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Immigration and Crime: Evidence from Canada

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Immigration and Crime: Evidence from Canada

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Abstract

There is growing belief in many developed countries, including Canada, that the large influx of the foreign-born population increases crime. Despite the heated public discussion, the immigrant-crime relationship is understudied in the literature. This paper identifies the causal linkages between immigration and crime using panel data constructed from the Uniform Crime Reporting Survey and the master files of the Census of Canada. This paper distinguishes immigrants by their years in Canada and defines three groups: new immigrants, recent immigrants and established immigrants. An instrumental variable strategy based on the historical ethnic distribution is used to correct for the endogenous location choice of immigrants. Two robust patterns emerge. First, new immigrants do not have a significant impact on the property crime rate, but with time spent in Canada, a 10% increase in the recent-immigrant share or established-immigrant share decreases the property crime rate by 2% to 3%. Neither underreporting to police nor the dilution of the criminal pool by the addition of law-abiding immigrants can fully explain the size of the estimates. This suggests that immigration has a spillover effect, such as changing neighbourhood characteristics, which reduces crime rates in the long run. Second, IV estimates are consistently more negative than their OLS counterparts. By not correctly identifying the causal channel, OLS estimation leads to the incorrect conclusion that immigration is associated with higher crime rates.

Keywords: Immigration; Crime

JEL Classification: F22, J15, K42

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1 Introduction

In most countries that have a large influx of immigrants each year, the general public and policy makers are concerned about the impact of the increasing foreign-born population on society. Many academic studies focus on whether immigrants displace native workers, drive down wages, or increase inequality [Borjas, 2003; Card, 2001, 2005, 2009]. Recent literature also looks at impacts beyond the employment rate and wages, including the housing market [Saiz, 2003, 2007; Sá, 2011], consumption prices [Cortes, 2008], and innovation [Hunt and Gauthier-Loiselle, 2010]. One important consequence of immigration that captures the headlines in the media but is understudied is the impact of immigration on crime.

International opinion surveys [Simon and Sikich, 2007; Simon and Lynch, 1999] compare the public views on immigration in seven developed countries: Australia, Canada, West Germany, East Germany, Great Britain, Japan, and the United States. Between 1995 and 2003, the percentage of respondents who believe immigrants increase crime grew in all six countries except for the United States.[1] Even in Canada, where over 60% of the respondents consider immigrants beneficial to the economy, there are still about 30% of the respondents who believe immigrants increase crime rates.

Despite the widespread public concern, evidence that a relation between immigration and crime exists, especially one that focuses on a causal linkage, is very limited. The goal of this study is to systematically assess the impact of immigration on crime, taking advantage of the high quality Census of Canada master files and the reliable source of crime statistics from the Uniform Crime Reporting Survey (UCR). The contribution is threefold.

First, by adopting an instrumental variable (IV) strategy, this paper establishes the causal relationship between the immigrant share and crime rates. An ordinary least squares (OLS) model faces several challenges. For example, reverse causality resulting from the endogenous location choice of immigrants could bias the estimates. On the one hand, immigrants may prefer to locate in areas with low or decreasing crime rates for a better quality of life. On the other hand, areas with higher or increasing crime rates may have lower housing prices, therefore, attract immigrants with few financial assets. Next, there could exist unobserved political or economic factors that attract

[1] Compared to Canada where 21% of the respondents who believe immigrants increase crime rate in the 1995, in the US there were 34% of the respondents who believe so. Although the percentage dropped in the US, it reached a similar magnitude to the share of respondents in Canada.

immigrants and affect crime rates at the same time, making the immigrant-crime relationship endogenous. To address these issues, this paper adopts an IV strategy that is based on the observation that immigrants tend to go to places where their families and friends are. The historical distribution of immigrants is used to allocate the inflow of new waves of immigrants to obtain the exogenous variation of immigrant shares. This paper finds that IV estimates are consistently more negative than OLS estimates. This robust pattern suggests that without correctly identifying the causal channel, OLS estimations tend to bias the estimates upwards and lead to the false conclusion that higher crime rate is correlated with a higher share of immigrants.

Second, this paper investigates the heterogeneous impact of immigration on crime rates along the years-since-arrival dimension. The impact on crime along this dimension has never been studied before and is likely important because newcomers face more challenges in the labour market compared to more established immigrants. Within the orthodox economic model of crime participation (Becker [1968], Ehrlich [1973], and see Freeman [1999] for a review), worse labour market outcomes mean lower opportunity costs for criminal activities. Therefore, new immigrants could have a different impact on the crime rates than more established immigrants. Three groups are defined: new immigrants (who have been in Canada for less than 5 years), recent immigrants (who have been in Canada for 5-10 years) and established immigrants (who have been in Canada for more than 10 years). The empirical results show a robust pattern: new immigrants that have been in Canada for less than five years do not have a significant impact on the property crime rate and, as they stayed longer, a 10% increase in the recent-immigrant share or established-immigrant share reduces the property crime rate by 2% to 3%. This pattern is robust to model specification and is further validated by falsification tests that utilize the structure of the panel data constructed for this paper. Bell et al. [2013] also distinguish immigrants by their relative economic outcomes by comparing the crime impact of asylum seekers and European Union workers in the United Kingdom. The pattern in this paper is consistent with their findings in the sense that immigrants who have better labour market opportunities do not increase crime rates.

Last but not least, this paper provides the first national evidence on the causal relationship between immigration and crime in the Canadian context. The Canadian experience is particularly interesting because its pioneering points-based selection system, which was first introduced in 1967, emphasizes the selection of those with skills suitable for Canada's labour market. Several countries, such as Australia, New Zealand and United Kingdom, have introduced similar policies in recent decades,[2] and many countries, including the United States, are considering taking a similar approach. As a result of the skill-oriented selection policy, the immigrant population in Canada is very different from that in the few countries where there are economic studies on the immigrant-crime relationship. In the United Kingdom,[3] Bell et al. [2013] find that asylum seekers slightly increase the property crime rates, while workers from the European Union countries do not have such an impact. One recent study in the United States [Spenkuch, 2013] and another in Italy [Bianchi et al., 2012] find that immigration slightly increases the crime rates. Nonetheless, as Figure 1 depicts, the rise of the immigrant population in Canada coincides with the trend of decreasing crime rates since the early 1990s. Understanding the implications of immigration in Canada, a major immigrant receiving country, is not only important for public knowledge and academic interests in Canada, but it is also valuable for countries that are considering adopting a similar immigrant selection policy.

To explore the underlying reasons of the large crime reduction effect of immigration, the Victimization Cycles of the General Social Survey (GSS) is investigated to supplement the core analysis. The analysis rules out the possibility that the crime reduction effect is due to immigrants being reluctant to contact police when crime happens. In addition, a simple accounting exercise suggests that a pure dilution effect (i.e., a large influx of a law-abiding population diluting the criminal pool) could explain at most 30% of the estimated effects. Therefore, this paper argues that an initial dilution effect could operate through a spillover effect, such as revitalizing the community. In the long run, immigrants could reduce crime rates. This conjecture is consistent with the existing evidence that a decrease in crime rates leads to future accumulative crime reduction [Funk and Kugler, 2003; Corman and Mocan, 2005; Caetano and Maheshri, 2013].

The rest of the paper is organized in the following way. Section 2 discusses related literature on immigration and crime. Section 3 describes the data sources and presents some summary statistics. Section 4 outlines the empirical model and discusses the construction and validity of the instrumental variable. Section 5 presents the OLS and IV results, as well as robustness and falsification tests. Section 6 discusses the possible mechanisms that could explain the magnitude

[2] Australia adopted a point system in 1979, New Zealand in 1991, United Kingdom in 2008.

[3] Although the United Kingdom currently has a point-based immigrant selection system, the two waves of immigrants the authors studied, arrived before the system was introduced.

of the estimates. Section 7 concludes.

2 Immigrant-Crime Relationship

The standard economic model of crime [Becker, 1968; Ehrlich, 1973; Freeman, 1999] assumes that individuals are rational. They weigh the cost and benefit between legal and illegal activities, and choose the option that makes them better off. The opportunity cost of crime takes into account the possibility of getting caught and the expected punishment.

Within this framework, the general public's worry that an increase in the immigrant population would increase the crime rates is plausible because the legitimate labour market does not provide as good opportunities for immigrants as it does for natives. For example, not only do studies find that new immigrants in Canada earn less than native-born workers, but this entry-earning disadvantage has been increasing since the 1990s [Aydemir and Skuterud, 2005; Frenette and Morissette, 2005; Green and Worswick, 2012]. Immigrants also have higher unemployment probabilities in the first five years after landing [McDonald and Worswick, 1997; Picot and Sweetman, 2012].

Moreover, immigrants could increase crime rates indirectly by increasing inequality, displacing native workers, and reducing the wages of natives. For instance, Borjas et al. [2006] find a strong negative correlation in the United States between immigration and wages, unemployment rates and the incarceration rates of US-born African Americans. In Canada, despite the importance of the subject, there are surprisingly few studies that look at the impact of immigration on the labour market outcomes of the natives. In the studies that are available, Aydemir and Borjas [2011] find that immigration has a negative impact on Canadian wages and Moore and Pacey [2003] find that immigrants in Canada contributed to the increasing inequality from 1980 to 1995.

Directly or indirectly, empirical evidence from labour market studies suggests that it is possible that immigration would increase crime rates in Canada. However, there also exist reasons to believe that the immigrant-crime relationship in Canada could operate in the opposite direction.

Ever since the late 1980s, the selection criteria of Canadas immigration policy has put more and more weight on human capital characteristics such as education, work experience, and official language ability, with the hope that newcomers can achieve long-term economic success [Green and Green, 2004]. Over time, the immigrant population in Canada has become more diversified and better educated [Ferrer and Riddell, 2008]. As argued by Lochner [2004], human capital investment increases the opportunity cost of crime through the forgone wages and the expected future loss due to incarceration. If so, better educated immigrants are less likely to be involved in criminal activities.

Furthermore, Citizenship and Immigration Canada (CIC) requires a complete criminal background check before admitting any new permanent resident.[4] The screening process is likely to select a law-abiding immigrant population. In addition, immigrants can be ordered to be deported if they are convicted of a serious crime,[5] and such removal orders cannot be appealed under many scenarios.[6] The deportation threat increases the expected cost of committing a crime for immigrants. Indeed, Samuel and Faustino-Santos [1991] find that first-generation immigrants are more law-abiding than comparable natives in Canada. At the aggregate geographic level, a large influx of a law-abiding population would dilute the pool of criminals and reduce crime rates.

These conflicting factors make it hard to infer the immigrant-crime relationship from theoretical reasoning or the existing literature. It is also not possible to make a simple generalization from the handful of studies in other countries. In the United States, earlier studies find that recent immigrants have no effect on the crime rates in metropolitan areas [Butcher and Piehl, 1998; Reid et al., 2005], while a recent study [Spenkuch, 2013] finds that immigration increases property crime rates. In Italy, Bianchi et al. [2012] find that immigrants increase the incidence of robberies but have no impact on other types of crimes. Bell et al. [2013] find that the large influx of asylum seekers to the UK slightly increases the property crime rate while the large influx of immigrants from EU accession countries does not have such an impact. These studies reach various conclusions due to the differences in the choice of methodology and time period. More importantly, immigration policies and immigrant populations vary greatly across countries. As a result, the immigrant-crime relationship differs by countries. Identifying this relationship in Canada is an important empirical matter.

