North America and South America which are weak and negative. There also seems to be no correlation between immigrants from South America and other. Concerning the correlations of interest, i.e., between crime rates and immigrant shares, every type of crime is moderately and positively correlated with each immigrant share, except for the correlation between violent crime and South America which is weak. Furthermore, each crime type seems to be strongly and positively correlated with each demographic and economic control variable. Lastly, crime rates have relatively large and negative correlations with the crime clearance rates.

Figure 5 in Appendix D shows the scatterplot of total crime rate and actual total immigrant share. The fitted line indicates that a linear regression is a suitable approximation of the relationship between the two variables of interest.

Figure 6 in Appendix D shows the scatterplot of the actual and predicted total immigrant share. The fitted line indicates that a linear regression is a suitable approximation of the relationship between the endogenous variable and instrumental variable in the first stage.

3.3.2 Case Study: South Korea (by continent)

Figure 7 shows the average crime rate over the years 2013-2019 by crime type. It appears that in this period of study, the average number of reported total crimes per 100,000 persons fluctuates over the years. Looking at its decompositions, this is mainly due to change in other crime which makes up the largest fraction of total crime. Violent crime remains relatively constant, whereas property crime reduces on a yearly basis and accounts for the smallest share. The considerable difference in the composition of crime types between Japan and Korea could be explained by the fact that both countries have their own operationalisation of each crime type. What illicit activities each country assigns to which crime type can be found in the description of the variables provided in Appendix A.

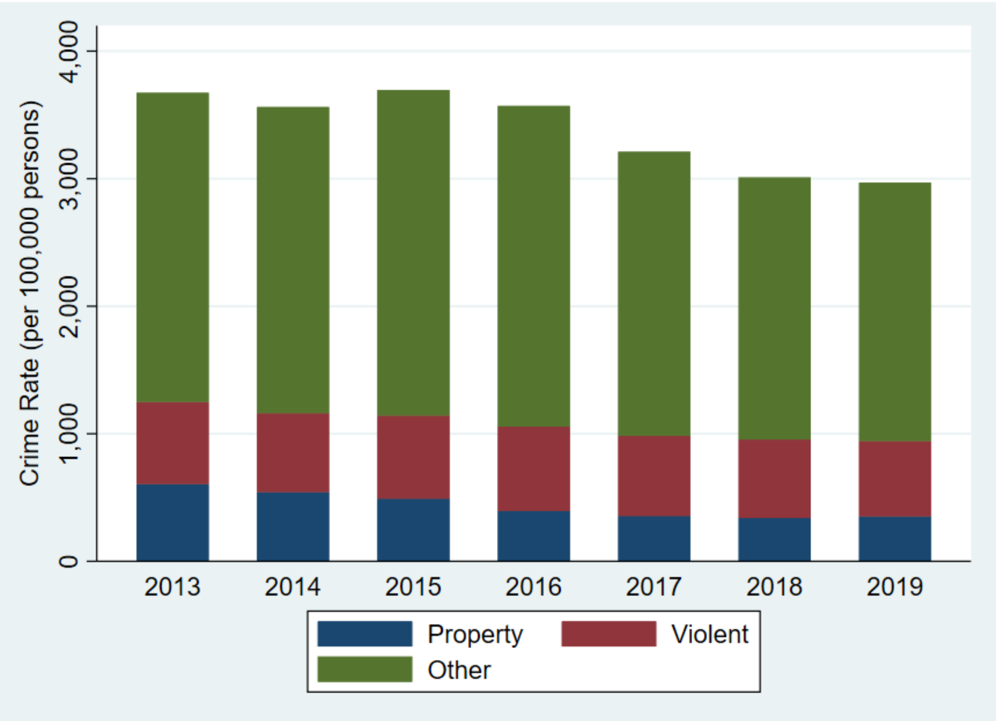

Figure 7: Average crime rate per year by crime type

Figure 8 in Appendix D exhibits the average crime rate per province. In terms of total crime, it is noticeable that Jeju is characterised with the highest rate, followed by Gwangju and Busan. On the other hand, Sejong, Jeollabuk-do and Jeollanam-do have the lowest crime rates. When evaluated at the province level, all three types of crime exhibit fluctuations across provinces.

Figure 9 presents the average immigrant share for the years 2013-2019 by continent. Korea appears to exhibit similar features as Japan. Total immigrant share increases on an annual basis, which especially comes from the rise in share of immigrants from Asia. Furthermore, Asian immigrants also make up the largest fraction of all immigrants.

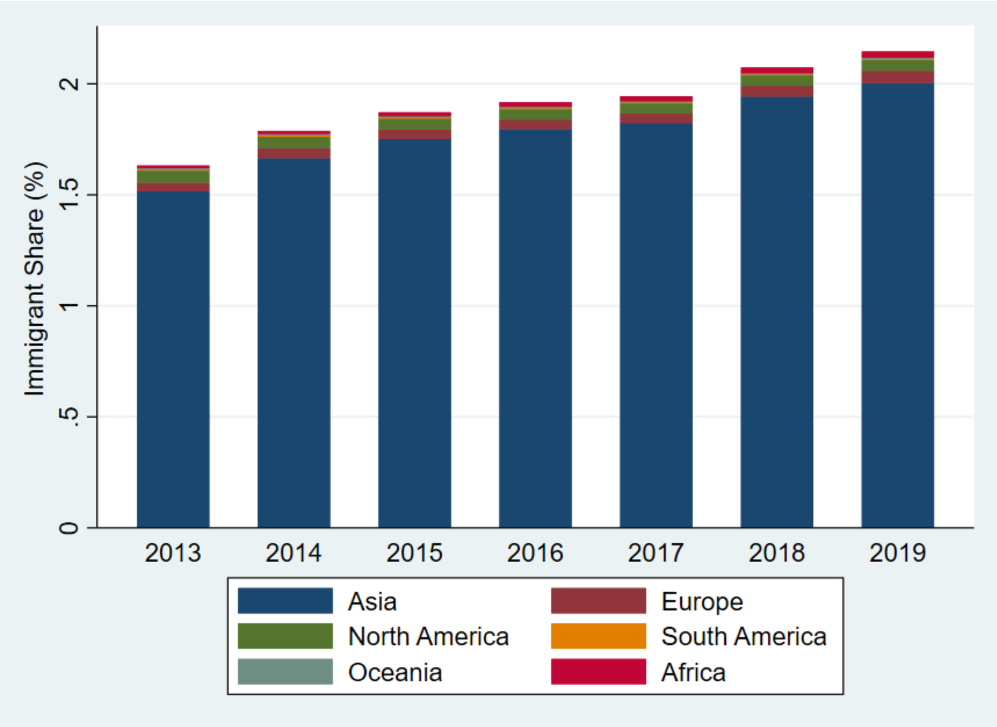

Figure 9: Average immigrant share per year by continent

Figure 10 in Appendix D presents the average immigrant share per province by continent. In terms of total immigrant share, Jeju has the highest percentage, followed by Gyeonggi-do, Chungcheongnam-do, and Seoul. On the other hand, Gangwon-do, Daegu and Daejeon have the lowest share of immigrants. Also at the province level, immigrants from Asia are the main determinant for differences across provinces and account for the largest fraction as well.

Table 3 provides the descriptive statistics of the variables used in this case study. It shows that Korea's total number of reported crimes is 3380.5 per 100,000 persons on average, where other crime constitutes the most and property crime the least, consistent with what is seen from the aforementioned figures. The average total share of immigrants in Korea is 1.91%, which appears to be tiny. Immigrants from Asia represent circa 93% of all immigrants, whilst those from the other five continents make up just a slight share. Furthermore, immigrants from any continent are overrepresented by men, except for those from South America. Concerning the demographics, it is interesting that Korea's share of young male in the total population is also relatively small, which makes up around one-tenth of the population, on average. This is likely largely explained by Korea's low fertility rates in combination with having one of the fastest-ageing population and highest life expectancies in the world, as stressed in the introduction as well. Regarding the economic indicators, Korea's average unemployment rate is 3.24%, which is about half of that of the OECD average at 6.52% over this period of study (OECD, 2021). Lastly, more than half of property crimes and even more than 80% of total and violent crimes are cleared by the police, on average.

Table 3: Descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Total crime rate (per 100,000 persons)	113	3380.499	558.719	1794.318	5455.605
Violent crime rate (per 100,000 persons)	113	629.689	107.908	277.472	1025.588
Property crime rate (per 100,000 persons)	113	439.640	136.396	249.578	981.297
Immigrant share total (%)	119	1.910	0.698	0.869	3.825
Immigrant share Asia (%)	119	1.785	0.669	0.797	3.579
Immigrant share Europe (%)	119	0.045	0.033	0.011	0.207
Immigrant share North America (%)	119	0.052	0.026	0.022	0.130
Immigrant share South America (%)	119	0.003	0.002	0.001	0.011
Immigrant share Oceania (%)	119	0.005	0.005	0.002	0.028
Immigrant share Africa (%)	119	0.020	0.010	0.004	0.052
Immigrant share total – male (%)	119	1.115	0.442	0.412	2.147
Immigrant share Asia – male (%)	119	1.040	0.427	0.343	2.017
Immigrant share Europe – male (%)	119	0.027	0.025	0.007	0.168
Immigrant share North America – male (%)	119	0.030	0.015	0.011	0.084
Immigrant share South America – male (%)	119	0.001	0.001	0.000	0.005
Immigrant share Oceania – male (%)	119	0.004	0.004	0.001	0.022
Immigrant share Africa – male (%)	119	0.014	0.008	0.002	0.044
Immigrant share total – female (%)	119	0.795	0.297	0.408	1.678
Immigrant share Asia – female (%)	119	0.745	0.281	0.375	1.563
Immigrant share Europe – female (%)	119	0.018	0.012	0.004	0.063
Immigrant share North America – female (%)	119	0.022	0.011	0.010	0.062
Immigrant share South America – female (%)	119	0.002	0.001	0.000	0.006
Immigrant share Oceania – female (%)	119	0.002	0.002	0.000	0.010
Immigrant share Africa – female (%)	119	0.006	0.003	0.001	0.015
Total population (1,000 persons)	119	3034.869	3194.480	122.153	13239.666
Young male (%)	119	9.896	0.733	7.999	11.436
Marriage rate (%)	119	5.342	0.796	3.900	8.200
Unemployment rate (%)	115	3.244	0.803	1.700	5.000
Real income per capita (1,000 KRW)	119	31816.605	7357.222	22122.838	52426.324
Total crime clearance rate (%)	113	82.393	4.588	70.642	91.652
Violent crime clearance rate (%)	113	87.381	3.038	78.802	92.643
Property crime clearance rate (%)	113	57.079	10.043	32.193	73.421

Table 4 in Appendix D exhibits the correlation between the variables in this case study. As expected, the correlations between the three types of crime rate are substantial and positive. The correlations between the seven immigrant shares are of considerable values and positive, except for that between Oceania and Africa, which is weak and negative. Concerning the correlations of interest, i.e., between crime rates and immigrant shares, total crime rate is positively correlated with each immigrant share, except with that of Africa. Violent crime rate exhibits the same pattern. Property crime rate is also similar but deviates in that it is negatively correlated with total and Asian immigrant share. In addition, each crime type is positively correlated with each demographic covariate, except with total population. Concerning the economic control variables, every crime rate is negatively correlated therewith. Lastly, crime rates have negative correlations with the crime clearance rates, except for violent crime with its clearance rate.

Figure 11 in Appendix D shows the scatterplot of total crime rate and actual total immigrant share. The fitted line indicates that a linear regression is a suitable approximation of the relationship between the two variables of interest.

Figure 12 in Appendix D shows the scatterplot of the actual and predicted total immigrant share. The fitted line indicates that a linear regression is a suitable approximation of the relationship between the endogenous variable and instrumental variable in the first stage.

3.3.3 Case Study: South Korea (by income class)

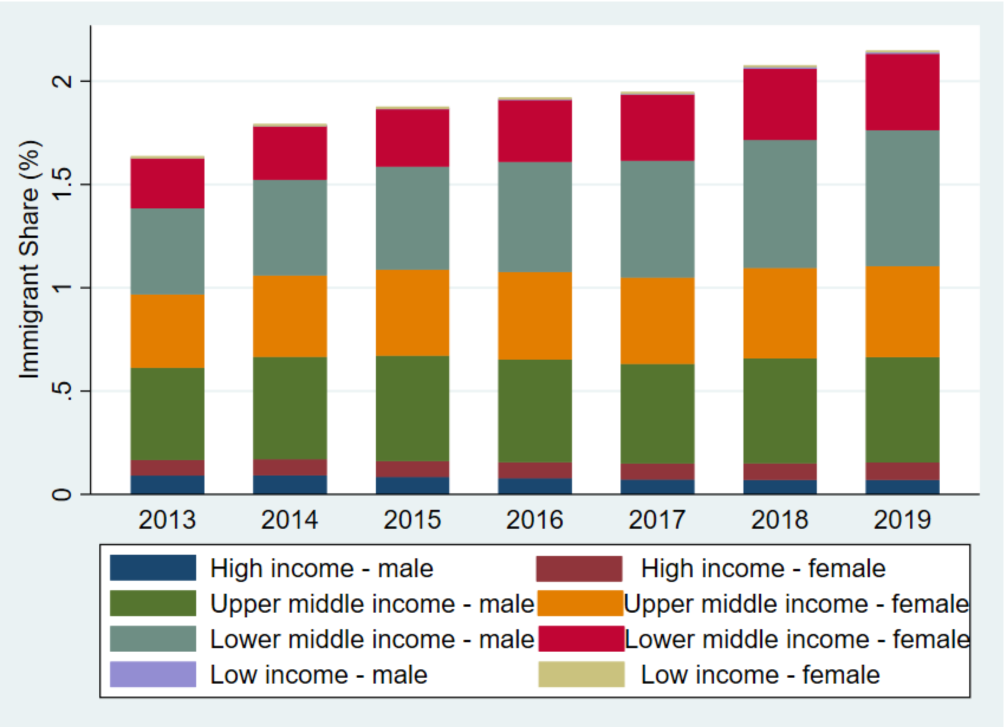

Figure 13: Average immigrant share per year by gender and income class

Figure 13 presents the average immigrant share for the years 2013-2019 by gender and income class. It is apparent that the annual increase in total immigrant share is mainly driven by rise in immigrants from upper and lower middle income countries who also account for the largest fraction. In both income classes, male immigrants overrepresent, whereas this is not graphically derivable for the high and low income classes.

Figure 14 in Appendix D presents the average immigrant share per province by gender and income class. Also at the province level, immigrants from upper and lower middle income countries are the main determinants for differences across provinces and account for the largest fraction as well. In both income classes, male immigrants overrepresent, whereas this is not graphically derivable for the high and low income classes.

Table 5 provides the descriptive statistics of just the immigrant shares by gender and income class in this case study as all other variables are already described in Table 3. Immigrants from upper and middle income classes represent together circa 91% of all immigrants, followed by high income class, whilst low income class immigrants make up the slightest share. Furthermore, the immigrant share from high income class is roughly equally represented by both sexes, something we could not derive from the figures. Immigrant shares from upper and middle income class are indeed overrepresented by men, in line with the figures. Moreover, low income class immigrants appear to be mainly represented by men, also a finding we could not derive from the figures.