[4] See CIC: http://www.cic.gc.ca/english/information/security/police-cert/intro.asp accessed on November 21, 2012.

[5] A crime is serious if: the maximum sentence someone could get is 10 or more years in prison, even if they get a shorter sentence or no time at all in prison, or the sentence that someone does get is more than six months in prison. See Community Legal Education Ontario:
http://www.cleo.on.ca/en/publications/mentill/crimes-can-lead-deportation-order

[6] See Canada Border Services Agency: http://www.cbsa-asfc.gc.ca/media/facts-faits/051-eng.html

3 Data

This paper uses three data sources. The main panel data is created by combining the Uniform Crime Reporting Survey (UCR) and the Census of Canada master files (years 1981, 1986, 1991, 1996, 2001 and 2006). To aid the interpretation of the findings, I also investigate the 1999 and 2009 General Social Survey - Victimization (GSS).

3.1 Main Analysis: Panel Data

UCR is an administrative data collected yearly from every municipal police service. It reports the actual number of incidents by crime category from 1962 to the present.[7] The offence definitions and the reporting procedures are uniform regardless of jurisdiction. It is the most reliable and the most widely used source of crime statistics in Canada.

There are two caveats to consider when using the UCR. First, UCR only reports the crime incidents that were detected by the police. Domestic violence, theft with low monetary value, and "victimless crimes" such as prostitution or possession of illegal drugs tend to be underreported [Schmalleger, 2000]. Second, UCR only records the most serious offence within each incident. Therefore, it tends to underreport the total number of actual incidents. For example, if a violent assault happened during a burglary, UCR would count it only as a violent crime (violent assault) and would not record the property crime (breaking and entering).

I deal with these caveats by assuming that the underreporting rates are constant over time and across municipalities. The assumption is reasonable because of procedural uniformity in UCD data collection. As discussed by Ehrlich [1996], this assumption implies that the reported crime rate is proportional to the actual but unobserved number of committed crimes and can be viewed as a proxy of the true value.

The Census of Canada master files (years 1981, 1986, 1991, 1996, 2001 and 2006) represent 20% of the Canadian population. Compared to the public use data, the large sample in the master file can mitigate the concern of sampling error [Aydemir and Borjas, 2011]. Three detailed geographic levels are available for creating a national-representative panel data: provinces and territories, census divisions (CD), and census subdivisions (CSD).[8] Among them, I choose the CD level for the

[7] The version used in this paper contains crime statistics from 1977 to 2010.

[8] Geographic code is defined hierarchically: each province consists of multiple CDs, each CD consists of multiple

following considerations.

The first and also the most fundamental consideration is the compatibility with the UCR responding units. Statistics Canada defines CD as a "group of neighbouring municipalities joined together for the purposes of regional planning and managing common services (such as police or ambulance services)."[9] As the crime reporting units tend to be subdivisions of CD's, crime statistics can be obtained by summing the number of incidents from various police services within a CD.

The second consideration is the tradeoff between sample size and cross-time comparability. Although the definition of provinces and territories is relatively stable, this level of aggregation yields only thirteen observations for each census year. So few observations do not provide enough statistical power for meaningful investigation. Yet, on the more disaggregated level, though the number of CSDs is large, the code, name and boundary definition change from census to census. These constant changes make the task of creating a comparable panel data very challenging.

Moreover, using slightly larger regional definition can lessen the concern that people travel from a different region to commit crime because a substantial share of crimes is committed by people who reside in a close neighbourhood or community [Hipp, 2007; Bernasco, 2010].

Everything taken into account, CD is the most suitable geographic level for the purpose of this study. Note that the actual CDs used in this study do not correspond to the exact Statistics Canada definition in any particular year. The definition of geographic unit is mostly based on the 2006 Standard Geographical Classification (SGC), adjusting for the previous boundary and code changes on the CSD level. The procedure creates 281 stable geographic units (referred to as "CD" henceforth) that cover all of Canada.[10]

Figure 2 depicts the percentage of immigrants in the population at the CD level across Canada. CDs that are close to the southern border have higher shares of immigrants, and there is a large variation across Canada. In the later analysis, I categorize immigrants into three groups: new immigrants (those who have been in Canada for less than 5 years), recent immigrants (those who have been in Canada for 5 to 10 years), and established immigrants (those who have been in Canada for over 10 years). On average, new and recent immigrants each account for around 2.5% of the

CSDs.

[9] Statistics Canada: http://www12.statcan.gc.ca/census-recensement/2011/ref/dict/geo008-eng.cfm, accessed on December 24, 2012.

[10] See Appendix A for details about the CD construction and recoding.

CD population and the shares vary from 0% to around 10% across CDs. See summary statistics in Table 1.[11]

3.2 Supplement: General Social Survey

As a supplement, I analyze the General Social Survey 1999 and 2009 Victimization Cycles (GSS). The victimization cycles are designed to gather security- and crime-related information to complement the official crime statistics. Table 2 shows the summary statistics of variables from the GSS. The population characteristics in GSS are consistent with those obtained from the census, demonstrating the comparability between the two data sources. Compared with the native population, immigrants are better educated, older, more likely to be married, and more likely to reside in metropolitan areas.

4 Empirical Methodology

4.1 First Difference Model

Let i index geographic region (census division [CD] in this paper) and t index year. The immigrant-crime relationship can be modelled as

$$\Delta\frac{Crime_{it}}{Pop_{it}} = \beta_0 + \beta_1\Delta\frac{Imm_{it}^N}{Pop_{it}} + \beta_2\Delta\frac{Imm_{it}^R}{Pop_{it}} + \beta_3\Delta\frac{Imm_{it}^E}{Pop_{it}} + \beta_4\Delta X_{it} + \theta_t + \varepsilon_{it} \tag{1}$$

where θ_t are year dummies, and ε_{it} is an error term. Δ denotes the first difference operator.[12] The first difference model is estimated to account for the CD fixed unobservables.

The dependent variable is the crime rate. It is defined as the number of incidents, $Crime$, divided by the total population, Pop. Imm^N, Imm^R and Imm^E are the number of new immigrants, recent immigrants and established immigrants respectively. The shares of each immigrant group are the key independent variables and the coefficients of interest are β_1, β_2 and β_3.

[11] Note on the number of observations: although there are totally 6 available censuses, the year 1981 is used to create historical ethnic distribution for IV construction. Censuses 1986, 1991, 1996, 2001 and 2006 are used for the main analysis. Therefore, the summary statistics in Table 1 only report 1374 observations, which is 5 years for 281 CDs, excluding CDs with unmatched UCR variables. In the following empirical section, the first difference model reduces 5 census years to 4 observations of each CD.

[12] Note that, because the census is carried out every 5 years, $\Delta y_t = y_t - y_{t-5}$

X controls for characteristics of each CD. It includes demographic variables such as population density [Glaeser and Sacerdote, 1999], gender composition [Heidensohn et al., 2007], age group size [Levitt, 1999], and the fraction of the population with less than high school education [Lochner, 2004, 2007]. It also includes a group of socioeconomic variables. The unemployment rate and average hourly wage are added to control for the legitimate labour market opportunities [Grogger, 1998; Gould et al., 2002]. The Gini coefficient is included to control for income inequality [Chiu and Madden, 1998; Kelly, 2000]. Effectiveness of the criminal justice system is approximated by the clearance rate [Wolpin, 1978; Ehrlich, 1996], which is defined as the percentage of incidents solved by the police. It can be viewed as a proxy of the cost of committing a crime.[13] See Table 1 for summary statistics and Appendix C for the detailed definition of each control variable.

All regressions are weighted by population to correct for heteroskedasticity. I also cluster standard errors to allow for serial correlation.

4.2 Falsification Test

The reference time of the census is mid-May, while the reference period of UCR is each calendar year (from January 1st to December 31st).[14] Figure 3 illustrates the timeline. The mismatch in reference periods raises two issues. First, matching year t census with year t UCR undercounts the share of immigrants by five months. Although the undercount does not affect the estimation *per se*, it affects the interpretation of the results. Second, some property crimes reported in the first five months of year t might happen before some new immigrants arrived in Canada, which makes the causal argument less compelling.

With these concerns in mind, I exploit the time structure of the annual UCR and the quinquennial census and estimate the following specification

$$\Delta \frac{Crime_{i,\boldsymbol{t+x}}}{Pop_{it}} = \beta_0 + \beta_1 \Delta \frac{Imm^N_{it}}{Pop_{it}} + \beta_2 \Delta \frac{Imm^R_{it}}{Pop_{it}} + \beta_3 \Delta \frac{Imm^E_{it}}{Pop_{it}} + \beta_4 \Delta X_{it} + \theta_t + \varepsilon_{it} \tag{2}$$

When $0 < x \leq 4$, the dependent variable is the crime rate x years later. This specification provides

[13] A crime can be cleared by charge or by ways other than the laying of a charge. For a more detailed definition and discussion of clearance, see Mahony and Turner [2012].

[14] Take $t = 2006$ as an example: new immigrants in 2006 are defined as those landed between June 2001 and May 2006, property crime in 2006 is defined as the total number of incidents happened between January 2006 and December 2006.

evidence of the impact of immigration on crime in the long run. When $-4 \leq x < 0$, the dependent variable is the crime rate x years ago. Because the current new-immigrant share should not affect previous years' crime rate, when x takes negative numbers, this specification serves as a falsification test.

4.3 Instrumental Variable Construction

OLS estimation of Equation (1) may be biased for several reasons. First, reverse causality might be an issue because an immigrant's location choice could be affected by the CD level crime rates. On the one hand, immigrants likely prefer locations with low or decreasing crime rates for a better quality of life. On the other hand, due to the lack of financial resources, newly arrived immigrants may reside in areas with higher or increasing crime rates due to lower housing costs. These two possibilities would bias the OLS estimates in opposite directions.

Second, even after controlling for a rich set of variables, there could still exist unobserved factors that attract immigrants and affect crime rates at the same time. For example, a more liberal local government may allocate more resources to improve immigrant settlement services and at the same time, invest in innovative policing strategies. Such unobserved factors would make the immigration-crime relationship endogenous. To be more specific, the endogeneity problem is

$$Cov(\Delta \frac{Imm_{it}^N}{Pop_{it}}, \varepsilon_{it}) \neq 0 \qquad , \qquad Cov(\Delta \frac{Imm_{it}^R}{Pop_{it}}, \varepsilon_{it}) \neq 0$$

To address these issues, I use an instrumental variable strategy introduced by Card [2001]. It is based on the observation that new immigrants tend to settle in areas where their families and friends are. In Canada, nearly 60% of newcomers identify their tie to families or friends as the primary reason for choosing their destination, and about 70% of new immigrants already had a network of families or friends in the area where they choose to reside [Chui, 2003]. For new immigrants, their families and friends are most likely to come from the same country or region. Therefore, it is reasonable to approximate the strength of the immigrant pull factor by the size of the existing immigrant population from the same source region.