Table 5: Descriptive statistics of immigrant shares by gender and income class

Variable	Obs	Mean	Std.Dev.	Min	Max
Immigrant share total (%)	119	1.910	0.698	0.869	3.825
Immigrant share high income (%)	119	0.158	0.084	0.085	0.429
Immigrant share upper middle income (%)	119	0.905	0.520	0.343	2.221
Immigrant share lower middle income (%)	119	0.839	0.339	0.235	1.713
Immigrant share low income (%)	119	0.008	0.006	0.000	0.033
Immigrant share total – male (%)	119	1.115	0.442	0.412	2.147
Immigrant share high income – male (%)	119	0.080	0.050	0.027	0.278
Immigrant share upper middle income – male (%)	119	0.493	0.271	0.175	1.147
Immigrant share lower middle income – male (%)	119	0.536	0.257	0.099	1.123
Immigrant share low income – male (%)	119	0.006	0.004	0.000	0.030
Immigrant share total – female (%)	119	0.795	0.297	0.408	1.678
Immigrant share high income – female (%)	119	0.079	0.038	0.042	0.235
Immigrant share upper middle income – female (%)	119	0.412	0.257	0.167	1.085
Immigrant share lower middle income – female (%)	119	0.303	0.095	0.136	0.590
Immigrant share low income – female (%)	119	0.002	0.002	0.000	0.011

Table 6 in Appendix D exhibits the correlation between the variables in this case study. As expected, the correlations between the three types of crime rate are substantial and positive. The correlations between the five immigrant shares (i.e., total and per income class) within both sexes together, as well as within male, and within female, are of considerable values and positive. When comparing total immigrant share between both sexes together, male, and female, their correlations are close to 1. Tremendous correlations are also observable for each per income class immigrant share comparison across those three. Concerning the correlations of interest, i.e., between crime rates and immigrant shares, total crime rate is positively correlated with each immigrant share, except with that of lower middle and low income class. Violent crime rate exhibits roughly the same pattern but differs in that it is uncorrelated with female immigrant share from low income class. Property crime rate is also similar to total crime rate but deviates in that it is negatively correlated with total immigrant share. In addition, each crime type is positively correlated with each demographic covariate, except with total population. Concerning the economic control variables, every crime rate is negatively correlated therewith. Lastly, crime rates have negative correlations with the crime clearance rates, except for violent crime with its clearance rate.

IV. Results

In the Japan and Korea case studies by continent, I will first discuss the OLS estimates. This is followed by the first stage outcomes regarding the instrument relevance condition. Lastly, IV estimates are compared to OLS, interpreted, and subject to some robustness checks. Concerning the Korea case study by income class, I solely discuss the OLS estimates. In line with the existing literature, mainly the violent and property crime impact of immigration will be assessed as this allows for investigation in accordance with the economic model of crime[2].

4.1 Case study: Japan

Table 7 exhibits the OLS regressions of the baseline and decomposed specification, controlled for all covariates and fixed effects. Results are interpreted in terms of standard deviation changes ex post where the standard deviations are taken from Table 1. Columns (2) and (3) show a negative violent crime and positive property crime impact of total immigrant share. However, the estimates are imprecise, the hypothesis that total share of immigrants has no effect on violent and property crime rate cannot be rejected at the 5% level. Furthermore, it

[2] Total crime is not as informative as it aggregates all activities regarding incompliance with the law; a change in any explanatory variable would indicate a change in the number of reported crimes irrespective of its nature.

seems that the effect on total crime is driven by property crimes, which might be explained by the fact that property crimes represent 73% of total crimes and their correlation is close to 1.

Table 7: OLS regressions of baseline and decomposed specification

VARIABLES	(1) Total crime rate	(2) Violent crime rate	(3) Property crime rate	(4) Total crime rate	(5) Violent crime rate	(6) Property crime rate
Immigrant share total	95.78	-1.657	103.9			
	(104.4)	(10.20)	(85.70)			
Immigrant share Asia				78.97	-3.809	80.73
				(119.8)	(11.87)	(97.71)
Immigrant share Europe				-264.5*	-53.59**	-103.3
				(147.9)	(21.85)	(131.3)
Immigrant share North Am.				5,250	-44.48	4,794*
				(3,245)	(214.1)	(2,754)
Immigrant share South Am.				220.5*	18.30	212.8**
				(110.3)	(21.93)	(91.33)
Immigrant share other				-407.7	102.3	403.9
				(2,698)	(304.6)	(2,209)
Log total population	-3,754***	-69.28	-3,364***	-4,133***	-41.37	-3,734***
	(1,268)	(102.8)	(1,068)	(1,273)	(115.5)	(1,062)
Young male	-51.77	5.413	-52.47	-57.02	4.660	-58.24
	(72.22)	(6.581)	(57.26)	(72.83)	(6.649)	(57.78)
Marriage rate	-52.42	2.941	-54.04	-62.85	2.797	-67.13
	(69.03)	(7.044)	(56.32)	(70.16)	(6.644)	(57.58)
Unemployment rate	1.925	-2.502	6.092	10.57	-2.911	15.42
	(26.31)	(2.295)	(21.68)	(23.30)	(2.223)	(18.80)
Log real income per capita	48.42	-13.08	88.31	47.03	-7.593	87.35
	(302.6)	(24.17)	(233.6)	(304.4)	(25.29)	(229.2)
Total crime clearance	-0.994			-1.185		
	(1.685)			(1.593)		
Violent crime clearance		0.0265			0.0261	
		(0.139)			(0.140)	
Property crime clearance			-0.173			-0.240
			(1.062)			(1.003)
Constant	55,103**	1,205	48,584***	60,510***	726.5	53,872***
	(20,601)	(1,498)	(17,156)	(20,667)	(1,644)	(17,116)
Prefecture FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	329	329	329	329	329	329
R-squared	0.888	0.216	0.877	0.892	0.232	0.882

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

When decomposing the total immigrant share into five source continents in columns (4)-(6), it is apparent that its negative impact on violent crime seems to find its roots from immigrants from Asia, Europe, and North America, significant for those from Europe. A 1 standard deviation increase in immigrant share from Europe is associated with a fall in the number of reported violent crimes of 53.59 × 0.031 = 1.66 standard deviations on average, *ceteris paribus*. Moreover, the positive property crime impact of total immigrant share is reflected by immigrants from all source continents except those from Europe, significant for those from South America. A 1 standard deviation increase in immigrant share from South America is associated with a rise in the number of reported property crimes of 58.31 standard deviations on average, *ceteris paribus*.

However, as discussed in the methodology section in detail, the explanatory variables of interest are likely endogenous in OLS. Measurement error, OVB, and endogeneity in the settlement pattern of immigrants are threats to identification of a causal effect on crime rate. Hence, IV regressions are employed which can provide a way to an unbiased interpretation. Following Card (2001), the instruments used in this study are assumed exogeneous. Thus, what remains for the instruments to be valid is to evaluate whether they are strong predictors of the endogenous variables. Table 8 reports the first stage regressions, controlled for all covariates and fixed effects, to assess this for every instrument. It is derivable that, except for predicted immigrant shares total and Asia, all other predicted immigrant shares can be considered relevant IVs as they have an F-statistic > 10. Thus, the IVs total and Asia do not predict their respective endogenous variable which implies that their IV estimates are not reliable.

Table 8: First stage regressions

VARIABLES	(1) Immigrant share total	(2) Immigrant share Asia	(3) Immigrant share Europe	(4) Immigrant share North Am.	(5) Immigrant share South Am.	(6) Immigrant share other
Immigrant $\widehat{\text{share}}$ total	-0.0737 (0.0828)					
Immigrant $\widehat{\text{share}}$ Asia		-0.125* (0.0649)				
Immigrant $\widehat{\text{share}}$ Europe			1.223*** (0.151)			
Immigrant $\widehat{\text{share}}$ North Am.				0.524*** (0.108)		
Immigrant $\widehat{\text{share}}$ South Am.					0.731*** (0.186)	
Immigrant $\widehat{\text{share}}$ other						0.877*** (0.215)
Constant	-101.6*** (12.00)	-97.18*** (11.85)	-1.999** (0.827)	-0.724* (0.377)	0.485 (5.139)	-0.127 (0.354)
Controls	YES	YES	YES	YES	YES	YES
Prefecture FE	YES	YES	YES	YES	YES	YES

Year FE	YES	YES	YES	YES	YES	YES
Observations	329	329	329	329	329	329
R-squared	0.910	0.912	0.280	0.774	0.302	0.613
F-statistic	0.79	3.70	65.48	23.58	15.39	16.65

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

Table 9 exhibits the IV regressions of the baseline and decomposed specification, controlled for all covariates and fixed effects. What is noticeable is many estimates have changed substantially in magnitude, and some in signs and significance. The following examinations on IV estimates are compared to their respective OLS counterpart. Columns (2) and (3) now show a positive effect of total immigrant share on both violent crime and property crime, although still not significant. Also here, the effect on total crime seems to be driven by property crimes.

Table 9: IV regressions of baseline and decomposed specification

VARIABLES	(1) Total crime rate	(2) Violent crime rate	(3) Property crime rate	(4) Total crime rate	(5) Violent crime rate	(6) Property crime rate
Immigrant share total	4,366	108.6	3,536			
	(4,961)	(213.8)	(4,108)			
Immigrant share Asia				2,093**	26.39	1,682**
				(1,018)	(55.40)	(813.3)
Immigrant share Europe				37.30	138.5	-34.46
				(11,863)	(386.4)	(9,282)
Immigrant share North Am.				22,255	-223.2	18,442
				(21,005)	(663.8)	(16,117)
Immigrant share South Am.				461.6	30.79	371.6
				(2,749)	(61.92)	(2,210)
Immigrant share other				-80,432	-1,247	-64,141
				(51,601)	(2,036)	(43,369)
Log total population	-32,658	-844.0	-26,835	-14,043**	-170.0	-11,505**
	(33,875)	(1,512)	(28,284)	(5,926)	(286.8)	(4,584)
Young male	-1,152	-23.39	-927.3	-306.0	-1.860	-249.7
	(1,293)	(55.93)	(1,060)	(201.5)	(9.320)	(163.2)
Marriage rate	-198.1	0.444	-159.1	106.8	3.911	72.14
	(348.2)	(12.05)	(275.7)	(248.0)	(9.641)	(201.0)
Unemployment rate	-127.1	-6.352	-112.0	-40.68	-3.336	-26.14
	(162.5)	(7.998)	(149.9)	(90.05)	(3.218)	(71.83)
Log real income per capita	-721.6	-23.76	-541.7	-1,102	-33.32	-835.0
	(1,483)	(31.94)	(1,228)	(1,049)	(41.70)	(846.7)
Total crime clearance	13.39			-1.227		
	(17.77)			(3.507)		
Violent crime clearance		-0.0152			-0.0230	
		(0.161)			(0.184)	
Property crime clearance			7.565			-0.106
			(10.13)			(2.340)
Constant	489,071	12,701	401,112	221,056**	3,012	180,029***

	(508,803)	(22,244)	(425,260)	(88,899)	(4,365)	(69,325)
Prefecture FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	329	329	329	329	329	329

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

When disaggregating the total immigrant share into five source continents in columns (4)-(6), it is noticeable that its positive effect on violent crime seems to be identified by immigrants from South America instead of North America, in addition to those from Asia and Europe. The estimate of immigrant share from Europe has become imprecise. Concerning the property crime impact of total immigration, its increase is now not reflected by immigrants from other continent anymore, whilst the estimate of those from Asia has become significant. This significance is also observable for total crime rate. A 1 standard deviation increase in immigrant share from Asia is associated with a rise in the number of reported property crimes of 1,682 × 0.603 = 1014.25 standard deviations on average, *ceteris paribus*.

A potential explanation for this finding could stem from what is seen in practice. Asian immigrants, who make up 80% of all immigrants, settle in Japan mainly for economic reasons. However, it is well known that foreign workers in Japan get exploited in terms of getting underpaid, overworked in unsafe environments, getting little or no training, as well as getting bullied (Denyer, 2018; McCurry, 2019; Zuo, 2019). The severity of this exploitation rose to such an extent that Japanese opposition parties stressed the abolishment of these issues under the current scheme before admission of new immigrant workers (Denyer, 2018). Hence, based on the economic model of crime, this implies that Asian immigrants are subject to much worse labour market outcomes relative to Japanese natives, which leads to a higher propensity for Asian immigrants to participate in crime for financial gain, i.e., property crime.

To show some robustness checks, Table 10 in Appendix E exhibits IV decomposed regression results for property crime by different controls. In column (1), a regression is performed without prefecture and year fixed effects where all estimates are significant. To account for unobserved heterogeneity across prefectures, column (2) includes prefecture fixed effects. The estimates undergo a tremendous change in magnitude, some change in sign, whilst all become not significant anymore as a result thereof. Adding year fixed effects to column (3) controls for unobserved heterogeneity over the years. It shows that the effects of all immigrant shares decrease in absolute values. When the demographic confounders are included in column (4), the coefficients of interest again experience an enormous change in magnitude where immigrant share Asia becomes significant. Addition of also the economic indicators and the crime clearance rate indicates that the estimates are robust to inclusion of control variables.

Lastly, Table 11 in Appendix E presents IV decomposed regression results for each type of crime, now measured in the number of reported crimes in logs and in levels. In both measures, each crime type experiences a change which corresponds to how the magnitude of its respective estimate in Table 9 compares to that of the other two crime types. That is, the estimates for property crime are close to those for total crime, while the estimates for violent crime are smaller in absolute values compared to those for property and total crime. Thus, these robustness checks also provide an indication that the estimates are robust to different measurements of crime.

4.2 Case study: South Korea (by continent)

Table 12 exhibits the OLS regressions of the baseline and decomposed specification by continent, controlled for all covariates and fixed effects. Results are interpreted in terms of standard deviation changes ex post where the standard deviations are taken from Table 3. Columns (1)-(3) show a negative crime impact of total immigrant share. However, the estimates are imprecise, the hypothesis that total share of immigrants has no effect on crime cannot be rejected at the 5% level.

When decomposing the total immigrant share into six source continents in columns (4)-(6), it is apparent that its negative impact on violent crime seems to find its roots from immigrants from Asia, North America, and Oceania, which are not significant, however. Moreover, the negative property crime impact of total immigrant share is reflected by immigrants from Asia and North America, significant for those from Asia. A 1 standard deviation increase in immigrant share from Asia is associated with a fall in the number of reported property crimes of 127.04 standard deviations on average, all else being equal. This contrasts the IV result found in the Japan case study. In order to potentially trace the origin of this contrasting result, the following paragraph examines the per continent impact of immigration by gender.

Table 12: OLS regressions of baseline and decomposed specification by continent

VARIABLES	(1) Total crime rate	(2) Violent crime rate	(3) Property crime rate	(4) Total crime rate	(5) Violent crime rate	(6) Property crime rate
Immigrant share total	-138.3	-24.75	-131.4			

	(185.1)	(44.09)	(81.03)			
Immigrant share Asia				-147.9	-53.47	-189.9**
				(237.9)	(49.12)	(87.96)
Immigrant share Europe				1,984	517.0	489.9
				(4,202)	(730.7)	(768.4)
Immigrant share North Am.				-4,985	-224.3	-48.61
				(5,727)	(976.6)	(1,063)
Immigrant share South Am.				43,763	1,942	4,093
				(41,790)	(9,655)	(10,631)
Immigrant share Oceania				-5,638	-436.4	8.778
				(11,547)	(2,205)	(2,320)
Immigrant share Africa				16,009	576.6	3,699
				(11,319)	(1,700)	(2,161)
Log total population	-733.5	-115.6	424.8	-380.4	109.5	695.6
	(2,340)	(446.1)	(719.7)	(2,383)	(511.1)	(854.5)
Young male	133.2	33.86	-48.29	-113.0	2.879	-115.7
	(451.4)	(82.53)	(122.2)	(453.4)	(82.10)	(107.5)
Marriage rate	-82.48	-26.69	51.03	35.10	-24.33	62.71
	(262.5)	(45.26)	(73.09)	(261.5)	(49.47)	(76.54)
Unemployment rate	-64.98	-36.12**	-41.14**	-5.794	-25.11*	-16.75
	(57.72)	(13.27)	(16.90)	(59.29)	(12.67)	(12.08)
Log real income per capita	1,153	-59.57	-277.7	-2.484	-154.4	-529.6*
	(1,623)	(170.0)	(237.3)	(1,297)	(210.5)	(257.9)
Total crime clearance	-35.81			-19.72		
	(25.75)			(28.47)		
Violent crime clearance		11.59**			10.45	
		(4.144)			(6.232)	
Property crime clearance			0.777			0.866
			(2.392)			(2.078)
Constant	-3,087	2,344	-378.8	11,893	1,062	521.0
	(30,785)	(6,404)	(11,074)	(32,177)	(6,324)	(10,152)
Province FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	113	113	113	113	113	113
R-squared	0.742	0.370	0.840	0.795	0.405	0.874

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

Table 13 in Appendix E shows the OLS regressions of the decomposed specifications by gender, and by gender and continent, controlled for all covariates and fixed effects. When total immigrant share is disaggregated by gender in columns (1)-(3), the interesting finding is that its negative effect on all crime types in Table 12 comes from female immigrants whilst male immigrants appear to increase them, significant for property crime. A 1 standard deviation increase in total female immigrant share is associated with a fall in the number of reported property crimes of 192.07 standard deviations on average, all else being equal. Furthermore, a

1 standard deviation increase in total male immigrant share is associated with a rise in the number of reported property crimes of 116.16 standard deviations on average, *ceteris paribus.*

When disaggregating total male immigrant share into six continents in columns (4)-(6), it is noticeable that its positive effect on total crime rate comes from male immigrants from Europe, South America, Oceania, and Africa, significant for those from Europe and Oceania. On the other hand, North American male immigrants tend to significantly decrease total crimes. Moreover, the positive violent crime impact of total male immigrant share is reflected by male immigrants from the same continents as for total crime, but only significant for those from Europe. A 1 standard deviation increase in male immigrant share from Europe is associated with a rise in the number of reported violent crimes of 67 standard deviations on average, all else being equal. In addition, the positive impact of total male immigrant share on property crime stems from male immigrants from all continents, except for Oceania, and only significant for those from Asia. A 1 standard deviation increase in male immigrant share from Asia is associated with an increase in the number of reported property crimes of 185.10 standard deviations on average, all else being equal.

Assessment of female immigrants in Columns (4)-(6) further show that female immigrants from Europe and Oceania significantly reduce total crime, which reflects the negative total female immigrant share impact in column (1). The negative violent crime impact of total female immigrants seems to come from those from all continents, except for Africa, although none is significant. Furthermore, the negative immigration impact of total female on property crime is derived from female immigrants from Asia and Africa, only significant for those from Asia. A 1 standard deviation increase in female immigrant share from Asia is associated with a fall in the number of reported property crimes of 250.65 standard deviations on average, *ceteris paribus*. Hence, it appears that the significant property crime reducing impact of immigration from Asia in Table 12 also originates from female immigrants. This raises the question as to whether in the Japan case study the effect of Asian immigrant share on property crime is also subject to such gender specific effects.

Likewise, due to endogeneity of the explanatory variables of interest in OLS, IV regressions are introduced with the intension to provide causal inference. Following Card (2001), the instruments used in this study are assumed exogeneous. To assess whether the IVs are strong predictors of the endogenous variables, Table 14 report the first stage regressions for both genders together, controlled for all covariates and fixed effects. Tables 15 and 16 in Appendix

E report the first stage regressions for male and female, respectively. It shows that, except for predicted female immigrant share from North America, all other predicted immigrant shares are irrelevant IVs as they have an F-statistic < 10. That is, these IVs do not predict their respective endogenous variable which implies that their IV estimates are not reliable. Hence, since all but one IV estimate is reliable, I will resume this case study with OLS robustness checks. For the sake of completeness, IV estimates by continent, as well as by gender, and by gender and continent are shown in Tables 17 and 18 in Appendix E, respectively.

Table 14: First stage regressions for both genders

VARIABLES	(1) Immigrant share total	(2) Immigrant share Asia	(3) Immigrant share Europe	(4) Immigrant share North Am.	(5) Immigrant share South Am.	(6) Immigrant share Oceania	(7) Immigrant share Africa
Immigrant $\widehat{\text{share}}$ total	0.106						
	(0.370)						
Immigrant $\widehat{\text{share}}$ Asia		0.0567					
		(0.349)					
Immigrant $\widehat{\text{share}}$ Europe			-1.175**				
			(0.419)				
Immigrant $\widehat{\text{share}}$ North Am.				-1.400			
				(2.005)			
Immigrant $\widehat{\text{share}}$ South Am.					0.831		
					(0.691)		
Immigrant $\widehat{\text{share}}$ Oceania						2.429*	
						(1.372)	
Immigrant $\widehat{\text{share}}$ Africa							0.357
							(0.302)
Constant	-79.71*	-76.46*	-0.102	1.020	-0.0812	-0.719	-1.351
	(41.81)	(40.31)	(2.730)	(3.032)	(0.128)	(0.526)	(0.886)
Controls	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	113	113	113	113	113	113	113
R-squared	0.835	0.842	0.614	0.444	0.445	0.558	0.730
F-statistic	0.08	0.03	7.86	0.49	1.45	3.14	1.40

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

To show some robustness checks, Table 19 in Appendix E exhibits OLS decomposed regressions of property crime rate by gender and different controls. In column (1), a regression is performed without fixed effects. When province fixed effects are included in column (2), all coefficients change drastically, and that of female immigrant share Asia becomes significant. Another substantial change in magnitude is observable when year fixed effects are included in column (3). Including demographic confounders in column (4) makes the estimate of male immigrant share Asia significant and that of Asian female immigration more precise, whilst both increase in absolute values. Addition of also the economic indicators and the crime clearance rate indicates that these significant estimates are robust to inclusion of covariates.

Lastly, Table 20 in Appendix E presents OLS decomposed regression results by gender for each type of crime, now measured in the number of reported crimes in logs and in levels. When assessing the log of crime, almost all estimates exhibit identical sign and significance as those in columns (4)-(6) in Table 13. In levels, however, the coefficients seem less persistent. Thus, these robustness checks also provide an indication that the estimates are somewhat robust to different measurements of crime.

4.3 Case study: South Korea (by income class)

Table 21 exhibits the OLS regressions of the baseline and decomposed specification by income class, controlled for all covariates and fixed effects. Results are interpreted in terms of standard deviation changes ex post where the standard deviations are taken from Table 5. Columns (1)-(3) show the same regressions with the negative insignificant crime impact of total immigrant share as in Table 10.

When decomposing the total immigrant share into four income classes in columns (4)-(6), it is apparent that its negative impact on violent crime seems to find its roots from immigrants from upper middle income class, which is significant. A 1 standard deviation increase in immigrant share from upper middle income class is associated with a fall in the number of reported violent crimes of 68.43 standard deviations on average, all else being equal. Furthermore, the negative property crime impact of total immigrant share is reflected by immigrants from upper and lower middle income class, significant for those from the former. A 1 standard deviation increase in immigrant share from upper middle income class is associated with a fall in the number of reported property crimes of 190.22 standard deviations on average, all else being equal. In order to potentially trace the origin of these results, the following paragraph examines the per income class impact of immigration by gender.

Table 21: OLS regressions of baseline and decomposed specification by income class

VARIABLES	(1) Total crime rate	(2) Violent crime rate	(3) Property crime rate	(4) Total crime rate	(5) Violent crime rate	(6) Property crime rate
Immigrant share total	-138.3	-24.75	-131.4			

	(185.1)	(44.09)	(81.03)			
Immigrant share high inc.				549.8	295.0	425.2
				(1,002)	(186.0)	(290.7)
Immigrant share upper middle inc.				-278.1	-131.6**	-365.8***
				(305.5)	(54.83)	(90.66)
Immigrant share lower middle inc.				-78.71	12.89	-27.84
				(479.9)	(83.99)	(138.7)
Immigrant share low inc.				-4,483	798.5	3,333
				(13,220)	(2,007)	(3,237)
Log total population	-733.5	-115.6	424.8	311.7	321.5	1,191*
	(2,340)	(446.1)	(719.7)	(2,796)	(450.7)	(660.4)
Young male	133.2	33.86	-48.29	78.82	-10.73	-142.8
	(451.4)	(82.53)	(122.2)	(504.8)	(92.02)	(114.5)
Marriage rate	-82.48	-26.69	51.03	-120.9	-34.37	45.85
	(262.5)	(45.26)	(73.09)	(266.7)	(42.76)	(71.10)
Unemployment rate	-64.98	-36.12**	-41.14**	-54.07	-27.15**	-21.17
	(57.72)	(13.27)	(16.90)	(63.73)	(12.31)	(13.92)
Log real income per capita	1,153	-59.57	-277.7	1,099	-71.89	-295.6*
	(1,623)	(170.0)	(237.3)	(1,653)	(171.5)	(162.5)
Total crime clearance	-35.81			-33.18		
	(25.75)			(26.02)		
Violent crime clearance		11.59**			12.62***	
		(4.144)			(4.284)	
Property crime clearance			0.777			0.779
			(2.392)			(2.030)
Constant	-3,087	2,344	-378.8	-16,945	-3,448	-10,340
	(30,785)	(6,404)	(11,074)	(30,600)	(5,677)	(8,782)
Province FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	113	113	113	113	113	113
R-squared	0.742	0.370	0.840	0.745	0.414	0.871

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

Table 22 in Appendix E shows the OLS regressions of the decomposed specifications by gender, and by gender and income class, controlled for all covariates and fixed effects. Columns (1)-(3) show the same regressions with the gender specific impact of total immigration on crime as in Table 13.

When disaggregating total male immigrant share into four income classes in columns (4)-(6), it is noticeable that its positive effect on total crime rate comes from male immigrants from high and lower middle income classes, although not significant. On the other hand, low income class male immigrants tend to significantly decrease total crimes: A 1 standard deviation increase in male immigrant share from low income countries is associated with a fall in the number of reported total crimes of 113 standard deviations on average, *ceteris paribus.*

Moreover, the positive violent crime impact of total male immigrant share is reflected by male immigrants from the same income classes as for total crime, but also none is significant. In addition, the positive impact of total male immigrant share on property crime stems from male immigrants from upper and middle income countries, where significance is neither found.

Assessment of female immigrants in columns (4)-(6) further show that the negative total female immigrant share impact on total and violent crime is derived from female immigrants from high and lower middle income countries, though none is significant. In contrast, low income class female immigrants tend to significantly raise violent crimes: A 1 standard deviation increase in female immigrant share from low income countries is associated with an increase in the number of reported violent crimes of 39.13 standard deviations on average, *ceteris paribus.* Additionally, the negative impact of total female immigrant share on property crime stems from female immigrants from upper and lower middle income countries, significant for those from the former. A 1 standard deviation increase in female immigrant share from upper middle income countries is associated with a reduction in the number of reported property crimes of 209.51 standard deviations on average, *ceteris paribus.* Hence, it appears that the significant property crime reducing impact of immigration from upper middle income class in Table 21 originates from female immigrants. On the other hand, low income class female immigrants tend to also raise property crimes significantly: A 1 standard deviation increase in female immigrant share from low income countries is associated with an increase in the number of reported property crimes of 64.20 standard deviations on average, *ceteris paribus.*

To show some robustness checks, Table 23 in Appendix E exhibits OLS decomposed regressions of property crime rate by gender and different controls. In column (1), a regression is performed without fixed effects. When province fixed effects are included in column (2), all coefficients change drastically, and some change in significance. Similar alterations are observable where low income class female immigration becomes significant after including year fixed effects in column (3). Including demographic confounders in column (4) makes the estimate of upper middle income class female immigrant share significant and increase in absolute values, whereas that of low income countries decreases. Addition of also the economic indicators and the crime clearance rate indicates that these significant estimates are robust to inclusion of covariates.

Lastly, Table 24 in Appendix E presents OLS decomposed regression results by gender for each type of crime, now measured in the number of reported crimes in logs and in levels. When assessing the log of crime, almost all estimates exhibit identical sign and significance as those in columns (4)-(6) in Table 22. In levels, however, the persistence of coefficients seems less convincing. Thus, these robustness checks also provide an indication that the estimates are more or less robust to different measurements of crime.

V. Conclusion

Japan and South Korea have fallen victim to the demographic conundrum due to their fast-ageing population and low fertility rate, as well as their record-high death counts and life expectancy. To avoid further economic recession as a result thereof, a voice for immigration was raised in Japan, and migrants are gradually accepted in South Korea, even though both nations are ethnically and linguistically homogenous. However, wariness of the immigrant inflow has also been present as almost half of Japanese natives say that immigrants are more responsible for crime occurrences compared to others, whilst South Koreans who think immigrants jeopardise public safety are more likely to develop nationalistic sentiments. It is of huge academic and social interest to assess whether this is actually the case or just stigma. Therefore, this thesis aims to answer the research question: "*What is the impact of immigration on crime?"*.

From the Japan case study, IV regressions for the decomposed specification show that, a 1 standard deviation increase in immigrant share from Asia is associated with a rise in the number of reported property crimes of 1014.25 standard deviations on average, *ceteris paribus*. Based on the economic model of crime, since Asian immigrants are subject to much worse labour market outcomes relative to Japanese natives, this leads to a higher propensity for Asian immigrants to participate in crime for financial gain, i.e., property crime.

From the South Korea case study by continent, OLS regressions of the decomposed specification by continent exhibit a negative property crime impact of immigrant share from Asia, which contrasts the IV result found in the Japan case study. Disaggregated further by gender and continent reveals that this contrasting result originates from female immigrants who decrease property crimes, whereas male immigrants appear to increase them. In addition, male immigrants from Europe seem to raise violent crimes.

From the South Korea case study by income class, the OLS regressions of the decomposed specification by income class indicate a violent crime and property crime reducing impact of immigrants from upper middle income class. Moreover, when disaggregated by gender and income class, female immigrants from low income class tend to raise violent crimes and property crimes, whereas those from upper middle income class decrease property crime. Hence, this suggests that the negative property crime impact of immigrants from upper middle income class originates from female immigrants.

Nevertheless, this paper is subject to a number of caveats which indicates that the aforementioned results should be interpreted with caution. In the Japan case study, a major caveat is that the instrument for immigrant share from Asia has a weak first stage, meaning that its IV estimate is not reliable. In both Korea case studies, the immigrant share variables are likely to be endogenous and hence a threat to identification of a causal effect on crime rate. In OLS, there can be measurement error in counting the number of immigrants by the census which biases the estimates of the share of immigrants. Additionally, OVB can still be an issue after accounting for several factors of crime and fixed effects. Lastly, endogeneity in the settlement pattern of immigrants is another matter of concern. Concerning the Korea case study by continent specifically, its IVs appeared to be completely irrelevant despite the fact that they are constructed following Altonji and Card (1991) and Card (2001), who are known for their instruments to be a strong predictor of prospective immigrants' choice of destination. A potential explanation for this contrasting result might be because the instrument is constructed with the year 2012, which is just one year prior to the period of study. As a consequence, when the past immigrants have settled at first, this one year does not allow for a sufficiently long timespan for the new immigrants to be aware of these ethnic clusters and settle therein. Hence, we should be cautious about drawing policy conclusions from this paper and additional research is warranted.

Regarding recommendations for future research, it is of interest to assess for the case of Japan whether the effect of Asian immigrant share on property crime is also subject to gender specific effects, as it is for Korea. Furthermore, it would be of substantial value added to come up with a valid IV to instrument for immigrants by income class. Lastly, a reanalysis of the Korea case study by continent many years later from now would provide data on more years than there are available at this point. This may facilitate a proper implementation of the instrumental variables approach using an IV that is constructed with a year that does allow for a sufficiently long timespan for the new immigrants to be aware of the established ethnic clusters and settle therein.

VI. Bibliography

Alonso-Borrego, C., Garoupa, N., & Vázquez, P. (2012). Does immigration cause crime? Evidence from Spain. *American Law and Economics Review, 14*(1), 165-191.

Altonji, J. G., & Card, D. (1991). *The effects of immigration on the labor market outcomes of natives* (NBER Working Paper No. 3123). National Bureau of Economic Research.

Baker, S.R. (2015), "Effects of Immigrant Legalization on Crime", *American Economic Review 105*(5): 210–13.

Bartel, A. P. (1989). Where do the new US immigrants live?. *Journal of Labor Economics, 7*(4), 371-391.

Becker, G.S. (1968). Crime and Punishment: An Economic Approach. *Journal of Political Economy 76*(2): 169–217

Bell, B., Fasani, F., & Machin, S. (2013). Crime and immigration: Evidence from large immigrant waves. *Review of Economics and Statistics*, *21*(3), 1278-1290.

Bianchi, M., Buonanno, P., & Pinotti, P. (2012). Do immigrants cause crime?. *Journal of the European Economic Association*, *10*(6), 1318-1347.

Caponi, V. & Plesca, M. (2014). Empirical Characteristics of Legal and Illegal Immigrants in the USA. *Journal of Population Economics 27*(4): 923–960.

Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics*, *19*(1), 22-64.

Chalfin, A. (2014). What is the contribution of Mexican immigration to US crime rates? Evidence from rainfall shocks in Mexico. *American Law and Economics Review*, *16*(1), 220-268.