The instrument uses the 1981 distribution of immigrants from a given source region across

CDs to allocate the new waves of immigrants from that region.[15] For instance, in 1981, 30% of immigrants from Eastern Asia lived in Toronto. In each of the later census years, the instrument variable would allocate 30% of Eastern Asian newcomers to Toronto. Formally, the predicted number of new immigrants and recent immigrants in CD i and year t are expressed as

$$\widehat{Imm}_{i,t}^{N} = \sum_g \frac{Imm_{i,1981,g}}{\sum_i Imm_{i,1981,g}} Imm_{t,g}^{N} = \sum_g \tau_{i,1981,g} Imm_{t,g}^{N}$$
$$\widehat{Imm}_{i,t}^{R} = \sum_g \frac{Imm_{i,1981,g}}{\sum_i Imm_{i,1981,g}} Imm_{t,g}^{R} = \sum_g \tau_{i,1981,g} Imm_{t,g}^{R}$$

where $Imm_{i,1981,g}$ is the number of all the immigrants from source region g in the year 1981 and CD i. $Imm_{t,g}^{N}$ and $Imm_{t,g}^{R}$ are the national numbers of new and recent immigrants from source region g in year t respectively. $\tau_{i,1981,g} = \frac{Imm_{i,1981,g}}{\sum_i Imm_{i,1981,g}}$ refers to CD i's share of immigrants from source region g in 1981. The IV specification is

$$\Delta \frac{Crime_{it}}{Pop_{it}} = \beta_0 + \beta_1 \Delta \frac{\widehat{Imm}_{it}^{N}}{Pop_{it}} + \beta_2 \Delta \frac{\widehat{Imm}_{it}^{R}}{Pop_{it}} + \beta_3 \Delta \frac{Imm_{it}^{E}}{Pop_{it}} + \beta_4 \Delta X_{it} + \theta_t + \varepsilon_{it} \tag{3}$$

Note that I only discuss the endogeneity and the IV construction for the shares of Imm^N and Imm^R. This is because the location choices of new immigrants and recent immigrants are more likely to be influenced by the historical settlement pattern than that of established immigrants. Although the instrument variable constructed in the same way for established immigrants does not violate the exclusion restriction,[16] the first stage is weak and could make the estimation inconsistent. In the following text, all the estimations assume that the location choice of established immigrants is the same as the location choice of the natives and includes established-immigrant share as a control variable in X. Nevertheless, this paper reports the results of the robustness check that includes $\widehat{Imm}^{E}$ as an instrument variable for Imm^E.

By construction, the variation of the IV comes from two directions: across CDs and over time. The variation across CDs comes from the immigrant distribution in 1981. I use eighteen source regions as shown in Table 3. The majority of immigrants go to the three largest metropolitan areas: Toronto, Montréal and Vancouver. Not surprisingly, Toronto hosted the largest share of immigrants

[15] The choice of the year 1981 is due to the constraint in data availability. Although historical censuses are currently available, the earliest year that provides comparable CD definition is 1981.

[16] See section 4.4 for a discussion on the validity of the IV.

from fourteen out of eighteen source regions in 1981. Among them are all the Asian and European regions, and most of the American and African regions. Central American and Northern African immigrants were mostly attracted to Montréal while most immigrants from Australia, New Zealand and Oceania chose to live in the Greater Vancouver area.

On the time dimension, if the growth of each immigrant group remains the same in the following years, the predicted number of new- and recent-immigrant share would yield no variation. This is not the case in Canada. Figure 4 shows the trends in population growth of selected immigrant groups. During the period from 1981 to 2006, there has been a large decline of Northern European immigrant population and a substantial rise in the Asian immigrant population.

4.4 Validity of Instrumental Variable

For the instrumental variables to be valid, the exclusion restriction requires[17]

$$\widehat{Imm}_{i,t}^{N} \perp\!\!\!\perp \varepsilon_{it} \mid Pop_{i,t}, X_{i,t} \qquad \text{i.e.,} \qquad \sum_{g} \tau_{i,1981,g} Imm_{t,g}^{N} \perp\!\!\!\perp \varepsilon_{it} \mid Pop_{i,t}, X_{i,t}$$

$$\widehat{Imm}_{i,t}^{R} \perp\!\!\!\perp \varepsilon_{it} \mid Pop_{i,t}, X_{i,t} \qquad \text{i.e.,} \qquad \sum_{g} \tau_{i,1981,g} Imm_{t,g}^{R} \perp\!\!\!\perp \varepsilon_{it} \mid Pop_{i,t}, X_{i,t}$$

These conditions must be satisfied in the following two dimensions. First, the ethnic distribution in 1981, $\tau_{i,1981,g}$, can affect crime rates only if it attracts more immigrants from the same ethnic group. To elaborate this point, consider a hypothetical example regarding immigrants from country *Alpha* and country *Beta*. CDs with a large *Alphanese* community in 1981 tend to attract more *Alphanese* immigrants in the later years. If *Alphanese* were less likely to commit crimes than immigrants from other countries, then these increasingly *Alphanese* CDs would see a drop in the crime rate. On the contrary, if the existing *Alphanese* criminal gangs attracted more members, then there would be a bigger increase in crime rates in these CDs. However, if the past settlement distribution induces crime due to ethnic conflict, such as by retaliation from the *Betanese* criminal gang, then $\tau_{i,1981,g}$ would be correlated with crime rates through a path other than by attracting new immigrants. This makes the IV strategy potentially invalid in the sense that it does not provide the causal interpretation of the "more immigrants - more (less) criminals - higher (lower) crime

[17] $A \perp\!\!\!\perp B \mid C$ means variable A and B are independent conditional on C. The sufficiency of these two conditions for the exclusion restriction is discussed in Appendix B.

rate" channel. Fortunately, because $\tau_{i,1981,g}$ is CD specific, the first difference model can deal with this concern. Moreover, since hate crimes that result from ethnic conflicts account for only a small share of total crime incidents[18] and tend to have a violent nature [Silver et al., 2002], this study minimizes this concern by focusing on crimes against property.

Second, the national number of new and recent immigrants from region g in year t, $Imm^N_{t,g}$ and $Imm^R_{t,g}$, cannot be correlated with the current year crime rates of an individual CD. This condition is satisfied because the total inflow of immigrants is affected mostly by factors that are not at the local level. For instance, national policy changes can shift the composition of the immigrant inflow. Examples are the 1976 Immigration Act and the 2002 Immigration and Refugee Protection Act, both of which shifted the composition of immigrant inflows away from the traditional European countries, and the expansion of the Live-in-Caregiver program, which has led to a large influx in Filipino immigrants. Political and economic factors in the source country also play a great role in the immigration composition change. Most noticeably, the transfer of sovereignty over Hong Kong and the opening up of mainland China resulted in a large inflow of immigrants. These factors affect the total number of immigrants at the national level and are independent from the CD level crime statistics.

The inclusion restriction for the validity of the IV requires

$$Cov(\Delta\frac{\widehat{Imm}^N_{i,t}}{Pop_{it}}, \Delta\frac{Imm^N_{i,t}}{Pop_{it}}) \neq 0 \qquad \text{and} \qquad Cov(\Delta\frac{\widehat{Imm}^R_{i,t}}{Pop_{it}}, \Delta\frac{Imm^R_{i,t}}{Pop_{it}}) \neq 0$$

Figure 5 plots the correlation between the actual variables (the change of new-immigrant share) and the instrumental variables (the predicted change of new-immigrant share) together with a weighted regression line. The correlation between the actual variable and the instrumental variable is strongly positive and significant. Formal first stage tests are reported in the next section.

[18] See Appendix Table 17 and Dowden and Brennan [2012] for hate crime statistics.

5 Results

5.1 First Difference Model and Falsification Test

Table 4 reports the results from OLS estimation of Equation (1). Estimations are weighted by population, and standard errors are clustered on the CD level. All the specifications include "log population density" to control for urban size. OLS estimation shows that CDs with higher population density tend to have a lower property crime rate. The baseline specification also controls for the share of 12 age groups, gender composition, the share of the married population, and the share of the rural population.

An important control variable is the population share with low education levels. As Lochner [2004, 2011] points out, education can significantly reduce the likelihood that an individual will commit a crime by increasing the legitimate labour market return. The OLS estimates agree with this prediction. A 10% increase in the population share with less than a high school education is correlated with around a 2% increase in the property crime rate.

The opportunity cost of crime, or the legitimate labour market opportunities, is controlled using the unemployment rate and the average hourly wage [Gould et al., 2002]. Gini coefficients are included in the estimation to control for income inequality [Chiu and Madden, 1998; Kelly, 2000]. Without adding the labour market variables (column [3] and column [4]), the OLS estimations show that the new-immigrant share is positively correlated with the property crime rate while the recent- and established-immigrant share are negatively correlated with the property crime rate. After controlling for the labour market variables (column [5] and column [6]), the coefficients for all three immigrant groups become more positive. This suggests that there exists a negative correlation between the immigrant share and labour market outcomes.[19]

The likelihood of getting caught affects an individual's criminal activity. To control for this factor, the clearance rate is used to approximate the effectiveness of police crime resolution, with clearance rate defined as (number of solved crime)/(number of total crime) and the dependent variable is (number of total crime/population). Directly controlling for clearance rate of the same crime category would introduce endogenous variation, and the coefficient of clearance rate is

[19] There is very limited evidence on the labour market impact of immigrants in Canada [see Aydemir and Borjas, 2007, 2011]. Further investigation of such impact is needed, but is beyond the scope of this paper.

negative by construction. To minimize the endogeneity concern, the clearance rate of violent crime is used in the property crime regressions. Table 4 reports results with and without clearance rate control. The estimates are robust to the inclusion of the clearance rate.

Section 4 discusses how the OLS estimates are likely to be biased due to the endogenous location choice of immigrants. The direction of the bias is not clear. Immigrants might prefer to choose CDs with lower or decreasing crime rates. Or the opposite: financially constrained immigrants might reside in CDs with higher or increasing crime rates. IV estimation can account for the endogeneity problem and correctly estimate the causal relationship.

Table 5 presents the IV estimation results of Equation (3). Compared to OLS, the coefficients of the control variables retain the same signs and magnitudes, while the coefficients of interest decline for all three immigrant groups regardless of the inclusion of control variables. From column (2) to column (6), the significant positive relationship between the property crime rate and the new-immigrant share disappears. The loss of significance is not due to larger standard errors, but rather is due to the decreased point estimates. The coefficients for recent-immigrant share and established-immigrant share become more negative in all cases.

There are several possible explanations for the decline in these coefficients. The first possibility is attenuation bias due to measurement error. However, an attenuation bias that makes OLS estimates close to zero can not explain the drop of the coefficient for new-immigrant share. A more likely explanation is the existence of an endogenous location choice of immigrants, such that new immigrants choose to reside in CDs with higher property crime rates. Another explanation comes from the construction of the instrumental variable. In their study of the impact of high-skilled immigrants on innovation, Hunt and Gauthier-Loiselle [2010] argue that this kind of IV coefficient reflects the effect of immigrants whose location choice is affected by the settlement pattern. Applied to this paper, the "local average treatment effect (LATE)" argument suggests that immigrants whose location choice is influenced by the settlement patterns of the previous immigrants are less likely to be involved in criminal activities. Although there is no direct empirical evidence to support this argument, social control and social disorganization theory in sociology and criminology literature speaks to this point [Simcha-Fagan and Schwartz, 1986; Sampson and Groves, 1989]. These studies find that communities in which residents tend to have local friends and family have reduced neighbourhood crime rates. Moreover, Dinovitzer et al. [2009] study the criminal activities of immigrant adolescents in Toronto. They argue that strong bonds to their families, a commitment to the values of education, and engagement in the community and public institutions all contribute to a lower involvement in such activities.