Chalfin, A. (2015). The long-run effect of Mexican immigration on crime in US cities: Evidence from variation in Mexican fertility rates. *American Economic Review*, *105*(5), 220-25.

Chiu, W. H., & Madden, P. (1998). Burglary and income inequality. *Journal of Public Economics*, *69*(1), 123-141.

D'Ambrogio, E. (2020). *Japan's ageing society*. Brussel: European Union.

Delvin, K., & Stokes, B. (2018). *Despite Rising Economic Confidence, Japanese See Best Days Behind Them and Say Children Face a Bleak Future*. Washington, D.C.: Pew Research Center.

Denyer, S. (2018, 12 7). *Japan passes controversial new immigration bill to attract foreign workers*. Retrieved from The Washington Post: https://www.washingtonpost.com/gdpr-consent/?next_url=https%3a%2f%2fwww.washingtonpost.com%2fworld%2fjapan-passes-controversial-new-immigration-bill-to-attract-foreign-workers%2f2018%2f12%2f07%2fa76d8420-f9f3-11e8-863a-8972120646e0_story.html

Di Tella, R., Edwards, S., & Schargrodsky, E. (Eds.). (2010). *The economics of crime: Lessons for and from Latin America*. University of Chicago Press.

Ehrlich, I. (1973). Participation in illegitimate activities: A theoretical and empirical investigation. *Journal of Political Economy*, *81*(3), 521-565.

Ehrlich, I. (1996). Crime, punishment, and the market for offenses. *Journal of Economic Perspectives*, *10*(1), 43-67.

Farrington, D. P. (1986). Age and crime. *Crime and justice*, *7*, 189-250.

Fougère, D., Kramarz, F., & Pouget, J. (2009). Youth unemployment and crime in France. *Journal of the European Economic Association*, *7*(5), 909-938.

Freeman, R. B. (1999). The Economics of Crime. *Handbook of Labor Economics*, *3*, 3529-3571.

Glaeser, E. L., & Sacerdote, B. (1999). Why is there more crime in cities?. *Journal of Political Economy*, *107*(S6), S225-S258.

Gould, E. D., Weinberg, B. A., & Mustard, D. B. (2002). Crime rates and local labor market opportunities in the United States: 1979–1997. *Review of Economics and Statistics*, *84*(1), 45-61.

Grogger, J. (1998). Market wages and youth crime. *Journal of Labor Economics, 16*(4), 756-791.

Hirschi, T., & Gottfredson, M. (1983). Age and the explanation of crime. *American Journal of Sociology*, *89*(3), 552-584.

IMF Special Data Dissemination Standard Plus: Japan. (2021, 07 20). Retrieved from IMF DISSEMINATION STANDARDS BULLETIN BOARD (DSBB): https://dsbb.imf.org/sdds-plus/dqaf-base/country/JPN/category/EMP00

Jozuka, E., Kwon, J., & Yeung, J. (2019, 12 30). *Japan's birth rate hits another record low in 2019*. Retrieved from CNN: https://edition.cnn.com/2019/12/25/asia/japan-birthrate-hnk-intl/index.html

Kelly, M. (2000). Inequality and crime. *Review of Economics and Statistics*, *82*(4), 530-539.

Kontis, V., Bennett, J., Mathers, C., Li, G., Foreman, K., & Ezzati, M. (2017, 02 21). Future life expectancy in 35 industrialised countries: projections with a Bayesian model ensemble. *The Lancet*, 1323-1335.

Levitt, S. D. (2002). Using electoral cycles in police hiring to estimate the effects of police on crime: Reply. *American Economic Review*, *92*(4), 1244-1250.

Lochner, L., & Moretti, E. (2004). The effect of education on crime: Evidence from prison inmates, arrests, and self-reports. *American Economic Review*, *94*(1), 155-189.

Machin, S., & Meghir, C. (2004). Crime and economic incentives. *Journal of Human Resources*, *39*(4), 958-979.

Machin, S., Marie, O., & Vujić, S. (2011). The crime reducing effect of education. *The Economic Journal*, *121*(552), 463-484.

Mastrobuoni, G. & Pinotti, P. (2015). Legal Status and the Criminal Activity of Immigrants. *American Economic Journal: Applied Economics 7*(2): 175–206.

McCurry, J. (2019, 01 02). *Fears of exploitation as Japan prepares to admit foreign workers*. Retrieved from The Guardian: https://www.theguardian.com/world/2019/jan/02/fears-of-exploitation-as-japan-prepares-to-admit-foreign-workers

National Statistics, Republic of China (Taiwan) (2021). *Latest indicators: Per Capita GNI (US dollars).* Retrieved from: https://eng.stat.gov.tw/point.asp?index=1

OECD (2021), *Unemployment rate (indicator).* Retrieved from: https://data.oecd.org/unemp/unemployment-rate.htm

Ozden, C., Testaverde, M., & Wagner, M. (2018). How and why does immigration affect crime? Evidence from Malaysia. *The World Bank Economic Review*, *32*(1), 183-202.

Pinotti, P. (2016). Immigrants and crime. In F. Fasani, *Refugees and Economic Migrants: Facts, policies and challenges* (pp. 115-123). London: CEPR Press.

Pinotti, P. (2017). Clicking on heaven's door: The effect of immigrant legalization on crime. *American Economic Review*, *107*(1), 138-68.

Population Census of Japan (2010). *Population Census of Japan.* Tokyo: Statistics Bureau of Japan.

Power, J. (2019, 05 11). *Why South Korea and Japan are slowly learning to accept foreign workers*. Retrieved from South China Morning Post: https://www.scmp.com/week-asia/economics/article/3009799/how-korea-and-japan-learned-stop-worrying-and-love-foreign

Quick, M. (2019, 10 14). *South Korea's population paradox*. Retrieved from BBC Worklife: The Generation Project: https://www.bbc.com/worklife/article/20191010-south-koreas-population-paradox

Raphael, S., & Winter-Ebmer, R. (2001). Identifying the effect of unemployment on crime. *The Journal of Law and Economics*, *44*(1), 259-283.

S.B. (2018, 07 13). *Why Japan is going to accept more foreign workers*. Retrieved from The Economist: https://www.economist.com/the-economist-explains/2018/07/13/why-japan-is-going-to-accept-more-foreign-workers

Shang, E., & Seung, J. (2015). Immigration, threat perception, and national identity: Evidence from South Korea. *International Journal of Intercultural Relations*, 53-62.

Song, J. (2019, 08 28). *South Korea's birth rate falls to new developed world low*. Retrieved from Financial Times: https://www-ft-com.eur.idm.oclc.org/content/16505438-c96c-11e9-a1f4-3669401ba76f

Spenkuch, J. L. (2014). Understanding the impact of immigration on crime. *American Law and Economics Review, 16*(1), 177-219.

Statistics Bureau of Japan. (2021). *e-Stat Portal Site of Official Statistics of Japan.* Retrieved from: https://www.e-stat.go.jp/en/regionalstatistics/ssdsview/prefectures

Statistics Korea. (2021). *KOSIS Portal Site of Official Statistics of Korea.* Retrieved from: https://kosis.kr/eng/index/index.do

Stock, J. H., & Watson, M. W. (2015). *Introduction to Econometrics*. New York: Pearson.

United Nations Statistics Division (2021). *Standard country or area codes for statistical use (M49).* Retrieved from: https://unstats.un.org/unsd/methodology/m49/

Wolpin, K. I. (1978). An economic analysis of crime and punishment in England and Wales, 1894-1967. *Journal of Political Economy*, *86*(5), 815-840.

World Bank (2021a). *World Bank Country and Lending Groups.* Retrieved from: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups

World Bank (2021b). *GNI per capita, Atlas method (current US$).* Retrieved from: https://data.worldbank.org/indicator/NY.GNP.PCAP.CD?name_desc=false

World Bank (2021c). *The World Bank Atlas method - detailed methodology.* Retrieved from: https://datahelpdesk.worldbank.org/knowledgebase/articles/378832-what-is-the-world-bank-atlas-method

Yamamoto, R. (2010). Migrants as a Crime Problem: The Construction of Foreign Criminality Discourse in Contemporary Japan. *International Journal of Comparative and Applied Criminal Justice*, 301-330.

Yamamoto, R., & Johnson, D. (2014). The Convergence of Control: Immigration and Crime in Contemporary Japan. In S. Bucerius, & M. Tonry, *The Oxford Handbook of Ethnicity, Crime, and Immigration* (pp. 738-765). New York: Oxford University Press.

Zuo, N. (2019, 08 25). *Migrant workers 'exploited' in Japan*. Retrieved from BBC: https://www.bbc.com/news/av/world-asia-49448757

VII. Appendices

Appendix A: Description of the variables

A.1 Case study: Japan

$crimerate_{it}$: crime rate defined as (number of reported crimes / total population) × 100,000 persons per prefecture per year. Three types of crimes are studied: total crime, violent crime, and property crime. Total crime consists of violent, property, and other crime. Violent crime is decomposed into homicide, arson, robbery, rape, assault, mass atrocity crimes (genocide, war crimes, and crimes against humanity), coercion, extortion, and blackmail. Property crime concerns theft. Other crime is disaggregated into intellectual offences (fraud, embezzlement, forgery, bribery, abuse of authority, breach of trust) and moral offences (gambling, obscenity) (Statistics Bureau of Japan, 2021).

$immigrantshare_{it}$: total share of immigrants defined as (total number of immigrants / total population) × 100 per prefecture per year. The Population Census of Japan (2010) uses the "*de jure* population concept for enumerating the people. That is, a person was enumerated at the place where he or she usually lived, and was counted as the population of the area including the place. The term "persons usually living" was defined in the census as those persons who had lived or were going to live for three months or more at their respective households at the census date. Persons who had no usual places of living in this sense were enumerated at the places where they were present at the date of the census" (p. 439).

$immigrantshare^{c}_{it}$: share of immigrants from source continent c defined as (number of immigrants from source continent c / total population) × 100 per prefecture per year, where c = Asia, Europe, North America, South America, other. The Population Census of Japan (2010) uses *de jure* enumeration.

$\ln(totalpopulation_{it})$: log of total population per prefecture per year. The Population Census of Japan (2010) uses *de jure* enumeration.

$youngmaleshare_{it}$: share of male aged 15-29 defined as (male population aged 15-29 / total population) × 100 per prefecture per year. The Population Census of Japan (2010) uses *de jure* enumeration.

$marriagerate_{it}$: crude marriage rate defined as (number of marriages / total population) × 1,000 persons per prefecture per year (Statistics Bureau of Japan, 2021).

$unemploymentrate_{it}$: unemployment rate defined as (unemployed persons / labour force) × 100 per prefecture per year. Based on Japan's Labour Force Survey, the IMF (2021) defines an unemployed person as someone "with no job and did no work at all during the reference week; ready to work if work is available; and did any job seeking activity or preparing to start business during the reference week (including waiting the outcome of job seeking activity done in the past)" (p.). The labour force consists of "The sum of Employed person and Unemployed person" (IMF, 2021, p.)

$\ln(realincomepc_{it})$: log of real income per capita in JPY, defined as log of (annual gross income inflated to 2015 JPY using the consumer price index / total population) per prefecture per year (Statistics Bureau of Japan, 2021).

$clearancerate_{it}$: crime clearance rate defined as (number of crimes cleared by police / number of reported crimes) × 100 per prefecture per year. Three types of crimes are studied: total crime, violent crime, and property crime (Statistics Bureau of Japan, 2021).

A.2 Case study: South Korea

$crimerate_{it}$: crime rate defined as (number of reported crimes / total population) × 100,000 persons per province per year. Three types of crimes are studied: total crime, violent crime, and property crime. Total crime consists of violent, property, and other crime. Violent crime is decomposed into homicide, arson, robbery, rape, assault, extortion, abduction, coercion, intrusion, infliction, and organisational crime. Property crime concerns breaches of trust, frauds, intentional property damage, theft, and embezzlement. Other crime is disaggregated into forgery, bribery, abuse of authority, obscenity, gambling, crime negligence, obstruction of official duties, obstruction of traffic, crime against the public, crime of rebellion or insurrection, interference with the exercise of the rights of others, escape and concealment of criminals, false accusation, violation of secrecy, perjury and destruction of evidence, abandonment, crime involving drinking water, other utilisation of water and inundation (Statistics Korea, 2021).

$immigrantshare^{g}_{it}$: total share of immigrants g defined as (total number of immigrants g / total population) × 100 per province per year, where g = both genders, male, female. The Population Census of Korea uses *de jure* enumeration, i.e., a person was enumerated whose period in the residence or period intended to reside at a fixed location is greater than three months at the census date. In line with the rules, all Korean and foreign residents residing within the territory of Korea were enumerated (Statistics Korea, 2021).

immigrantshare$^{g,c}_{it}$: (1) total share of immigrants g from continent c defined as (total number of immigrants g from continent c / total population) × 100 per province per year, where g = both genders, male, female, and c = Asia, Europe, North America, South America, Oceania, Africa; (2) total share of immigrants g from income class c defined as (total number of immigrants g from income class c / total population) × 100 per province per year, where g = both genders, male, female, and c = high income, upper middle income, lower middle income, low income. The Population Census of Korea uses *de jure* enumeration (Statistics Korea, 2021).

ln*(totalpopulation*$_{it}$*)*: log of total population per province per year. The Population Census of Korea uses *de jure* enumeration (Statistics Korea, 2021).

youngmaleshare$_{it}$: share of male aged 15-29 defined as (male population aged 15-29 / total population) × 100 per province per year. The Population Census of Korea uses *de jure* enumeration (Statistics Korea, 2021).

marriagerate$_{it}$: crude marriage rate defined as (number of marriages / total population) × 1,000 persons per province per year (Statistics Korea, 2021).

unemploymentrate$_{it}$: unemployment rate defined as (unemployed persons / economically active population) × 100 per province per year, where economically active population is employed persons + unemployed persons. (Statistics Korea, 2021).

ln*(realincomepc*$_{it}$*)*: log of real income per capita in KRW, defined as log of (annual gross income inflated to 2015 KRW using the consumer price index / total population) per province per year (Statistics Korea, 2021).

clearancerate$_{it}$: crime clearance rate defined as (number of crimes cleared by police / number of reported crimes) × 100 per province per year. Three types of crimes are studied: total crime, violent crime, and property crime (Statistics Korea, 2021).