IV results reveal a crime reduction pattern along the years-since-arrival dimension. Although a higher new-immigrant share does not have an impact on the property crime rate, as immigrants stay longer in Canada, a higher share of recent and established immigrants reduces the property crime rate. Estimation using Equation (2) further validates this pattern.

Table 6 presents the estimation results when later-year UCR is matched with current-year census, i.e., $0 < x \leq 4$. Note that the definitions of new-, recent- and established-immigrant share are the same as those in the baseline specification. Thus, their years-since-arrival is relative to the census year t, not to the UCR year $t + x$.

Within each column, the smaller IV coefficients compared to OLS coefficients and the crime reduction pattern across new-, recent- and established-immigrant share remains robust. Across columns, after x years, each group of immigrants defined in the baseline model would be in Canada for x years longer. As x gets bigger, the coefficients for the three immigrant shares become more negative. This pattern supports the conclusion drawn from the baseline model: as immigrants stay in Canada longer, their crime reduction effect gets larger. The coefficients of new immigrants change from insignificant to -0.3 starting at $x = 2$. This suggests that new immigrants are most likely to experience hardship in the first couple of years after arrival.

When the current year census is matched with the previous year UCR, i.e., $-4 \leq x < 0$, Equation (2) can be used as a falsification test. The coefficient β_1 should be 0, or less positive, because it estimates the causal relationship of new immigrants on property crimes that happened x years before they came to Canada. Estimates in Table 7 confirm this prediction. Note that the positive effect in column (1) and column (2) (where $x = -1$) does not contradict the prediction. Because census is collected in the middle of year t, the new-immigrant group includes some immigrants that arrived in the later half of year $t - 1$.

In Table 7, coefficients for recent immigrants estimate the causal relationship of their share on the property crime rate when they were x years "newer" in Canada. Although none of the estimates is significantly different from 0, the value of the estimates gets larger as x gets more negative, which is also consistent with the baseline results. When $x = 4$, recent immigrants are four years "newer" (they would have been in Canada for 1 to 6 years) and β_2 is positive in column (7) and column (8).

5.2 Robustness Check

As immigrants stay in Canada longer, concerns about job opportunities, income, and other aspects play larger roles in their location choice than the size of the ethnic community. Therefore, the instrumental variable strategy would yield a weaker first stage for Imm^E. For this reason, the baseline model uses only instrumental variables for Imm^N and Imm^R and includes Imm^E as an additional control variable. The assumption is that the location choice of established immigrants is the same as the location choice of natives. As a robustness check, the instrumental variables for all three immigrant groups Imm^N, Imm^R, and Imm^E are used, estimating the following model

$$\Delta \frac{Crime_{it}}{Pop_{it}} = \beta_0 + \beta_1 \Delta \frac{\widehat{Imm}_{it}^N}{Pop_{it}} + \beta_2 \Delta \frac{\widehat{Imm}_{it}^R}{Pop_{it}} + \beta_3 \Delta \frac{\widehat{Imm}_{it}^E}{Pop_{it}} + \beta_4 \Delta X_{it} + \theta_t + \varepsilon_{it} \tag{4}$$

Table 8 reports the results.

All the estimates are more negative than those in Table 5. The coefficient for established-immigrant share, β_3, is no longer significant with the full set of control variables in column (6). This is likely due to the weaker first stage of established-immigrant share, leading to inconsistent estimates and wrong inferences. Nevertheless, the crime reduction pattern of the coefficients is robust.

Table 8 shows that the first stage estimates get weaker as immigrants stay longer in Canada. To increase the strength of the first stage, the instrumental variable for the recent-immigrant share can be redefined and a robustness check performed, since those immigrants who have been in Canada for 5 to 10 years would have been in Canada for 0 to 5 years in the previous census (thus, they would have been "new" immigrants back then). The predicted share of recent immigrants can be replaced by the 5-year lag of predicted share of new immigrants as the instrument for recent-immigrant share. Formally, I estimate the following model

$$\Delta \frac{Crime_{it}}{Pop_{it}} = \beta_0 + \beta_1 \Delta \frac{\widehat{Imm}_{it}^N}{Pop_{it}} + \beta_2 \Delta \frac{\widehat{Imm}_{i,t-5}^N}{Pop_{i,t-5}} + \beta_3 \Delta \frac{Imm_{it}^E}{Pop_{it}} + \beta_4 \Delta X_{it} + \theta_t + \varepsilon_{it} \tag{5}$$

To get the correct count of the lagged new-immigrant population in a CD, the census question "where did you live 5 years ago" is used instead of "where do you live now." Table 9 shows that this specification does not affect the estimation results.

Taking the first difference, the baseline specification in Equation (1) removes CD level unobservables that are time invariant. However, there might still exist time-varying unobservables. For instance, the strength of informal social crime control might increase or decrease over time and be unobservable to researchers. To deal with this concern, as an additional robustness check, CD dummies are included in both the baseline model and the falsification test. The specifications become

$$\begin{aligned} \Delta\frac{Crime_{it}}{Pop_{it}} &= \beta_0 + \beta_1\Delta\frac{Imm^N_{it}}{Pop_{it}} + \beta_2\Delta\frac{Imm^R_{it}}{Pop_{it}} + \beta_3\Delta\frac{Imm^E_{it}}{Pop_{it}} + \beta_4\Delta X_{it} + \theta_t + \boldsymbol{\theta_i} + \varepsilon_{it} \\ \Delta\frac{Crime_{i,t+x}}{Pop_{it}} &= \beta_0 + \beta_1\Delta\frac{Imm^N_{it}}{Pop_{it}} + \beta_2\Delta\frac{Imm^R_{it}}{Pop_{it}} + \beta_3\Delta\frac{Imm^E_{it}}{Pop_{it}} + \beta_4\Delta X_{it} + \theta_t + \boldsymbol{\theta_i} + \varepsilon_{it} \end{aligned} \tag{6}$$

where θ_i indicates the dummy variables for CDs.

Table 10 reports the OLS and IV results of Equations (6). Compared to the coefficients in column (6) of the OLS results in Table 4 and those in Table 6, the most obvious change in column (1) and column (2) is the decline of coefficients for all three immigrant groups, indicating the existence of time-varying CD-specific unobservables that bias the OLS estimates. The magnitudes of the IV estimates are similar to those of the OLS coefficients but are less significant due to the increased standard errors. Nevertheless, the estimates with CD dummies are comparable to the IV estimates with the baseline specification. This robustness check suggests that the instrumental variable strategy can deal with the time-varying unobservables.

The next robustness check regards the population size. Since the majority of immigrants lives in census metropolitan areas (CMAs),[20] the analysis can be restricted to these areas. As a CMA by definition has a population of at least 100,000 people, only CD's of at least this size are included. This yields 65 CDs for the sample. Table 11 reports the IV estimates using only those CDs. Because sampling errors in CDs with a smaller population affect the precision of the estimates, regressions are weighted by cell size throughout this paper. With only large CDs,

[20]Statistics Canada defines census metropolitan area as an area consisting of one or more neighbouring municipalities situated around a core. A census metropolitan area must have a total population of at least 100,000 of which 50,000 or more live in the core. Using the General Social Survey, Table 2 shows that over 90% of immigrants live in CMAs. This share is slightly higher than the estimates obtained from the census. In the census data, about 85% of immigrants reside in CMAs.

this table compares the estimates with and without population weighting. The point estimates of new and recent immigrants are similar to the baseline estimates regardless of weighting. Across columns when x takes different values, the crime reduction pattern along the years-since-arrival dimension also remains robust but is less precisely estimated. The comparison between weighted and unweighted results demonstrates the importance of using weights to achieve more precise estimates by correcting for heteroskedasticity.

5.3 Demographic Composition

Summary statistics in Table 2 show that immigrants are better educated, older, and more likely to reside in CMAs than natives. To see whether these differences play a role in the immigrant-crime relationship, Table 12 presents the OLS and IV results with demographic variables (education rate, female rate, marriage rate, and age group rate) defined separately for immigrants and natives. Estimation is based on the following specification

$$\begin{aligned}\Delta\frac{Crime_{it}}{Pop_{it}} = \quad & \beta_0 + \beta_1\Delta\frac{Imm^N_{it}}{Pop_{it}} + \beta_2\Delta\frac{Imm^R_{it}}{Pop_{it}} + \beta_3\Delta\frac{Imm^E_{it}}{Pop_{it}} \\ & + \beta_4\boldsymbol{\Delta X_{Native,it}} + \beta_5\boldsymbol{\Delta X_{Immig,it}} + \theta_t + \varepsilon_{it} \qquad (7)\end{aligned}$$

In this table, each regression includes a full set of controls as in column (6) of Table 4. The indicator for including the control variable groups specifies whether the variables are defined for immigrants and natives separately. For example, "married (separate)" means that the share of the married population enters in the regression as two variables: the share among the immigrants, and the share among the natives. Hence, the specification in column (2) includes age groups, education groups, unemployment rate, and wage defined for the whole population and female share, married share, and rural share defined for immigrants and natives separately.[21]

In most cases, the immigrant-crime relationship established in the baseline model is robust when control variables are defined separately for immigrants and natives. However, when the age groups are defined separately, the negative impact of recent-immigrant share on the crime rates is no longer significant. The loss of significance comes from both the smaller (in absolute value) point estimates and the larger standard error. Although the evidence is not conclusive due to the

[21] There are six variables for this group of controls, instead of three in the baseline specification.

increased standard error, it suggests that the different age composition between immigrants and natives plays a role in the crime reduction effect of recent immigrants.

5.4 Detailed Property Crime Categories

Property crime can be broken down into the following five subcategories: breaking and entering, motor vehicle theft, non-motor vehicle theft, possession of stolen goods, and fraud. Figure 6 depicts the trend of each type from 1977 to 2010. Among them, non-motor vehicle theft and breaking and entering account for the majority of the total property crime rate.

Table 13 presents the OLS and IV results for each of the four larger crime subcategories. A 10% increase of new immigrants decreases the breaking and entering rate by around 5%, while raising the motor vehicle theft rate by 6%. As they stay longer, recent immigrants decrease motor theft rate and have a large crime reduction effect on the non-motor vehicle theft rate. Recent immigrants and established immigrants generally do not increase any of the subcategory rates, with the exception of the fraud rate. A 10% increase of established immigrants raises the fraud rate by about 3%.

5.5 Immigrants by Country of Birth

Spenkuch [2013] finds that immigrants increase property crime rates in the US if the immigrants are from Mexico. Bell et al. [2013] find that asylum seekers to the UK slightly increase the property crime rate but European Union workers have no impact. Both studies emphasize the importance of studying the immigrant-crime relationship by subgroups of immigrants. This section categorizes immigrants into four larger groups by country: African countries, Asian countries, European countries, and South and Central American countries. Table 1 shows the average share of each group of new and recent immigrants across CDs. On average, Asian immigrants who arrived between 0 and 10 years ago account for about 2.5% of the CD population. New and recent European immigrants account for 1.1% of the CD population. The average shares for African immigrants and South and Central American immigrants are much smaller.

IV results in Table 14 show that the crime-increasing effect of new immigrants is most apparent for African immigrants, followed by immigrants from South and Central America, and less so for immigrants from Asian countries. New immigrants from Europe, on the other hand, do not increase property crime rates. A higher share of new European immigrants decreases the property crime rate by a substantial amount.

All four groups of immigrants show a crime-reducing effect once they are more established than recent immigrants. Even though the coefficients of recent South and Central American immigrants are not significant, the sign and the relative magnitude compared to the coefficients of new South and Central American immigrants agree with the general crime reduction pattern along the years-since-arrival dimension.

Compared to other immigrants, immigrants from Europe do not face difficulties such as language barriers, transferability of foreign experience, or employer discrimination [Aydemir and Skuterud, 2005; Ferrer and Riddell, 2008; Oreopoulos, 2011]. The relative magnitude of the estimates across country groups is consistent with the interpretation that the immigrant-crime relationship is affected by the available labour market opportunities.

Note that the further breakdown of immigrants into four large subcategories reduced the variation of the three key independent variables. Also, the much larger standard errors of all the estimates reflects the weak first stage of the IV estimates. Therefore, we need to interpret the estimates in this section with caution.

6 Interpretation of the Crime-Reducing Effect

The empirical results obtained from the previous sections show that an increase in the new-immigrant share does not have statistically significant impact on the property crime rate while a higher share of more established immigrants actually decreases the property crime rate. This section discusses the possible reasons for the crime reduction effect.

To assist with the discussion, consider a simple accounting exercise that takes into consideration only the composition effect. Assume the crime rate among immigrants is c_M and among natives is c_N. Let M represent the total number of immigrants, N represent the total number of natives, and ΔM represent the change in the number of immigrants. α_M and α_N are the possibilities of reporting a crime to police for immigrants and natives respectively. Then the total number of crimes can be expressed as $Mc_M + Nc_N$ and the total number of crimes that are documented in UCR is $Mc_M\alpha_M + Nc_N\alpha_N$.

If the immigrant share increases by 1 percentage point

$$\frac{M+\Delta M}{M+N+\Delta M}-\frac{M}{M+N}=0.01$$

then the change of crime rates that would be captured in the UCR is

$$\frac{Mc_M\alpha_M+\Delta Mc_M\alpha_M+Nc_N\alpha_N}{M+N+\Delta M}-\frac{Mc_M\alpha_M+Nc_N\alpha_N}{M+N}=0.01(c_M\alpha_M-c_N\alpha_N) \tag{8}$$

The key variables that will influence a change in total crime rate are the crime rates and the reporting rates among immigrants and natives.[22]

6.1 Underreporting: Cultural Background

Studies have found that cultural background affects an individual's preferences, behaviour, and economic outcomes [Antecol, 2000; Guiso et al., 2006]. In the context of this paper, cultural background might play a role in an individual's willingness to contact authorities when a crime occurs. If immigrants are less likely to contact police, i.e., $\alpha_M < \alpha_N$, then such underreporting behaviour could appear to be a crime-reducing effect.

To investigate the magnitude of any underreporting, the 1999 and 2009 Victimization Cycles of the General Social Survey (GSS) were analyzed. These two cycles (cycle 13 and cycle 23) collect information to help understand how Canadians perceive crime and the justice system,[23] including their willingness to contact police.

Table 15 presents the estimation results of the following specification

$$C_i=\gamma_0+\gamma_1 Imm_i^N+\gamma_2 Imm_i^R+\gamma_3 Imm^E+\beta_5 X_i+\varepsilon \tag{9}$$

In columns (1) and (2), the dependent variable C_i is a dummy variable that takes value 1 if the respondent contacted police as a victim of a crime in the previous 12 months. In columns (3) and (4), C_i takes value 1 if the respondent contacted police as a witness to a crime in the previous 12

[22] The algebra of Equation (8) can be found in Appendix D.

[23] There are three more GSS cycles that collect information on criminal victimization: cycle 3 (year 1988), cycle 8 (year 1993) and cycle 18 (year 2004). However, due to confidentiality concerns, the public use data of these three cycles do not have detailed enough identifiers that allow me to categorize immigrants by their years-since-arrival. They are therefore left out of the analysis.

months. Imm_i^N, Imm_i^R, and Imm_i^E are dummy variables indicating whether the respondent is a new immigrant, recent immigrant, or established immigrant. X_i indicates other control variables.

Because all of the control variables are mutually exclusive dummy variables, γ_1, γ_2 and γ_3, estimated using a linear probability model (coefficients presented in the first panel), are the differences in the police-contacting probabilities between the three immigrant groups and natives. For a robustness check, average marginal effects of a logit model are also presented in this table.

The estimation results show that all three groups of immigrants tend to contact police less often than natives, either as victims or witnesses. Although the underreporting rates are statistically significant, the magnitudes do not justify the crime-reducing effect found in this paper for the following two reasons.

First, the relative magnitudes of the underreporting are the opposite of the crime reduction pattern along the years-since-arrival dimension. Results in the earlier sections show that more established immigrants have a bigger crime-reducing effect. If such effect comes from the underreporting behaviour, the findings would suggest that more established immigrants contact police less often. On the contrary, estimation with GSS data shows that, although new immigrants are less likely to contact police compared to natives, the difference gets smaller with increasing duration of residency in Canada.

Second, the size of the underreporting is not large enough to account for the size of the crime-reducing effect. Assume the crime rates among immigrants and natives are the same. Averaging the national property crime rate from the year 1977 to the year 2010 yields crime rates $c_M = c_N = 0.05$. To demonstrate an extreme case, consider the largest coefficients of new immigrants in column (2). A reporting rate difference of 0.06 would yield a crime rate change of only 0.0003, or 0.03%, which is much smaller than the estimated crime-reducing effect of 0.2% to 0.3% for recent immigrants, or 0.1% to 0.15% for established immigrants.

Therefore, although there exists a significant difference between immigrants and natives in terms of the frequency of contacting police, the crime reduction effect of immigrants cannot be attributed to the underreporting behaviour.

6.2 Dilution Effect: Influx of Law-Abiding Populations

Another possible explanation of the negative immigrant-crime relationship is that immigrants to Canada are more law-abiding, i.e., $c_M < c_N$.

Estimation of c_M and c_N requires individual-level crime statistics. Unfortunately, crime statistics do not usually collect immigrant identifiers and, at most, collect limited ethnicity information.[24] Existing empirical evidence does not provide a clear picture of criminal behaviour comparisons between immigrants and natives. Nevertheless, Samuel and Faustino-Santos [1991] find that immigrants are underrepresented in the prison population in Canada. Correctional Service of Canada [Trevethan and Rastin, 2004] reports that, among offenders, visible minority offenders are less likely to be "entrenched" in a criminal lifestyle compared to the Caucasian offenders.[25]

If immigrants in Canada are more law-abiding, a large influx of such persons would reduce the density of the criminal population and decrease the crime rate at the aggregate level. A quick look at the national trend supports this interpretation (See Figure 7). In the past three decades, even though the actual count of the property crime incidents has not fallen much, once the population increase is taken into account, the property crime rate shows a clear decreasing pattern.

Still, dilution is not the whole story. Even under the most extreme case, when $c_M = 0$ and $\alpha_N = 1$, i.e., immigrant crime rate is zero and natives report all the crimes that occur, Equation (8) implies that a 0.2% drop in crime rate would require the existing crime rate for natives to be 20%. This number is simply too high. Even at the highest level, the year 1991 reports a total crime rate of only 10% and a property crime rate of only 6%.

The above analysis shows that neither underreporting nor dilution can fully explain the large crime reduction effects of immigrants, suggesting a spillover effect at play. That is, not only do immigrants themselves commit less crimes, they can reduce the crime rates in the long run through channels such as changing the neighbourhood characteristics [Hiebert, 2000] or impacting the behaviour of natives. Related to this point, there is existing empirical evidence that finds a

[24] For example, the United States only records black/white identifier. Canada, Australia and New Zealand only permit aboriginal/non-aboriginal identifier [Tonry, 1997].

[25] Note that although there is a higher share of visible minority in the immigrant population, visible minority and immigrant are not the same concept. By "entrenched," the authors mean the visible minority offenders tend to have less extensive criminal histories, are incarcerated less often for offences against the person, and are lower in risk and need than Caucasian offenders.

reduction in the crime rate often leads to future accumulative crime reduction [Funk and Kugler, 2003; Corman and Mocan, 2005; Caetano and Maheshri, 2013], called "broken window" theory in criminology. Formal tests of any spillover effects require further studies that are beyond the scope of this paper.

7 Conclusion

There has been an increasing concern in countries receiving immigrants that immigration raises crime. However, such concern lacks empirical support. One important challenge of identifying the impact of immigration on crime is reverse causality, or the endogenous location choice of immigrants. On the one hand, immigrants might choose to settle in areas with low crime rates for a better quality of life. On the other hand, areas with high crime rates might have lower housing prices and therefore attract immigrants with few financial resources. This paper uses an instrumental variable strategy that is based on the observation that immigrants tend to go to communities where their families and friends reside.

This paper studies the heterogeneous impact of immigration on crime rates along the years-since-arrival dimension. The impact on crime along this dimension has not been previously studied. This study finds that new immigrants do not have a significant impact on property crime rates, but as they stay longer, more established immigrants actually decrease property crime rates significantly. This pattern is robust to model specification and different ways of including the instrument variables. It is further validated by falsification tests that utilize the structure of the panel data constructed for this paper.

This paper rules out the possibility that immigrants simply do not report to police when crime happens. Similarly, it finds that dilution of the criminal pool by the addition of law-abiding immigrants can not fully explain the size of the estimates. Therefore, the paper concludes that immigration has a spillover effect, such as changing the neighbourhood characteristics and affecting the behaviour of the native population, reducing crime rates in the long run.

This paper establishes the causal relationship between immigration and crime rates in Canada, but it raises more questions. Does immigration reduce crime by affecting labour market outcomes? Do immigrants settle in lower income communities and revitalize them? Is it possible that the spill over effect operates through family ties and affects second-generation immigrants? The answers to these questions are important, but they are beyond the scope of this study. Further research is needed.

References

Antecol, H. (2000). An Examination of Cross-Country Differences in the Gender Gap in Labor Force Participation Rates. *Labour Economics*, 7:409–426.

Aydemir, A. and Borjas, G. J. (2007). Cross-Country Variation in the Impact of International Migration: Canada, Mexico, and the United States. *Journal of the European Economic Association*, 5(June 2007):663–708.

Aydemir, A. and Borjas, G. J. (2011). Attenuation Bias in Measuring the Wage Impact of Immigration. *Journal of Labor Economics*, 29(1):69–113.

Aydemir, A. and Skuterud, M. (2005). Explaining the Deteriorating Entry Earnings of Canada's Immigrant Cohorts, 1966-2000. *Canadian Journal of Economics*, 38(2):641–672.

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

Bell, B., Fasani, F., and Machin, S. (2013). Crime and Immigration: Evidence from Large Immigrant Waves. *Review of Economic and Statistics*, 95(4):1278–1290.

Bernasco, W. (2010). A Sentimental Journey to Crime: Effects of Residential History on Crime Location Choice. *Criminology*, 48(2):389–416.

Bianchi, M., Buonanno, P., and Pinotti, P. (2012). Do Immigrants Cause Crime? *Journal of European Economic Association*, 10(6):1318–1347.

Borjas, G. J. (2003). The Labor Demand Curve is Downward Sloping: Reexaming the Impact of Immigration on the Labor Market. *The Quarterly Journal of Economics*, 118(4):1335–1374.

Borjas, G. J., Grogger, J., and Hanson, G. H. (2006). Immigration and African-American Employment Opportunities: The Response of Wages, Employment, and Incarceration to Labor Supply Shocks. *NBER Working Paper*, 12518.