Appendix B: List of countries by continent (based on United Nations Statistics Division)

Asia: Bahrain, Brunei Darussalam, Cyprus, Hong Kong, Israel, Japan, Kuwait, Macao, Oman, Qatar, Saudi Arabia, Singapore, Taiwan, United Arab Emirates, China, Georgia, Indonesia, Iran, Iraq, Jordan, Kazakhstan, Lebanon, Malaysia, Maldives, Thailand, Turkey, Turkmenistan, Bangladesh, Bhutan, Cambodia, India, Laos, Mongolia, Myanmar, Nepal, Pakistan, Philippines, Sri Lanka, Timor-Leste, Uzbekistan, Afghanistan, Syria, Tajikistan, Yemen, Azerbaijan, Armenia, Vietnam, Kyrgyzstan, Palestine[3]

Europe: Andorra, Austria, Belgium, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Switzerland, United Kingdom, Albania, Belarus, Bosnia and Herzegovina, Bulgaria, Kosovo, Montenegro, North Macedonia, Russia, Serbia, Moldova, Ukraine

North America: Antigua and Barbuda, Bahamas, Barbados, Canada, St. Kitts and Nevis, Trinidad and Tobago, United States, Belize, Costa Rica, Cuba, Dominica, Dominican Republic, Grenada, Guatemala, Jamaica, Mexico, St. Lucia, El Salvador, Honduras, Nicaragua, Haiti, Panama

South America: Chile, Uruguay, Argentina, Brazil, Colombia, Ecuador, Guyana, Paraguay, Peru, Suriname, Venezuela, Bolivia

Oceania: Australia, Nauru, New Zealand, Palau, Fiji, Tonga, Samoa, Kiribati, Papua New Guinea, Solomon Islands, Vanuatu

Africa: Mauritius, Seychelles, Botswana, Equatorial Guinea, Gabon, Libya, Namibia, South Africa, Algeria, Angola, Benin, Cameroon, Comoros, Republic of the Congo, Cote d'Ivoire, Djibouti, Egypt, Eswatini, Ghana, Kenya, Cape Verde, Lesotho, Mauritania, Morocco, Nigeria, Senegal, Tanzania, Tunisia, Zambia, Zimbabwe, Burkina Faso, Burundi, Central African Republic, Chad, Democratic Republic of the Congo, Eritrea, Ethiopia, Gambia, Guinea, Guinea-Bissau, Liberia, Madagascar, Malawi, Mali, Mozambique, Niger, Rwanda, Sierra Leone, Somalia, South Sudan, Sudan, Togo, Uganda

[3] West Bank and Gaza

Appendix C: List of countries by income class (based on World Bank Atlas method)

High income countries (GNI per capita ≥ $12,536): Andorra, Australia, Antigua and Barbuda, Austria, Bahamas, Bahrain, Barbados, Belgium, Brunei Darussalam, Canada, Chile, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, Ireland, Israel, Italy, Japan, Kuwait, Latvia, Lithuania, Luxembourg, Macao, Malta, Mauritius, Nauru, Netherlands, New Zealand, Norway, Oman, Palau, Panama, Poland, Portugal, Qatar, Romania, Saudi Arabia, Seychelles, Singapore, Slovakia, Slovenia, Spain, St. Kitts and Nevis, Switzerland, Trinidad and Tobago, United Arab Emirates, United Kingdom, United States, Uruguay, Taiwan[4]

Upper middle income countries ($4,046 ≤ GNI per capita ≤ $12,535): Albania, Argentina, Armenia, Azerbaijan, Belarus, Belize, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, China, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, Equatorial Guinea, Fiji, Gabon, Georgia, Grenada, Guatemala, Guyana, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kosovo, Lebanon, Libya, Malaysia, Maldives, Mexico, Montenegro, Namibia, North Macedonia, Paraguay, Peru, Russia, Serbia, South Africa, St. Lucia, Suriname, Thailand, Tonga, Turkey, Turkmenistan, Samoa, Venezuela

Lower middle income countries ($1,036 ≤ GNI per capita ≤ $4,045): Algeria, Angola, Bangladesh, Benin, Bhutan, Bolivia, Cambodia, Cameroon, Comoros, Republic of the Congo, Cote d'Ivoire, Djibouti, Egypt, El Salvador, Eswatini, Ghana, Honduras, India, Kenya, Kiribati, Kyrgyzstan, Cape Verde, Laos, Lesotho, Mauritania, Moldova, Mongolia, Morocco, Myanmar, Nepal, Nicaragua, Nigeria, Pakistan, Papua New Guinea, Philippines, Senegal, Solomon Islands, Sri Lanka, Tanzania, Timor-Leste, Tunisia, Ukraine, Uzbekistan, Vanuatu, Vietnam, Zambia, Zimbabwe, Palestine

Low income countries (GNI per capita ≤ $1,035): Afghanistan, Burkina Faso, Burundi, Central African Republic, Chad, Democratic Republic of the Congo, Eritrea, Ethiopia, Gambia, Guinea, Guinea-Bissau, Haiti, Liberia, Madagascar, Malawi, Mali, Mozambique, Niger, Rwanda, Sierra Leone, Somalia, South Sudan, Sudan, Syria, Tajikistan, Togo, Uganda, Yemen

[4] World Bank does not recognise Taiwan as a separate country, hence no provision of its GNI per capita. Instead, I obtained its GNI per capita of 26594 in current USD from the National Statistics, Republic of China (Taiwan) (2021).

Appendix D: Descriptive statistics

D.1 Case study: Japan

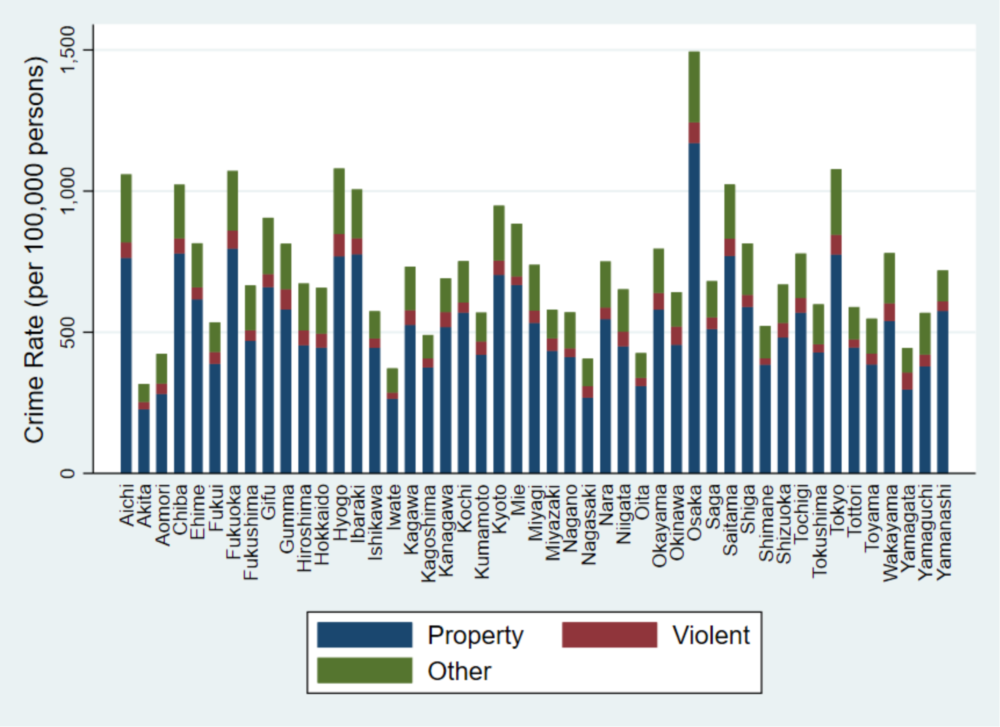

Figure 2: Average crime rate per prefecture by crime type

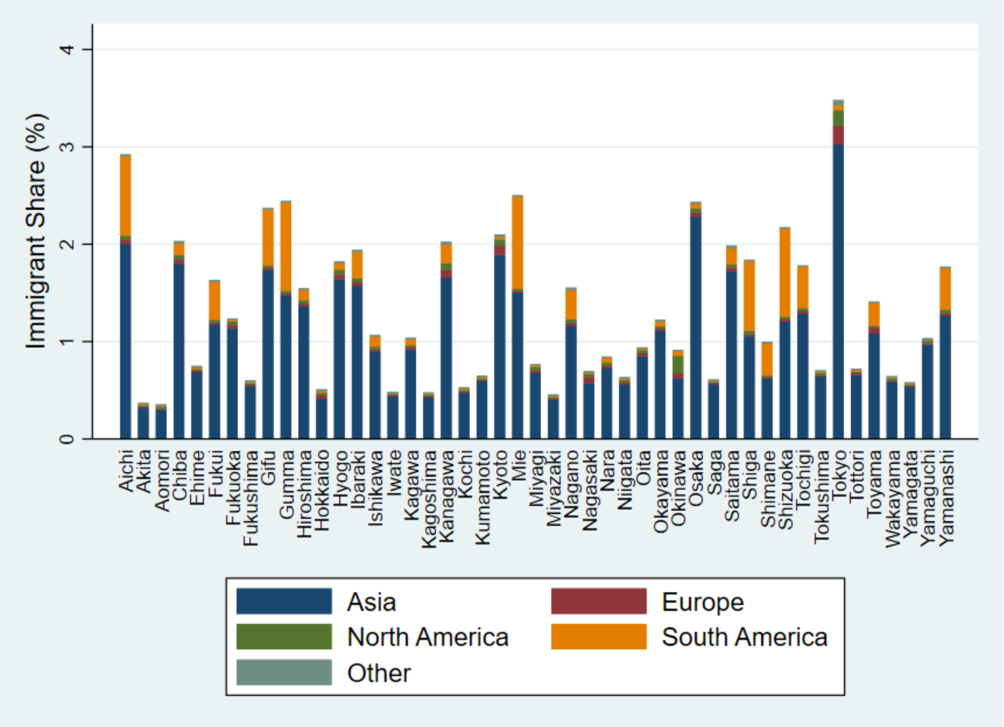

Figure 4: Average immigrant share per prefecture by source continent

Table 2: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Total crime rate	1.000								
(2) Violent crime rate	0.624	1.000							
(3) Property crime rate	0.994	0.571	1.000						
(4) Immigrant share total	0.485	0.398	0.467	1.000					
(5) Immigrant share Asia	0.524	0.456	0.507	0.953	1.000				
(6) Immigrant share Europe	0.239	0.320	0.216	0.554	0.649	1.000			
(7) Immigrant share North America	0.185	0.375	0.164	0.403	0.450	0.721	1.000		
(8) Immigrant share South America	0.174	0.047	0.168	0.636	0.379	-0.065	-0.053	1.000	
(9) Immigrant share other	0.343	0.359	0.328	0.628	0.725	0.809	0.646	0.003	1.000
(10) Total population	0.556	0.542	0.532	0.643	0.740	0.685	0.510	0.050	0.801
(11) Young male	0.608	0.497	0.593	0.638	0.642	0.485	0.560	0.278	0.531
(12) Marriage rate	0.640	0.561	0.622	0.460	0.488	0.542	0.671	0.088	0.536
(13) Unemployment rate	0.488	0.364	0.489	-0.192	-0.128	0.104	0.300	-0.316	0.098
(14) Real income per capita	0.640	0.483	0.619	0.828	0.865	0.639	0.398	0.324	0.685
(15) Total crime clearance rate	-0.779	-0.413	-0.773	-0.491	-0.531	-0.273	-0.172	-0.174	-0.372
(16) Violent crime clearance rate	-0.730	-0.366	-0.724	-0.425	-0.448	-0.271	-0.260	-0.158	-0.375
(17) Property crime clearance rate	-0.760	-0.476	-0.753	-0.507	-0.561	-0.327	-0.248	-0.137	-0.422

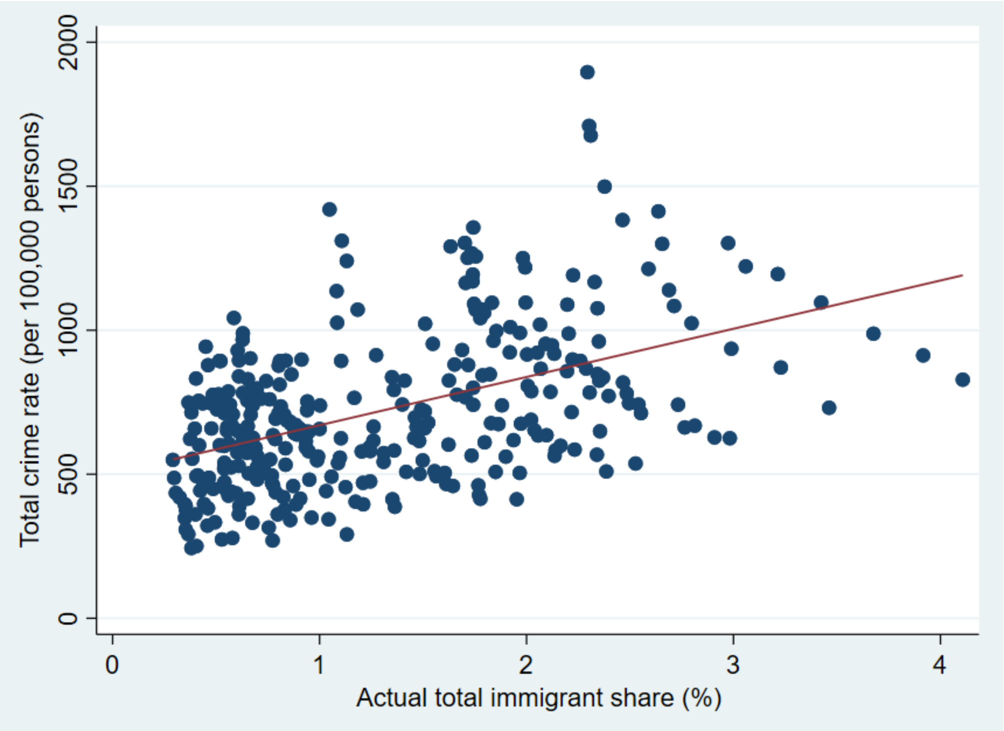

Figure 5: Scatterplot of total crime rate and actual total immigrant share with fitted line

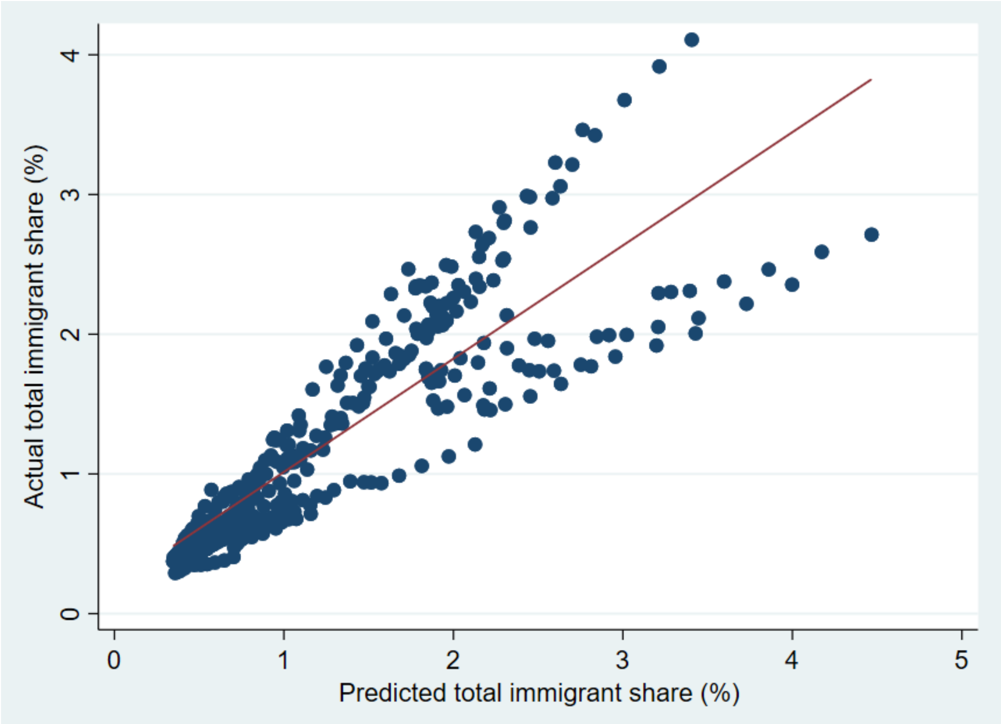

Figure 6: Scatterplot of actual and predicted total immigrant share with fitted line

D.2 Case study: South Korea (by continent)

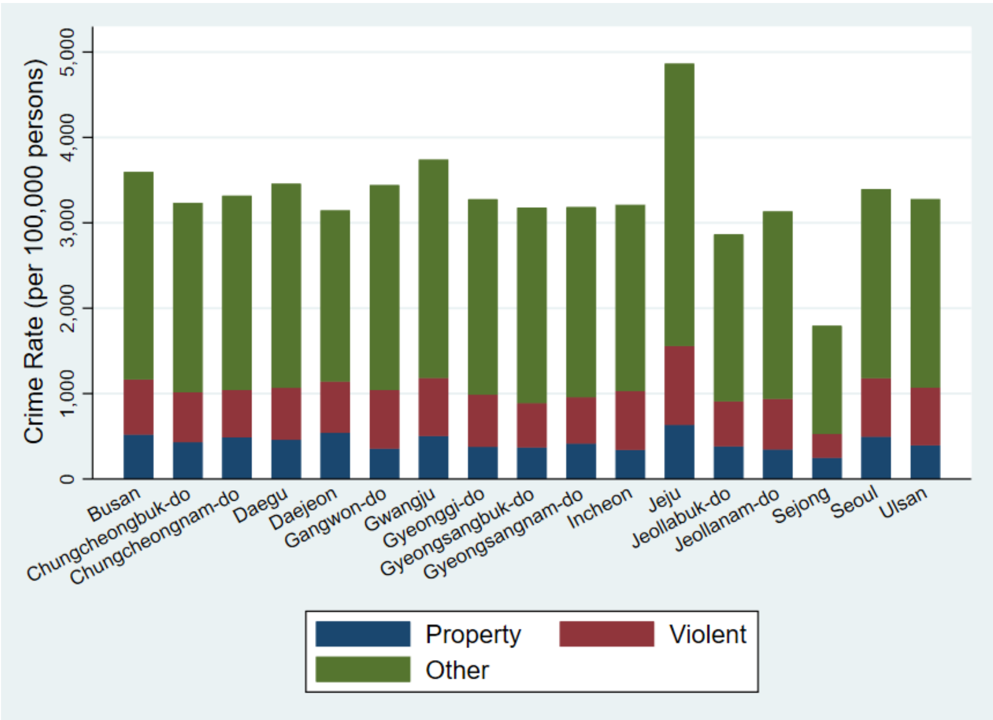

Figure 8: Average crime rate per province by crime type

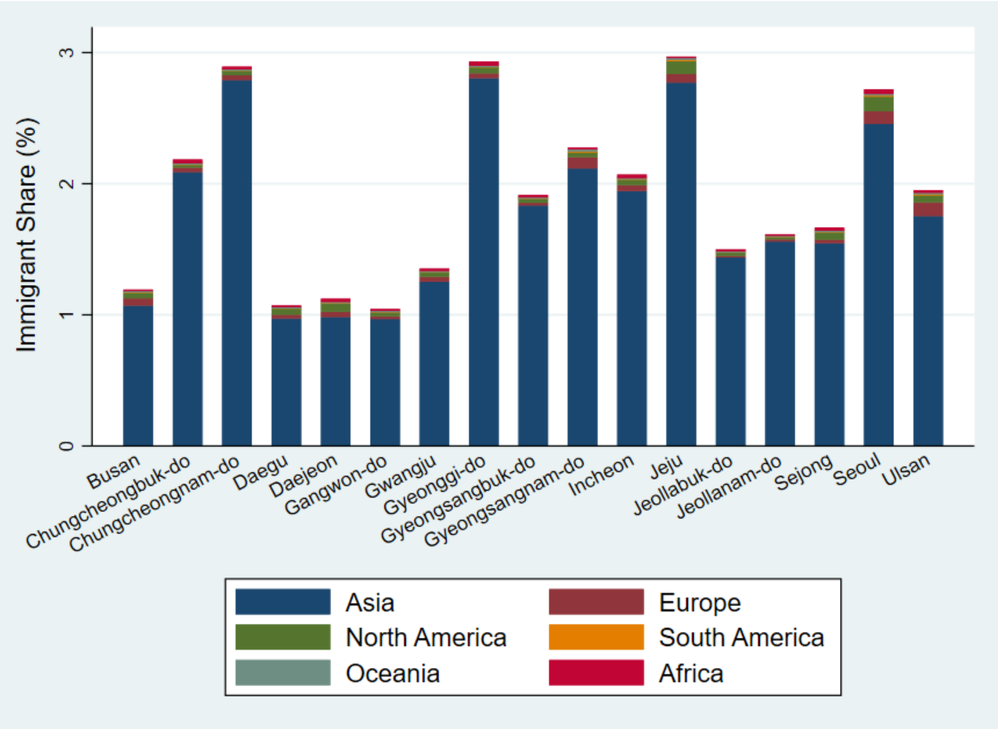

Figure 10: Average immigrant share per province by continent

Table 4: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Total crime rate	1.000									
(2) Violent crime rate	0.806	1.000								
(3) Property crime rate	0.699	0.404	1.000							
(4) Immigrant share total	0.096	0.178	-0.095	1.000						
(5) Immigrant share Asia	0.080	0.148	-0.117	0.997	1.000					
(6) Immigrant share Europe	0.123	0.294	0.100	0.408	0.341	1.000				
(7) Immigrant share North America	0.418	0.545	0.411	0.397	0.336	0.608	1.000			
(8) Immigrant share South America	0.040	0.214	0.102	0.463	0.412	0.574	0.747	1.000		
(9) Immigrant share Oceania	0.364	0.378	0.259	0.387	0.335	0.772	0.582	0.466	1.000	
(10) Immigrant share Africa	-0.370	-0.125	-0.351	0.463	0.445	0.291	0.199	0.475	-0.064	1.000
(11) Total population	-0.095	-0.044	-0.068	0.439	0.430	0.171	0.308	0.403	0.038	0.471
(12) Young male	0.274	0.293	0.359	-0.276	-0.310	0.238	0.229	0.049	0.143	0.007
(13) Marriage rate	0.463	0.297	0.613	0.239	0.211	0.327	0.499	0.259	0.415	-0.027
(14) Unemployment rate	-0.292	-0.089	-0.272	-0.036	-0.051	0.104	0.094	0.299	-0.183	0.393
(15) Real income per capita	-0.205	-0.004	-0.240	0.507	0.481	0.546	0.302	0.442	0.235	0.478
(16) Total crime clearance rate	-0.441	-0.188	-0.728	-0.130	-0.106	-0.163	-0.514	-0.287	-0.255	0.108
(17) Violent crime clearance rate	-0.274	0.046	-0.683	-0.038	-0.027	-0.064	-0.287	-0.052	-0.150	0.158
(18) Property crime clearance rate	-0.296	-0.038	-0.621	-0.135	-0.116	-0.175	-0.419	-0.214	-0.266	0.158

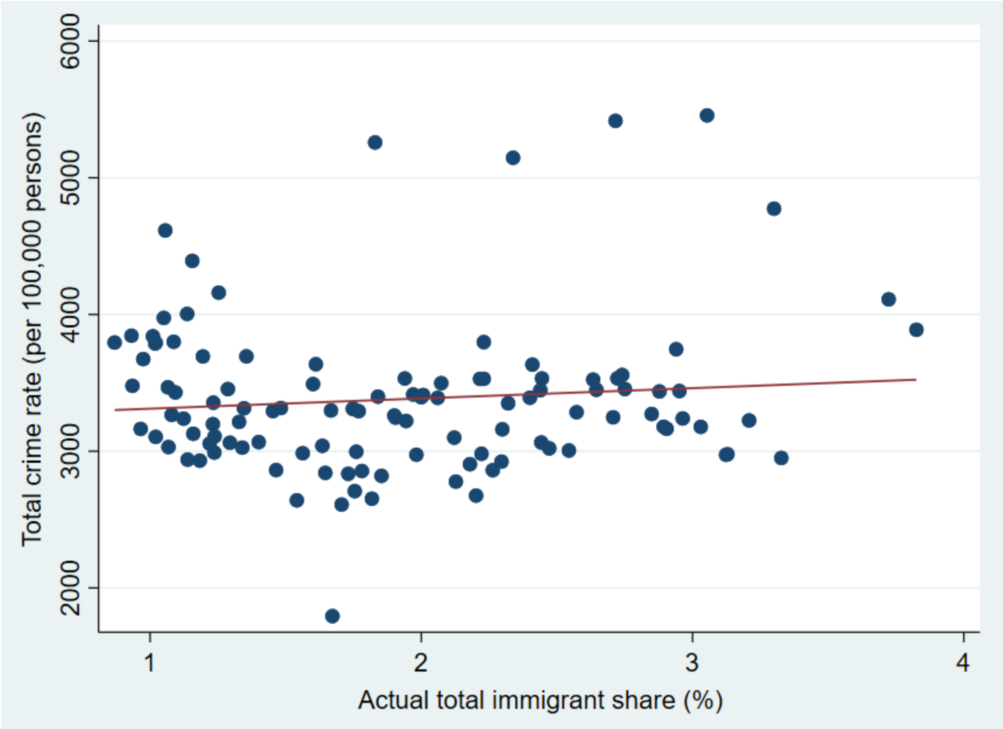

Figure 11: Scatterplot of total crime rate and actual total immigrant share with fitted line

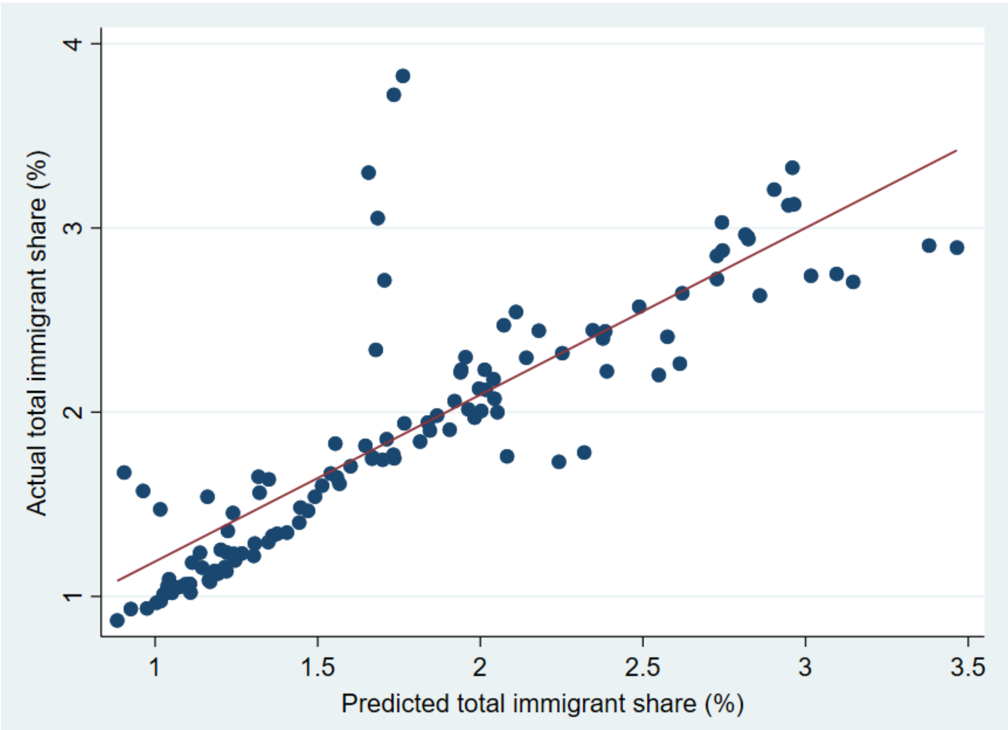

Figure 12: Scatterplot of actual and predicted total immigrant share with fitted line

D.3 Case study: South Korea (by income class)

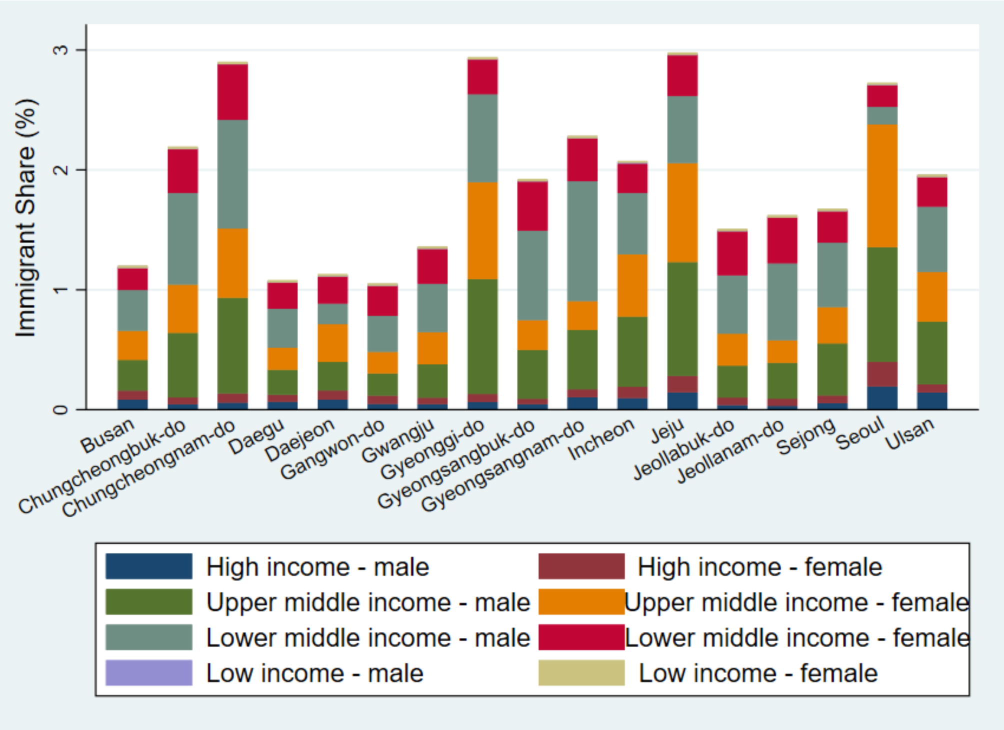

Figure 14: Average immigrant share per province by gender and income class

Table 6: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) Total crime rate	1.000																
(2) Violent crime rate	0.806	1.000															
(3) Property crime rate	0.699	0.404	1.000														
(4) Imm. share total	0.096	0.178	-0.095	1.000													
(5) Imm. share H	0.336	0.507	0.305	0.462	1.000												
(6) Imm. share UM	0.247	0.366	0.092	0.899	0.668	1.000											
(7) Imm. share LM	-0.259	-0.321	-0.405	0.557	-0.323	0.145	1.000										
(8) Imm. share L	-0.349	-0.014	-0.413	0.351	0.122	0.325	0.176	1.000									
(9) Imm. share total – m	0.047	0.067	-0.139	0.964	0.313	0.773	0.714	0.266	1.000								
(10) Imm. share H – m	0.354	0.484	0.343	0.398	0.958	0.566	-0.286	0.009	0.303	1.000							
(11) Imm. share UM – m	0.247	0.321	0.083	0.944	0.607	0.985	0.275	0.274	0.857	0.530	1.000						
(12) Imm. share LM – m	-0.243	-0.317	-0.386	0.574	-0.292	0.171	0.987	0.148	0.748	-0.233	0.308	1.000					
(13) Imm. share L – m	-0.328	-0.019	-0.391	0.366	0.115	0.334	0.196	0.983	0.282	0.003	0.284	0.167	1.000				
(14) Imm. share total – f	0.155	0.318	-0.017	0.917	0.621	0.964	0.247	0.430	0.777	0.485	0.943	0.237	0.442	1.000			
(15) Imm. share H – f	0.268	0.471	0.217	0.485	0.927	0.715	-0.330	0.253	0.285	0.779	0.630	-0.332	0.247	0.718	1.000		
(16) Imm. share UM – f	0.240	0.402	0.099	0.822	0.710	0.983	0.002	0.367	0.658	0.586	0.937	0.020	0.375	0.955	0.781	1.000	
(17) Imm. share LM – f	-0.269	-0.287	-0.404	0.438	-0.364	0.054	0.902	0.231	0.529	-0.390	0.149	0.822	0.252	0.241	-0.283	-0.048	1.000
(18) Imm. share L – f	-0.349	0.001	-0.405	0.254	0.120	0.248	0.096	0.881	0.180	0.024	0.203	0.076	0.780	0.329	0.229	0.288	0.138
(19) Total population	-0.095	-0.044	-0.068	0.439	0.330	0.590	-0.086	0.174	0.359	0.252	0.559	-0.026	0.147	0.500	0.390	0.604	-0.239
(20) Young male	0.274	0.293	0.359	-0.276	0.184	-0.049	-0.534	-0.136	-0.312	0.312	-0.105	-0.482	-0.160	-0.185	-0.006	0.011	-0.608
(21) Marriage rate	0.463	0.297	0.613	0.239	0.508	0.445	-0.310	-0.280	0.204	0.586	0.449	-0.233	-0.263	0.259	0.343	0.426	-0.480
(22) Unemployment rate	-0.292	-0.089	-0.272	-0.036	0.167	0.115	-0.296	0.305	-0.099	0.118	0.053	-0.252	0.222	0.064	0.210	0.177	-0.376
(23) Real income pc	-0.205	-0.004	-0.240	0.507	0.433	0.504	0.163	0.047	0.471	0.447	0.508	0.185	0.038	0.492	0.358	0.484	0.080
(24) Tot. crime clear. rate	-0.441	-0.188	-0.728	-0.130	-0.463	-0.337	0.359	0.305	-0.067	-0.442	-0.333	0.316	0.287	-0.205	-0.431	-0.332	0.430
(25) Viol. crime clear. rate	-0.274	0.046	-0.683	-0.038	-0.217	-0.172	0.232	0.339	-0.050	-0.270	-0.194	0.166	0.305	-0.016	-0.121	-0.143	0.380
(26) Prop. crime clear. rate	-0.296	-0.038	-0.621	-0.135	-0.387	-0.283	0.244	0.399	-0.111	-0.409	-0.303	0.202	0.375	-0.153	-0.309	-0.253	0.325