Butcher, K. F. and Piehl, A. M. (1998). Cross-City Evidence on the Relationship between Immigration and Crime. *Journal of Policy Analysis and Management*, 17(3):457–493.

Caetano, G. and Maheshri, V. (2013). Do "Broken Windows" Matter? Identifying Dynamic Spillovers in Criminal Behavior. *Working Paper*.

Card, D. (2001). Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration. *Journal of Labor Economics*, 19(1):22–64.

Card, D. (2005). Is the New Immigration Really So Bad? *The Economic Journal*, 115(507):F300–F323.

Card, D. (2009). Immigration and Inequality. *American Economic Review*, 99(2):1–21.

Chiu, W. H. and Madden, P. (1998). Burglary and Income Inequality. *Journal of Public Economics*, 69(1):123–141.

Chui, T. (2003). Longitudinal Survey of Immigrants to Canada: Process, Progress and Prospects. *Statistics Canada*, Catalogue(89-611-XIE).

Corman, H. and Mocan, N. (2005). Carrots, Sticks, and Broken Windows. *Journal of Law and Economics*, 48(1):235–266.

Cortes, P. (2008). The Effect of Low-Skilled Immigration on U.S. Prices: Evidence from CPI Data. *Journal of Political Economy*, 116(3):381–422.

Dinovitzer, R., Hagan, J., and Levi, R. (2009). Immigration and Youthful Illegalities in a Global Edge City. *Social Forces*, 88(1):337–372.

Dowden, C. and Brennan, S. (2012). Police-Reported Hate Crime in Canada, 2010. *Juristat - Statistics Canada*, Catalogue(85-002-X).

Ehrlich, I. (1973). Participation in Illegitimate Activities: A Theoretical and Empirical Investigation. *Journal of Political Economy*, 81(3):521.

Ehrlich, I. (1996). Crime, Punishment, and the Market for Offenses. *Journal of Economic Perspectives*, 10(1):43–67.

Ferrer, A. and Riddell, W. C. (2008). Education, Credentials, and Immigrant Earnings. *Canadian Journal of Economics*, 41(1):186–216.

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

Frenette, M. and Morissette, R. (2005). Will They Ever Converge? Earnings of Immigrant and Canadian-Born Workers over the Last Two Decades. *International Migration Review*, 39(1):228–257.

Funk, P. and Kugler, P. (2003). Dynamic Interactions between Crimes. *Economics Letters*, 79(3):291–298.

Glaeser, E. L. and Sacerdote, B. (1999). Why Is There More Crime in Cities ? *Journal of Political Economy*, 107(56):225–258.

Gould, E. D., Weinberg, B. A., and Mustard, D. B. (2002). Crime Rates and Local Labor Market Opportunities in the United States: 1979-1997. *Review of Economics and Statistics*, 84(February):45–61.

Green, A. G. and Green, D. (2004). The Goals of Canada's Immigration Policy: A Historical Perspective. *Canadian Journal of Urban Research*, 13(1):102–139.

Green, D. A. and Worswick, C. (2012). Immigrant Earnings Profiles in the Presence of Human Capital Investment: Measuring Cohort and Macro Effects. *Labour Economics*, 19(2):241–259.

Grogger, J. (1998). Market Wages and Youth Crime. *Journal of Labor Economics*, 16(4):756–791.

Guiso, L., Sapienza, P., and Zingales, L. (2006). Does Culture Affect Economic Outcomes? *Journal of Economic Perspectives*, 20(2):23–48.

Heidensohn, F., Gelsthorpe, L., and Silvestri, M. (2007). Gender and Crime. *The Oxford Handbook of Criminology*, 12:381–420.

Hiebert, D. (2000). Immigration and the Changing Canadian City. *The Canadian Geographer/Le Géographe Canadien*, 122(1).

Hipp, J. R. (2007). Block, Tract, and Levels of Aggregation: Neighborhood Structure and Crime and Disorder as a Case in Point. *American Sociological Review*, 72(5):659–680.

Hunt, J. and Gauthier-Loiselle, M. (2010). How Much Does Immigration Boost Innovation? *American Economic Journal: Macroeconomics*, 2(410):31–56.

Kelly, M. (2000). Inequality and Crime. *Review of Economics and Statistics*, 82(4):530–539.

Levitt, S. D. (1999). The Limited Role of Changing Age Structure in Explaining Aggregate Crime Rates. *Criminology*, 37(3):581–598.

Lochner, L. (2004). Education, Work, and Crime: A Human Capital Approach. *International Economic Review*, 45(3):811–843.

Lochner, L. (2007). Education and Crime. *Social Networks*, (2004):1–14.

Lochner, L. (2011). Non-Production Benefits of Education: Crime, Health, and Good Citizenship. *NBER Working Paper*, (16722).

Mahony, T. H. and Turner, J. (2012). Police-Reported Clearance Rates in Canada, 2010. *Juristat - Statistics Canada*, 85-002-X.

McDonald, J. T. and Worswick, C. (1997). Unemployment Incidence of Immigrant Men in Canada. *Canadian Public Policy*, 23(4):353–373.

Moore, E. G. and Pacey, M. A. (2003). Changing Income Inequality and Immigration in Canada, 1980-1995. *Canadian Public Policy*, 29(1):33–52.

Oreopoulos, P. (2011). Why Do Skilled Immigrants Struggle in the Labor Market? A Field Experiment with Thirteen Thousand Resumes. *American Economic Journal: Economic Policy*, 3(4):148–171.

Picot, G. and Sweetman, A. (2012). Making It in Canada: Immigration Outcomes and Policies. *IRPP Study*, (29).

Reid, L. W., Weiss, H. E., Adelman, R. M., and Jaret, C. (2005). The Immigration-Crime Relationship: Evidence Across US Metropolitan Areas. *Social Science Research*, 34(4):757–780.

Sá, F. (2011). Immigration and House Prices in the UK. *IZA Discussion Paper*, (5893).

Saiz, A. (2003). Room in the Kitchen for the Melting Pot: Immigration and Rental Prices. *Review of Economics and Statistics*, 85(3):502–521.

Saiz, A. (2007). Immigration and Housing Rents in American Cities. *Journal of Urban Economics*, 61(2):345–371.

Sampson, R. J. and Groves, W. B. (1989). Community Structure and Crime: Testing Community Social-Disorganization Theory. *American Journal of Sociology*, 94(4):774–802.

Samuel, T. J. and Faustino-Santos, R. (1991). Canadian Immigrants and Criminality. *International Migration*, 29(1):51–76.

Schmalleger, F. (2000). *Canadian Criminal Justice Today: An Introductory Text for the Twenty-First Century*. Prentice Hall.

Silver, W., Mihorean, K., and Taylor-Butts, A. (2002). Hate Crime in Canada. *Juristat - Statistics Canada*, 24(85-002-XPE).

Simcha-Fagan, O. and Schwartz, J. E. (1986). Neighborhood and Delinquency: An Assessment of Contextual Effects. *Criminology*, 24(4):667–699.

Simon, R. J. and Lynch, J. P. (1999). A Comparative Assessment of Public Opinion toward Immigrants and Immigration Policies. *International Migration Review*, 33(2):455–467.

Simon, R. J. and Sikich, K. W. (2007). Public Attitudes toward Immigrants and Immigration Policies across Seven Nations. *International Migration Review*, 41(4):956–962.

Spenkuch, J. (2013). Understanding the Impact of Immigration on Crime. *American Law and Economics Review*, (Forthcoming).

Tonry, M. (1997). Ethnicity, Crime, and Immigration. *Crime and Justice*, 21(1997):1.

Trevethan, S. and Rastin, C. J. (2004). A Profile of Visible Minority Offenders in the Federal Canadian Correctional System. *Correctional Service of Canada*.

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.

Appendix

A Geograpic area definition

To create an over-time comparable set of geographic units, changes on the census sub-division (CSD) level are adjusted according to the Standard Geographical Classification (SGC) concordance tables. The definition is largely based on SGC 2006.

In the concordance table, there are three types of changes.

1. "Change to": Such changes include the name change as well as the code change and are one-to-one changes. Affected CSD codes in the census prior to 2006 are adjusted to be the same as the code in the census 2006.

2. "Part of": This type of change means that several CSDs in the previous census year are combined to become one new CSD in the later census year. Affected CSD codes are defined according to the later year census code.

3. "Equivalent to": This type of changes mean that several CSDs in the later census year are equivalent to a bigger CSD in the previous census year. Affected CSD codes are defined according to the previous year census code.

Table 16 shows the total number of observations affected by these code definitions in each census year. Despite the frequent changes on the CSD level, definitions of CDs remain relatively constant except for two periods. The first period was from 1986 to 1991, when there were 24 new CD's defined in Quebec and British Columbia. The second period was from 1996 to 2001, due to the newly created Nunavut Territory in 1999.

For most cases, CD boundaries have remained unchanged.

B Sufficiency of the IV exclusive restriction

Technically, the exclusive restriction requires

$$Cov(\Delta\frac{\widehat{Imm_{it}^N}}{Pop_{it}}, \varepsilon_{it}) = 0 \qquad , \qquad Cov(\Delta\frac{\widehat{Imm_{it}^R}}{Pop_{it}}, \varepsilon_{it}) = 0$$

Take new immigrants for example

$$\begin{aligned} Cov(\Delta\frac{\widehat{Imm_{it}^N}}{Pop_{it}}, \varepsilon_{it}) &= E(Cov(\Delta\frac{\widehat{Imm_{it}^N}}{Pop_{it}}, \varepsilon_{it} \mid Pop_{it}, X_{it}, Pop_{i,t-1}, X_{i,t-1})) \\ &= E(Cov(\frac{\widehat{Imm_{it}^N}}{Pop_{it}}, \varepsilon_{it} \mid Pop_{it}, X_{it}, Pop_{i,t-1}, X_{i,t-1})) \\ &\quad -E(Cov(\frac{\widehat{Imm_{i,t-1}^N}}{Pop_{i,t-1}}, \varepsilon_{it} \mid Pop_{it}, X_{it}, Pop_{i,t-1}, X_{i,t-1})) \end{aligned}$$

where

$$\begin{aligned} & E(Cov(\frac{\widehat{Imm_{it}^N}}{Pop_{it}}, \varepsilon_{it} \mid Pop_{it}, X_{it}, Pop_{i,t-1}, X_{i,t-1})) \\ = \quad & E(\frac{1}{Pop_{it}} Cov(\widehat{Imm_{it}^N}, \varepsilon_{it} \mid Pop_{it}, X_{it}, Pop_{i,t-1}, X_{i,t-1})) \\ = \quad & 0 \end{aligned}$$

The last equation is satisfied by the independent condition Equation (4.4).

C Variable definition

Incidents rate

The respondents to UCR are municipal police services. Since census districts (CD) are defined as "groups of neighbouring municipalities joined together for the purposes of regional planning and managing common services (such as police or ambulance services),"[26] they usually contain several municipal police services. Therefore, incidents' counts by municipal police services belonging to the same CD are aggregated.

The incident rate is the total number of incidents of a CD divided by the total population of that CD (obtained from census data).