Appendix E: Regression results

E.1 Case study: Japan

Table 10: IV decomposed regressions of property crime rate by different controls

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
Immigrant share Asia	323.9***	7,076	3,095	1,674**	1,678**	1,682**
	(61.25)	(14,867)	(3,869)	(850.7)	(828.9)	(813.3)
Immigrant share Europe	-12,127***	3,504	735.2	375.9	-17.64	-34.46
	(3,361)	(41,898)	(24,974)	(10,654)	(9,421)	(9,282)
Immigrant share North Am.	1,428***	-79,177	-15,296	18,038	18,345	18,442
	(479.6)	(149,020)	(43,359)	(21,060)	(17,205)	(16,117)
Immigrant share South Am.	-302.4***	-4,715	1,012	399.2	371.3	371.6
	(96.88)	(14,249)	(6,418)	(2,227)	(2,200)	(2,210)
Immigrant share other	26,438**	-449,934	-181,966	-63,229	-63,923	-64,141
	(10,673)	(836,243)	(210,243)	(40,628)	(41,971)	(43,369)
Log total population				-11,461**	-11,475**	-11,505**
				(4,848)	(4,842)	(4,584)
Young male				-276.7*	-249.2	-249.7
				(157.3)	(160.0)	(163.2)
Marriage rate				72.14	71.21	72.14
				(199.5)	(203.4)	(201.0)
Unemployment rate					-26.01	-26.14
					(72.25)	(71.83)
Log real income per capita					-836.7	-835.0
					(844.2)	(846.7)
Property crime clearance						-0.106
						(2.340)
Constant	195.3***	3,259	408.8	166,896**	179,616**	180,029***
	(53.10)	(4,300)	(2,369)	(69,131)	(72,518)	(69,325)
Prefecture FE	NO	YES	YES	YES	YES	YES
Year FE	NO	NO	YES	YES	YES	YES
Observations	329	329	329	329	329	329

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

Table 11: IV decomposed regressions of crime in logs and in levels

VARIABLES	(1) Log total crime	(2) Log violent crime	(3) Log property crime	(4) Total crime	(5) Violent crime	(6) Property crime
Immigrant share Asia	0.761	0.224	0.730	172,025	3,689	136,212
	(0.494)	(0.881)	(0.469)	(112,835)	(4,732)	(89,357)
Immigrant share Europe	-2.457	1.465	-2.264	-1.039e+06	-15,271	-830,199
	(4.082)	(8.311)	(4.116)	(1.081e+06)	(23,321)	(833,543)
Immigrant share North Am.	11.59	-4.607	10.97	2.980e+06*	37,392	2.363e+06*
	(7.510)	(12.74)	(7.884)	(1.710e+06)	(46,635)	(1.271e+06)
Immigrant share South Am.	0.258	0.984	0.208	64,211	1,846	54,037
	(0.761)	(0.988)	(0.689)	(191,939)	(4,817)	(151,557)
Immigrant share other	-18.90	-13.76	-14.75	-5.164e+06	-127,407	-4.051e+06
	(20.79)	(34.98)	(20.50)	(4.688e+06)	(166,113)	(3.820e+06)
Log total population	-3.401	0.585	-3.666	-1.269e+06*	-24,051	-1.013e+06**
	(2.688)	(4.541)	(2.687)	(665,207)	(24,119)	(515,500)
Young male	-0.121	0.0107	-0.139	-15,943	-522.2	-12,513
	(0.0911)	(0.176)	(0.0962)	(19,918)	(670.8)	(15,780)
Marriage rate	0.0630	0.0684	0.0500	10,663	442.8	7,840
	(0.0937)	(0.185)	(0.0851)	(21,222)	(573.6)	(16,728)
Unemployment rate	-0.000737	-0.0587	0.0168	-6,999	-217.2	-5,624
	(0.0329)	(0.0627)	(0.0345)	(9,292)	(223.3)	(7,272)
Log real income per capita	0.0537	-0.323	0.238	-52,323	-1,282	-42,708
	(0.507)	(0.736)	(0.542)	(107,579)	(3,243)	(84,823)
Total crime clearance	-0.00302**			280.3		
	(0.00150)			(309.8)		
Violent crime clearance		0.000171			-3.109	
		(0.00338)			(13.51)	
Property crime clearance			-0.00198			259.7
			(0.00138)			(210.1)
Constant	58.04	2.940	58.88	1.910e+07*	368,974	1.527e+07*
	(41.60)	(69.02)	(42.74)	(1.007e+07)	(379,417)	(7.859e+06)
Prefecture FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	329	329	329	329	329	329

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

E.2 Case study: South Korea (by continent)

Table 13: OLS regressions of decomposed specifications by gender, and by gender and continent

VARIABLES	(1) Total crime rate	(2) Violent crime rate	(3) Property crime rate	(4) Total crime rate	(5) Violent crime rate	(6) Property crime rate
Immigrant share total – male	313.8	107.6*	262.8**			
	(541.2)	(59.96)	(104.7)			
Immigrant share total – female	-730.9	-198.2*	-646.7***			
	(651.5)	(102.1)	(202.2)			
Immigrant share Asia – male				-860.4	-68.31	433.5***
				(873.8)	(84.88)	(117.1)
Immigrant share Europe – male				22,367***	2,680**	283.9
				(5,702)	(941.7)	(1,883)
Immigrant share North Am. – male				-20,996**	-1,057	1,049
				(8,615)	(1,062)	(2,025)
Immigrant share South Am. – male				87,434	37,584*	11,924
				(87,479)	(18,869)	(15,911)
Immigrant share Oceania – male				26,041**	3,328	-344.2
				(10,407)	(4,202)	(4,149)
Immigrant share Africa – male				19,464	606.9	914.7
				(11,325)	(2,191)	(2,751)
Immigrant share Asia – female				1,058	-2.839	-892.0***
				(1,045)	(111.1)	(154.0)
Immigrant share Europe – female				-44,035**	-4,386	279.2
				(15,749)	(2,704)	(4,466)
Immigrant share North Am. – female				568.7	-805.0	2,240
				(20,078)	(2,992)	(4,405)
Immigrant share South Am. – female				130,482	-4,695	27,472
				(76,247)	(18,214)	(24,391)
Immigrant share Oceania – female				-111,332**	-21,153	-19,600
				(46,756)	(17,663)	(17,185)
Immigrant share Africa – female				14,219	2,206	15,138
				(25,437)	(4,683)	(11,534)
Log total population	-203.3	49.26	887.9	1,168	317.3	1,082
	(2,590)	(416.6)	(696.9)	(1,614)	(511.9)	(775.1)
Young male	36.17	3.911	-130.6	42.02	12.74	-216.2*
	(489.6)	(88.48)	(114.3)	(393.7)	(82.99)	(107.2)
Marriage rate	-153.7	-48.40	-10.58	-243.0	-65.53	21.83
	(244.8)	(41.68)	(66.81)	(183.8)	(43.64)	(68.42)
Unemployment rate	-55.20	-33.68**	-32.23*	-10.69	-24.57**	-5.873
	(53.81)	(12.35)	(16.56)	(45.50)	(11.04)	(10.09)
Log real income per capita	1,035	-92.81	-385.4**	506.2	-116.6	-553.2**
	(1,742)	(178.9)	(165.2)	(1,101)	(214.2)	(195.5)
Total crime clearance	-35.37			-37.71		
	(27.08)			(22.22)		
Violent crime clearance		12.54***			7.967	
		(4.259)			(5.175)	
Property crime clearance			0.540			0.214
			(2.045)			(1.905)
Constant	-7,493	845.9	-4,135	-17,714	-2,257	-3,653
	(27,241)	(5,329)	(9,459)	(18,225)	(5,944)	(8,698)

Province FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	113	113	113	113	113	113
R-squared	0.746	0.392	0.868	0.847	0.478	0.903

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

Table 15: First stage regressions for male

VARIABLES	(1) Immigrant share total – male	(2) Immigrant share Asia – male	(3) Immigrant share Europe – male	(4) Immigrant share North Am. – male	(5) Immigrant share South Am. – male	(6) Immigrant share Oceania – male	(7) Immigrant share Africa – male
Immigrant $\widehat{\text{share}}$ total – male	0.0189						
	(0.325)						
Immigrant $\widehat{\text{share}}$ Asia – male		-0.00565					
		(0.308)					
Immigrant $\widehat{\text{share}}$ Europe – male			-1.498				
			(0.859)				
Immigrant $\widehat{\text{share}}$ North Am. – male				-0.686			
				(2.385)			
Immigrant $\widehat{\text{share}}$ South Am. – male					0.201		
					(1.112)		
Immigrant $\widehat{\text{share}}$ Oceania – male						2.829*	
						(1.345)	
Immigrant $\widehat{\text{share}}$ Africa – male							0.360
							(0.302)
Constant	-39.12*	-37.79*	0.645	0.0487	-0.0366	-0.410	-1.116
	(18.46)	(17.84)	(1.901)	(1.648)	(0.0753)	(0.300)	(0.793)
Controls	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	113	113	113	113	113	113	113
R-squared	0.833	0.849	0.584	0.495	0.297	0.610	0.662
F-statistic	0.00	0.00	3.05	0.08	0.03	4.42	1.42

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

Table 16: First stage regressions for female

VARIABLES	(1) Immigrant share total – female	(2) Immigrant share Asia – female	(3) Immigrant share Europe – female	(4) Immigrant share North Am. – female	(5) Immigrant share South Am. – female	(6) Immigrant share Oceania – female	(7) Immigrant share Africa – female
Immigrant $\widehat{\text{share total}}$ – female	0.509						
	(0.381)						
Immigrant $\widehat{\text{share Asia}}$ – female		0.397					
		(0.391)					
Immigrant $\widehat{\text{share Europe}}$ – female			-0.343				
			(0.341)				
Immigrant $\widehat{\text{share North}}$ Am. – female				2.427***			
				(0.661)			
Immigrant $\widehat{\text{share South}}$ Am. – female					0.932		
					(0.583)		
Immigrant $\widehat{\text{share Oceania}}$ – female						1.097	
						(1.134)	
Immigrant $\widehat{\text{share Africa}}$ – female							0.0654
							(0.252)
Constant	-45.33*	-42.62*	-0.580	-1.221	-0.0317	-0.232	-0.198
	(25.04)	(24.33)	(0.962)	(0.744)	(0.0692)	(0.179)	(0.156)
Controls	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	113	113	113	113	113	113	113
R-squared	0.803	0.796	0.660	0.465	0.503	0.465	0.796
F-statistic	1.79	1.03	1.01	13.48	2.56	0.94	0.07

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

Table 17: IV regressions of baseline and decomposed specification by continent

VARIABLES	(1) Total crime rate	(2) Violent crime rate	(3) Property crime rate	(4) Total crime rate	(5) Violent crime rate	(6) Property crime rate
Immigrant share total	9,411	969.9	7,837			
	(34,881)	(8,339)	(56,182)			
Immigrant share Asia				-157.8	31.74	-147.5
				(1,043)	(528.1)	(623.5)
Immigrant share Europe				-1,017	-5,089	10,442
				(36,358)	(19,895)	(39,293)
Immigrant share North Am.				12,617	10,735	-13,380
				(51,673)	(30,058)	(58,131)
Immigrant share South Am.				97,253	-70,619	74,266
				(358,066)	(179,549)	(390,975)
Immigrant share Oceania				7,884	24,818	-42,590
				(155,681)	(74,134)	(163,113)
Immigrant share Africa				23,575	19,538	-12,945
				(111,053)	(57,594)	(108,931)
Log total population	-49,374	-5,138	-39,358	-1,717	-2,718	3,722
	(185,909)	(43,012)	(286,267)	(18,357)	(10,141)	(18,691)
Young male	-3,979	-418.2	-3,646	-603.6	-99.07	-265.2
	(14,616)	(3,730)	(24,858)	(770.8)	(280.4)	(526.8)
Marriage rate	-2,881	-323.1	-2,319	-218.3	-189.4	228.1
	(11,075)	(2,566)	(17,496)	(778.7)	(429.8)	(763.5)
Unemployment rate	913.5	64.35	771.3	155.0	10.27	4.746
	(3,486)	(834.9)	(5,677)	(187.0)	(82.80)	(105.1)
Log real income per capita	2,018	34.60	242.5	-61.43	-50.34	-887.4
	(7,739)	(1,072)	(6,848)	(1,906)	(815.4)	(1,737)
Total crime clearance	-90.05			0.638		
	(269.9)			(62.13)		
Violent crime clearance		10.92			19.25	
		(12.63)			(28.04)	
Property crime clearance			-10.56			-1.653
			(94.36)			(11.24)
Constant	739,798	78,916	610,150	35,903	41,187	-36,519
	(2.843e+06)	(654,902)	(4.384e+06)	(261,375)	(141,031)	(248,585)
Province FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	113	113	113	113	113	113
Number of province	17	17	17	17	17	17

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

Table 18: IV regressions of decomposed specifications by gender, and by gender and continent

VARIABLES	(1) Total crime rate	(2) Violent crime rate	(3) Property crime rate	(4) Total crime rate	(5) Violent crime rate	(6) Property crime rate

Immigrant share total – male	33,627	-154,702	40,761			
	(161,259)	(4.717e+07)	(541,486)			
Immigrant share total – female	-6,790	22,431	-6,545			
	(41,491)	(6.897e+06)	(95,619)			
Immigrant share Asia – male				-13,257	516.2	1,821
				(90,837)	(2,141)	(6,234)
Immigrant share Europe – male				28,343	5,953	4,137
				(193,743)	(11,034)	(35,661)
Immigrant share North Am. – male				41,317	-1,513	-6,153
				(429,421)	(13,196)	(42,030)
Immigrant share South Am. – male				-2.507e+06	384,520	682,322
				(2.330e+07)	(670,597)	(2.576e+06)
Immigrant share Oceania – male				30,302	46,316	56,805
				(1.196e+06)	(61,577)	(287,559)
Immigrant share Africa – male				-112,314	5,775	40,656
				(919,578)	(22,210)	(88,865)
Immigrant share Asia – female				12,533	-953.7	-1,928
				(92,603)	(2,559)	(7,490)
Immigrant share Europe – female				35,775	-11,423	-28,049
				(903,248)	(37,346)	(118,243)
Immigrant share North Am. – female				-448,259	23,063	84,532
				(3.134e+06)	(74,759)	(288,426)
Immigrant share South Am. – female				3.270e+06	-115,674	-533,887
				(1.951e+07)	(396,157)	(1.531e+06)
Immigrant share Oceania – female				854,867	-279,446	-418,898
				(1.242e+07)	(446,446)	(1.803e+06)
Immigrant share Africa – female				-1.049e+06	-16,625	134,194
				(6.160e+06)	(115,071)	(400,577)
Log total population	-63,123	298,318	-77,275	35,491	1,394	-4,732
	(285,946)	(9.085e+07)	(1.013e+06)	(181,300)	(4,273)	(14,637)
Young male	-10,627	52,839	-13,531	4,084	15.56	-475.4
	(51,088)	(1.610e+07)	(177,131)	(24,118)	(395.8)	(1,369)
Marriage rate	-7,607	35,801	-9,219	470.3	-69.93	-53.92
	(36,801)	(1.092e+07)	(123,713)	(5,677)	(198.5)	(377.7)
Unemployment rate	1,981	-9,329	2,501	-88.05	-32.64	13.14
	(9,318)	(2.834e+06)	(33,180)	(885.9)	(29.01)	(142.1)
Log real income per capita	-1,923	11,815	-4,549	-11,485	726.2	1,775
	(22,394)	(3.637e+06)	(57,577)	(94,194)	(2,259)	(8,093)
Total crime clearance	-111.3			-228.6		
	(405.6)			(1,414)		
Violent crime clearance		-482.4			7.652	
		(150,550)			(15.51)	
Property crime clearance			-40.55			-5.873
			(585.5)			(35.01)
Constant	1.093e+06	-5.135e+06	1.366e+06	-333,318	-32,696	42,794
	(5.050e+06)	(1.565e+09)	(1.783e+07)	(1.442e+06)	(60,627)	(218,047)
Province FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	113	113	113	113	113	113
Number of province	17	17	17	17	17	17