Gini coefficient

A Gini coefficient is constructed following Kelly [2000]. Assuming income follows log-normal distribution $\log Y \sim N(\mu_y, \sigma_Y^2)$, then the mean income and median income can be expressed as $\text{Mean}(Y) = \exp(\mu_Y + \frac{1}{2}\sigma_Y^2)$, $\text{Med}(Y) = \exp(\mu_y)$. Therefore, $\lg(\text{Mean}(Y)/\text{Med}(Y)) = 1/2\sigma_Y^2$. The Gini coefficient can be calculated using: $\text{Gini} = 2\Phi(\sigma_Y/\sqrt{2}) - 1$, where Φ is the CDF of the standard normal distribution. If the log-normal assumption fails, the calculated index is not exactly a Gini coefficient, but still captures the income inequality.

Hourly wage

Hourly wage is calculated using the annual income from wage and salary divided by the hours worked in the reference year. It is s calculated only for people aged 15 years to 65 years. Hours worked is calculated by multiplying the weeks worked by 40, if the respondent to worked full time, or 20 if the respondent to work part time. The value is adjusted according to the CPI to the 2002 level.

Unemployment rate

Unemployment rate is calculated for less educated people, aged 15 years to 65 years.

Clearance rate

Clearance rates are calculated by dividing the number of crimes that are cleared by the total number of reported incidents. It is commonly used in criminology literature as a measure of the effectiveness and strictness of the justice system.

[26] Statistics Canada: http://www12.statcan.ca

D Proof of Equation (8)

Let M represent the total number of immigrants, N represent the total number of natives, and ΔM represent the change in the number of immigrants. c_M and c_N are the crime rates for immigrants and natives, respectively. α_M and α_N are the possibility of reporting a crime to police for immigrants and natives respectively. Then, the total number of crimes can be expressed as $Mc_M + Nc_N$, and the total number of crime that is documented in UCR is $Mc_M\alpha_M + Nc_N\alpha_N$.

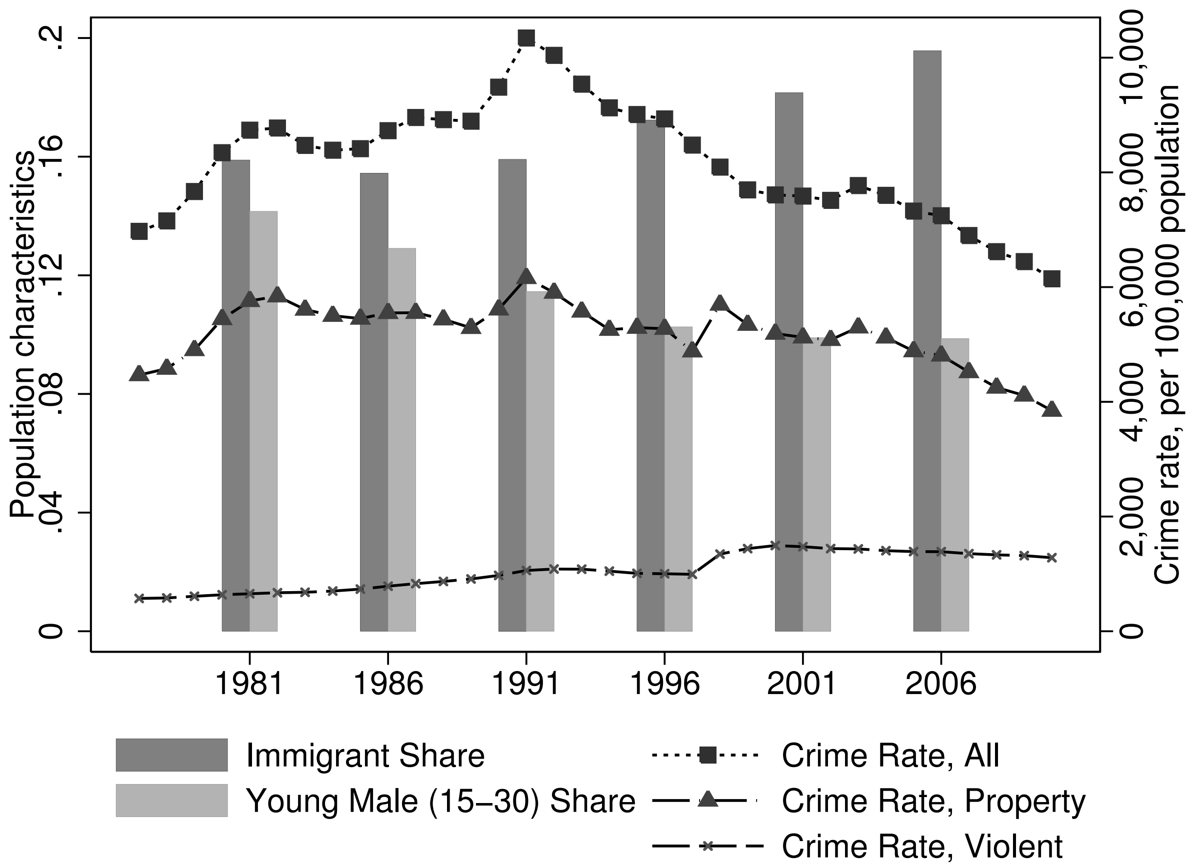
If the immigrant rate increases by 1%

$$\frac{M + \Delta M}{M + N + \Delta M} - \frac{M}{M + N} = 0.01$$

then the change in crime rate would be

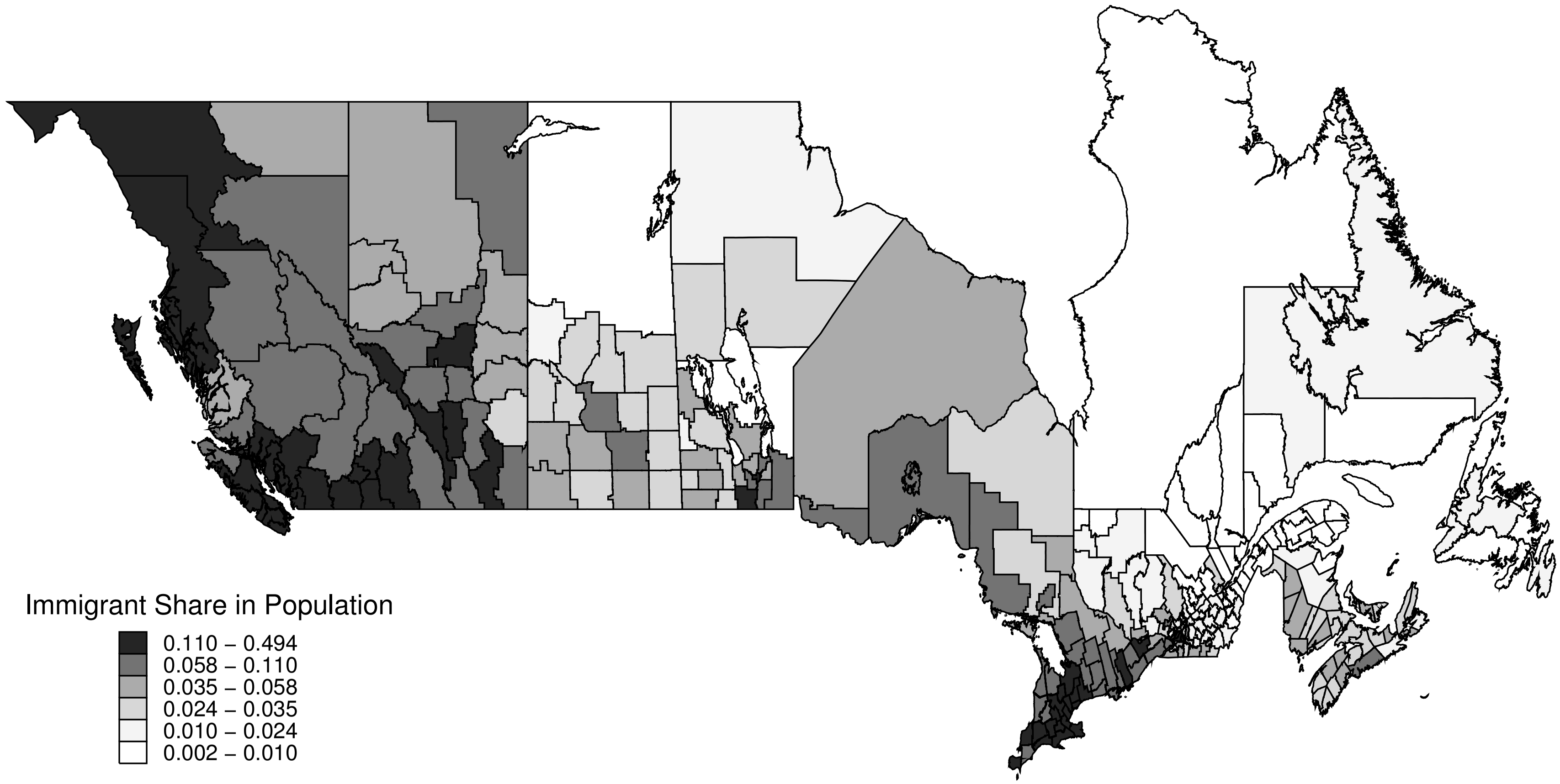
$$\begin{aligned}
& \frac{Mc_M\alpha_M + \Delta M c_M\alpha_M + Nc_N\alpha_N}{M + N + \Delta M} - \frac{Mc_M\alpha_M + Nc_N\alpha_N}{M + N} \\
= \quad & \frac{M + \Delta M}{M + N + \Delta M} c_M\alpha_M + \frac{N}{M + N + \Delta M} c_N\alpha_N - \frac{M}{M + N} c_M\alpha_M - \frac{N}{M + N} c_N\alpha_N \\
= \quad & \left(\frac{M + \Delta M}{M + N + \Delta M} - \frac{M}{M + N}\right) c_M\alpha_M + \left(1 - \frac{M + \Delta M}{M + N + \Delta M} - 1 + \frac{M}{M + N}\right) c_N\alpha_N \\
= \quad & 0.01(c_M\alpha_M - c_N\alpha_N)
\end{aligned}$$

Figure 1: Trend of Immigrant Share, Young Male Share, Crime Rates, Canada, 1977-2010



Source: Uniform Crime Reporting Survey (1977-2010) and Census of Canada (1981, 1986, 1991, 1996, 2001, 2006)
Note: Crime rates are displayed as the number of incidents per 100,000 population. Immigrant rate is defined as the number of immigrants devided by the total population. Young male rate is defined as the number of male aged 15 to 30 devided by the total population.

Figure 2: Distribution of Immigrants on Census Division Level across Canada, 2001



Source: Census of Canada (2001)

Note: Due to the quality of the map data, this figure does not show the three territories: Yukon, Northwest Territories, and Nunavut. The average immigrant share in the three territories is 0.075.