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

Table 19: OLS decomposed regressions of property crime rate by gender and different controls

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
Immigrant share Asia – male	51.26	-61.25	236.7	461.7***	434.4***	433.5***
	(56.48)	(262.7)	(184.7)	(113.5)	(118.7)	(117.1)
Immigrant share Europe – male	-2,547***	-1,960	-637.9	652.4	340.2	283.9
	(820.0)	(2,744)	(2,293)	(1,690)	(1,714)	(1,883)
Immigrant share North Am. – male	8,261***	5,593	2,543	351.6	1,024	1,049
	(1,939)	(5,181)	(3,572)	(1,983)	(1,997)	(2,025)
Immigrant share South Am. – male	-35,919	-40,359	6,616	15,684	12,472	11,924
	(26,469)	(36,751)	(23,349)	(18,947)	(16,360)	(15,911)
Immigrant share Oceania – male	3,736	-2,515	3,443	-630.6	-206.8	-344.2
	(4,824)	(7,562)	(6,203)	(4,391)	(4,233)	(4,149)
Immigrant share Africa – male	1,787	322.8	1,779	931.6	904.2	914.7
	(2,012)	(3,785)	(3,715)	(2,823)	(2,730)	(2,751)
Immigrant share Asia – female	-222.0*	-695.7**	-550.6**	-916.5***	-891.0***	-892.0***
	(121.3)	(306.8)	(213.0)	(173.7)	(148.9)	(154.0)
Immigrant share Europe – female	2,103	1,559	-618.8	-257.0	152.0	279.2
	(1,460)	(6,800)	(6,190)	(4,302)	(4,163)	(4,466)
Immigrant share North Am. – female	-1,369	-76.69	1,102	4,393	2,251	2,240
	(3,786)	(8,597)	(5,455)	(4,356)	(4,403)	(4,405)
Immigrant share South Am. – female	40,482	5,504	16,689	20,922	27,843	27,472
	(27,296)	(34,847)	(19,915)	(23,199)	(24,307)	(24,391)
Immigrant share Oceania – female	3,655	33,518	-24,456	-22,520	-20,275	-19,600
	(15,423)	(25,919)	(22,138)	(17,956)	(18,155)	(17,185)
Immigrant share Africa – female	-29,402***	-6,049	15,423	14,113	15,197	15,138
	(8,220)	(18,289)	(14,038)	(11,553)	(11,328)	(11,534)
Log total population				1,093	1,095	1,082
				(738.6)	(758.1)	(775.1)
Young male				-268.0**	-215.7*	-216.2*
				(116.0)	(108.1)	(107.2)
Marriage rate				-5.050	21.05	21.83
				(61.39)	(66.30)	(68.42)
Unemployment rate					-5.612	-5.873
					(10.06)	(10.09)
Log real income per capita					-556.7**	-553.2**
					(203.4)	(195.5)
Property crime clearance						0.214
						(1.905)
Constant	494.9***	916.1***	584.9***	-12,622	-3,783	-3,653
	(37.15)	(82.39)	(114.1)	(9,954)	(8,459)	(8,698)
Province FE	NO	YES	YES	YES	YES	YES
Year FE	NO	NO	YES	YES	YES	YES
Observations	113	113	113	113	113	113
R-squared	0.507	0.700	0.867	0.897	0.903	0.903

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

Table 20: OLS decomposed regressions of crime in logs and in levels by gender

VARIABLES	(1) Log total crime	(2) Log violent crime	(3) Log property crime	(4) Total crime	(5) Violent crime	(6) Property crime
Immigrant share Asia – male	-0.235	-0.147	0.427**	-10,539	-4,030	1,063
	(0.214)	(0.129)	(0.201)	(17,571)	(2,629)	(7,479)
Immigrant share Europe – male	5.273***	3.674**	1.830	265,195	83,656**	78,692
	(1.300)	(1.384)	(3.055)	(193,321)	(28,717)	(49,313)
Immigrant share North Am. – male	-5.418**	-1.715	1.023	-188,954	-1,615	-109,312
	(2.112)	(1.687)	(2.920)	(365,748)	(41,697)	(76,734)
Immigrant share South Am. – male	21.34	46.85*	22.81	5.523e+06	1.020e+06*	897,243
	(24.36)	(24.72)	(31.64)	(4.048e+06)	(536,597)	(827,932)
Immigrant share Oceania – male	6.786**	4.004	-1.309	102,786	188,362	-347,992
	(2.855)	(6.248)	(6.877)	(606,507)	(177,603)	(259,287)
Immigrant share Africa – male	5.616*	1.139	1.045	163,239	-12,289	-137,705
	(2.816)	(3.442)	(4.697)	(189,932)	(49,149)	(80,364)
Immigrant share Asia – female	0.325	0.0824	-0.851***	44,988**	-216.2	18,468*
	(0.237)	(0.166)	(0.222)	(17,102)	(3,128)	(10,547)
Immigrant share Europe – female	-10.86**	-6.463	-1.847	-861,459*	-184,792**	-178,853*
	(3.937)	(4.170)	(7.454)	(417,005)	(68,064)	(87,046)
Immigrant share North Am. – female	1.447	-0.799	3.349	-969,056**	-143,059*	-420,578***
	(4.919)	(4.966)	(7.059)	(427,426)	(68,122)	(121,899)
Immigrant share South Am. – female	28.60	-12.05	54.71	-8.174e+06**	-1.216e+06*	-1.778e+06
	(19.34)	(28.66)	(43.58)	(3.772e+06)	(598,553)	(1.043e+06)
Immigrant share Oceania – female	-22.50*	-20.70	-30.41	250,784	-515,349	598,408
	(12.23)	(26.15)	(30.97)	(1.887e+06)	(564,512)	(750,695)
Immigrant share Africa – female	2.954	1.510	31.15*	2.197e+06	241,173	511,809
	(6.589)	(7.096)	(16.30)	(1.875e+06)	(219,633)	(344,984)
Log total population	1.339***	1.400*	2.666*	61,071	62,787***	-9,880
	(0.387)	(0.764)	(1.306)	(94,921)	(12,552)	(39,474)
Young male	0.0207	0.0482	-0.351*	5,322	288.4	-3,475
	(0.103)	(0.127)	(0.176)	(8,950)	(1,922)	(3,094)
Marriage rate	-0.0675	-0.101	0.0167	-2,277	-2,111*	4,265*
	(0.0501)	(0.0673)	(0.109)	(4,517)	(1,170)	(2,080)
Unemployment rate	-0.00501	-0.0413**	-0.0282	651.1	-378.5	-1,141
	(0.0129)	(0.0177)	(0.0163)	(3,247)	(393.0)	(698.8)
Log real income per capita	0.183	-0.149	-0.697*	-19,492	-4,063	-9,740
	(0.299)	(0.356)	(0.366)	(57,099)	(6,329)	(9,321)
Total crime clearance	-0.00781			340.1		
	(0.00540)			(981.1)		
Violent crime clearance		0.0127			132.7	
		(0.00873)			(121.2)	
Property crime clearance			0.00131			-139.7*
			(0.00302)			(73.05)
Constant	-10.53**	-9.097	-14.21	-513,014	-823,707***	349,382
	(4.584)	(8.982)	(13.36)	(2.072e+06)	(150,826)	(620,424)
Province FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	113	113	113	113	113	113
R-squared	0.867	0.479	0.931	0.627	0.584	0.848

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

E.3 Case study: South Korea (by income class)

Table 22: OLS regressions of decomposed specifications by gender, and by gender and income class

VARIABLES	(1) Total crime rate	(2) Violent crime rate	(3) Property crime rate	(4) Total crime rate	(5) Violent crime rate	(6) Property crime rate
Immigrant share total – male	313.8	107.6*	262.8**			
	(541.2)	(59.96)	(104.7)			
Immigrant share total – female	-730.9	-198.2*	-646.7***			
	(651.5)	(102.1)	(202.2)			
Immigrant share high inc. – male				4,577	969.2*	-233.7
				(3,130)	(485.4)	(597.4)
Immigrant share upper middle inc. – male				-2,137	-442.7	218.0
				(2,608)	(450.3)	(381.4)
Immigrant share lower middle inc. – male				1,049	90.24	304.4
				(1,244)	(153.2)	(223.0)
Immigrant share low inc. – male				-28,251**	-3,757*	-2,540
				(11,286)	(2,024)	(1,851)
Immigrant share high inc. – female				-8,488	-1,433	1,319
				(9,844)	(845.2)	(1,752)
Immigrant share upper middle inc. – female				1,960	280.4	-815.2**
				(1,770)	(264.4)	(322.3)
Immigrant share lower middle inc. – female				-4,094	-394.8	-685.9
				(3,514)	(516.5)	(629.1)
Immigrant share low inc. – female				84,668	19,566**	32,101**
				(60,346)	(7,440)	(11,975)
Log total population	-203.3	49.26	887.9	-1,376	-34.46	991.7
	(2,590)	(416.6)	(696.9)	(3,197)	(504.4)	(606.1)
Young male	36.17	3.911	-130.6	388.3	53.04	-191.4*
	(489.6)	(88.48)	(114.3)	(384.3)	(73.27)	(95.43)
Marriage rate	-153.7	-48.40	-10.58	-375.6	-54.44	63.06
	(244.8)	(41.68)	(66.81)	(282.2)	(53.33)	(69.95)
Unemployment rate	-55.20	-33.68**	-32.23*	-42.29	-21.80*	-13.29
	(53.81)	(12.35)	(16.56)	(59.50)	(12.10)	(11.44)
Log real income per capita	1,035	-92.81	-385.4**	634.0	-154.8	-393.0**
	(1,742)	(178.9)	(165.2)	(1,470)	(162.3)	(163.7)
Total crime clearance	-35.37			-34.73		
	(27.08)			(21.87)		
Violent crime clearance		12.54***			8.630*	
		(4.259)			(4.435)	
Property crime clearance			0.540			1.461
			(2.045)			(1.545)
Constant	-7,493	845.9	-4,135	15,035	3,092	-5,490
	(27,241)	(5,329)	(9,459)	(37,144)	(6,517)	(7,464)
Province FE	YES	YES	YES	YES	YES	YES

Year FE	YES	YES	YES	YES	YES	YES
Observations	113	113	113	113	113	113
R-squared	0.746	0.392	0.868	0.781	0.494	0.904

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

Table 23: OLS decomposed regressions of property crime rate by gender and different controls

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
Immigrant share high inc. – male	599.2	1,363***	210.2	-186.6	-150.9	-233.7
	(461.2)	(356.7)	(500.6)	(585.3)	(594.9)	(597.4)
Immigrant share upper middle inc. – male	1,158***	-26.94	-344.8	146.7	179.0	218.0
	(302.0)	(525.2)	(671.3)	(436.0)	(389.4)	(381.4)
Immigrant share lower middle inc. – male	-664.6***	45.46	352.7	307.3	316.3	304.4
	(133.6)	(217.0)	(244.3)	(239.4)	(231.5)	(223.0)
Immigrant share low inc. – male	3,811	-1,593	-4,537	-2,287	-2,636	-2,540
	(3,528)	(2,820)	(3,138)	(1,887)	(1,978)	(1,851)
Immigrant share high inc. – female	-630.4	-1,408	49.09	1,494	1,232	1,319
	(708.5)	(1,173)	(1,305)	(1,761)	(1,825)	(1,752)
Immigrant share upper middle inc. – female	-1,052***	-411.9	-137.7	-769.0**	-777.5**	-815.2**
	(334.0)	(388.9)	(474.5)	(343.9)	(311.6)	(322.3)
Immigrant share lower middle inc. – female	352.7	-1,701**	-1,031	-678.0	-737.7	-685.9
	(213.3)	(660.8)	(822.2)	(699.3)	(646.2)	(629.1)
Immigrant share low inc. – female	-23,487***	22,724	37,960**	31,666**	31,607**	32,101**
	(6,238)	(16,196)	(16,064)	(11,935)	(11,862)	(11,975)
Log total population				1,084*	1,036*	991.7
				(613.0)	(576.3)	(606.1)
Young male				-226.2*	-183.4*	-191.4*
				(108.3)	(95.05)	(95.43)
Marriage rate				47.68	57.71	63.06
				(70.93)	(75.01)	(69.95)
Unemployment rate					-11.92	-13.29
					(10.42)	(11.44)
Log real income per capita					-426.0**	-393.0**
					(163.9)	(163.7)
Property crime clearance						1.461
						(1.545)
Constant	580.7***	1,083***	868.6***	-13,100	-5,557	-5,490
	(57.53)	(133.4)	(207.0)	(8,247)	(6,918)	(7,464)
Province FE	NO	YES	YES	YES	YES	YES
Year FE	NO	NO	YES	YES	YES	YES
Observations	113	113	113	113	113	113
R-squared	0.500	0.721	0.876	0.898	0.903	0.904

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

Table 24: OLS decomposed regressions of crime in logs and in levels by gender

VARIABLES	(1) Log total crime	(2) Log violent crime	(3) Log property crime	(4) Total crime	(5) Violent crime	(6) Property crime
Immigrant share high inc. – male	0.962	1.372*	0.00812	237,802**	61,430**	36,830***
	(0.792)	(0.719)	(1.011)	(85,928)	(21,974)	(12,509)
Immigrant share upper middle inc. – male	-0.538	-0.737	0.0951	-140,719**	-3,735	-29,448**
	(0.663)	(0.697)	(0.697)	(61,229)	(8,506)	(10,417)
Immigrant share lower middle inc. – male	0.268	0.142	0.351	61,399*	1,466	12,822**
	(0.319)	(0.239)	(0.381)	(30,358)	(4,362)	(5,462)
Immigrant share low inc. – male	-5.694*	-5.026	-6.157*	-494,456	-70,217	-114,614*
	(3.143)	(3.353)	(3.294)	(341,340)	(72,326)	(57,409)
Immigrant share high inc. – female	-1.266	-1.734	2.377	-726,409***	-166,703**	-242,487***
	(2.295)	(1.294)	(2.933)	(163,211)	(59,162)	(42,800)
Immigrant share upper middle inc. – female	0.494	0.501	-0.717	149,589***	4,857	46,328***
	(0.471)	(0.424)	(0.544)	(47,884)	(8,522)	(9,609)
Immigrant share lower middle inc. – female	-0.999	-0.587	-1.044	-140,705*	-18,690	-12,702
	(0.911)	(0.791)	(1.086)	(74,829)	(11,663)	(11,481)
Immigrant share low inc. – female	21.96	29.21**	59.42***	3.989e+06***	501,346***	1.190e+06***
	(15.08)	(11.48)	(20.22)	(1.126e+06)	(143,772)	(261,519)
Log total population	0.776	0.960	2.284**	8,380	46,477***	-46,626*
	(0.809)	(0.779)	(0.966)	(63,183)	(15,418)	(26,335)
Young male	0.0878	0.0939	-0.295*	14,983	1,135	-123.6
	(0.108)	(0.114)	(0.156)	(13,299)	(2,056)	(2,253)
Marriage rate	-0.0901	-0.0785	0.0732	-6,783	-2,281	4,309*
	(0.0753)	(0.0830)	(0.116)	(7,693)	(1,605)	(2,072)
Unemployment rate	-0.00965	-0.0328*	-0.0419*	3,450	66.23	-268.5
	(0.0168)	(0.0187)	(0.0219)	(3,370)	(400.6)	(496.9)
Log real income per capita	0.226	-0.226	-0.414	-31,628	-9,842	-14,079*
	(0.372)	(0.239)	(0.302)	(40,858)	(6,100)	(6,722)
Total crime clearance	-0.00758			470.9		
	(0.00563)			(628.0)		
Violent crime clearance		0.0137*			55.82	
		(0.00761)			(134.5)	
Property crime clearance			0.00349			-100.7**
			(0.00256)			(45.46)
Constant	-3.470	-1.929	-14.18	422,239	-484,244**	931,309**
	(9.703)	(9.779)	(11.88)	(925,093)	(178,405)	(382,324)
Province FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	113	113	113	113	113	113
R-squared	0.812	0.506	0.931	0.638	0.623	0.881

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