Figure 3: Timeline Illustration of UCR and Census

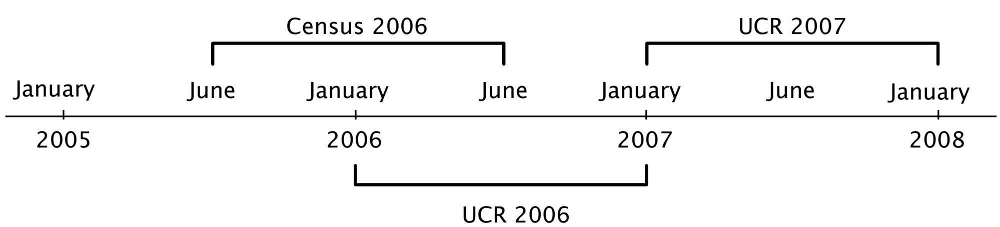
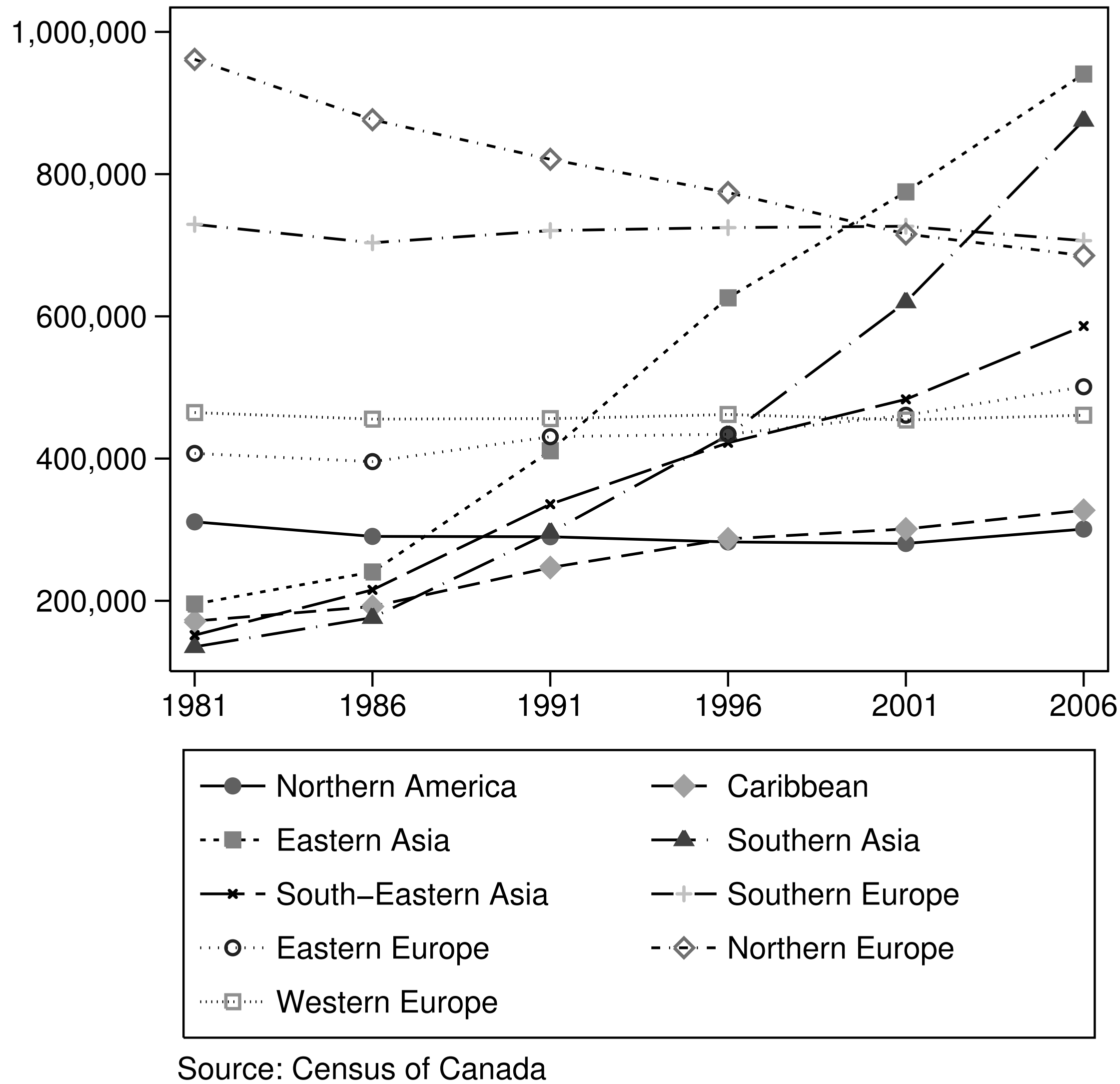
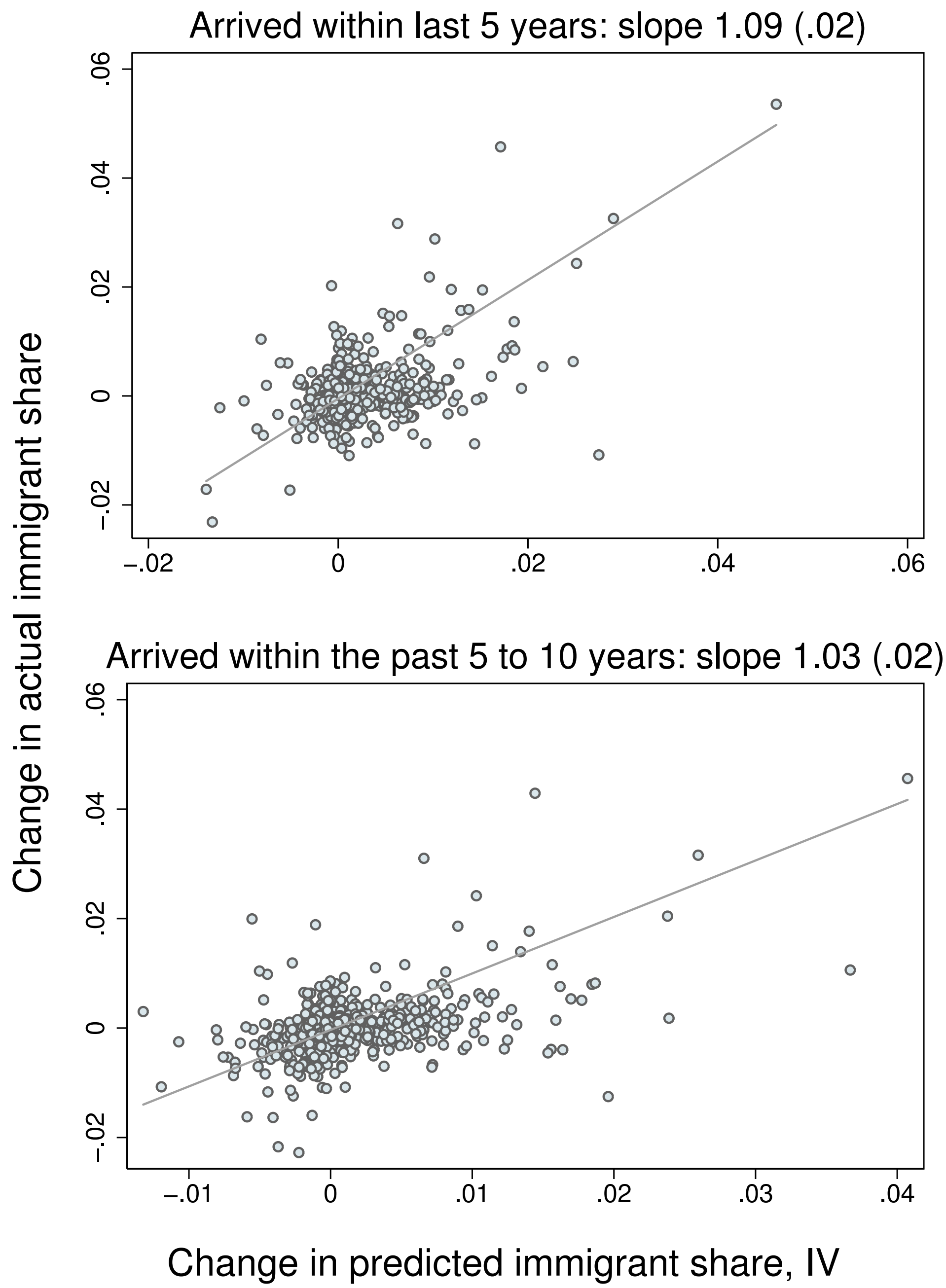


Figure 4: National Total Immigrants Trend by Selected Regions



Source: Census of Canada (1981, 1986, 1986, 1991, 1996, 2001, 2006)
Note: This graph does not show the smaller groups of the eighteen source regions.

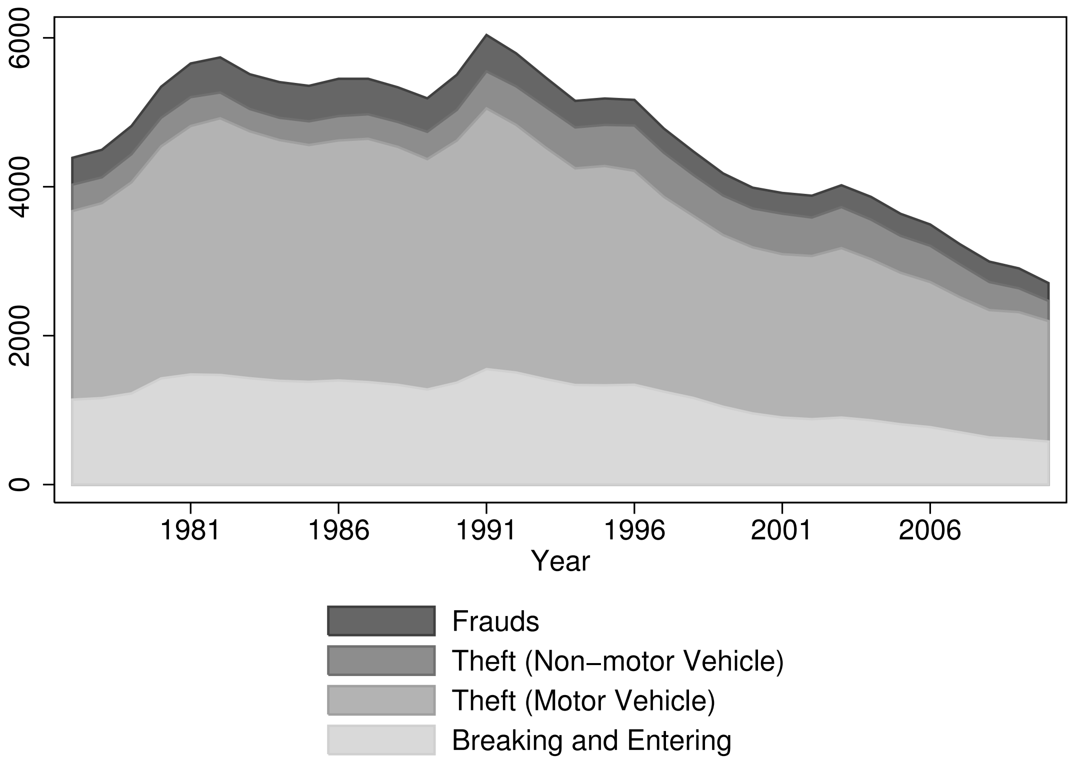
Figure 5: Changes in Predicted versus Actual Immigrant Share



Source: Uniform Crime Reporting Survey and Census of Canada (1986, 1986, 1991, 1996, 2001, 2006)

Note: Fitted line does not include control variables. It shows the "raw" correlation between the change of actual and predicted immigrant share.

Figure 6: Property crime rate per 100,000, Canada, 1977-2010



Source: Uniform Crime Reporting Survey (1977-2010)
Note: "Theft" includes both "major theft" (value over $5,000) and "minor theft" (value below $5,000) .

Figure 7: Crime Rates versus Actual Number of Incidents

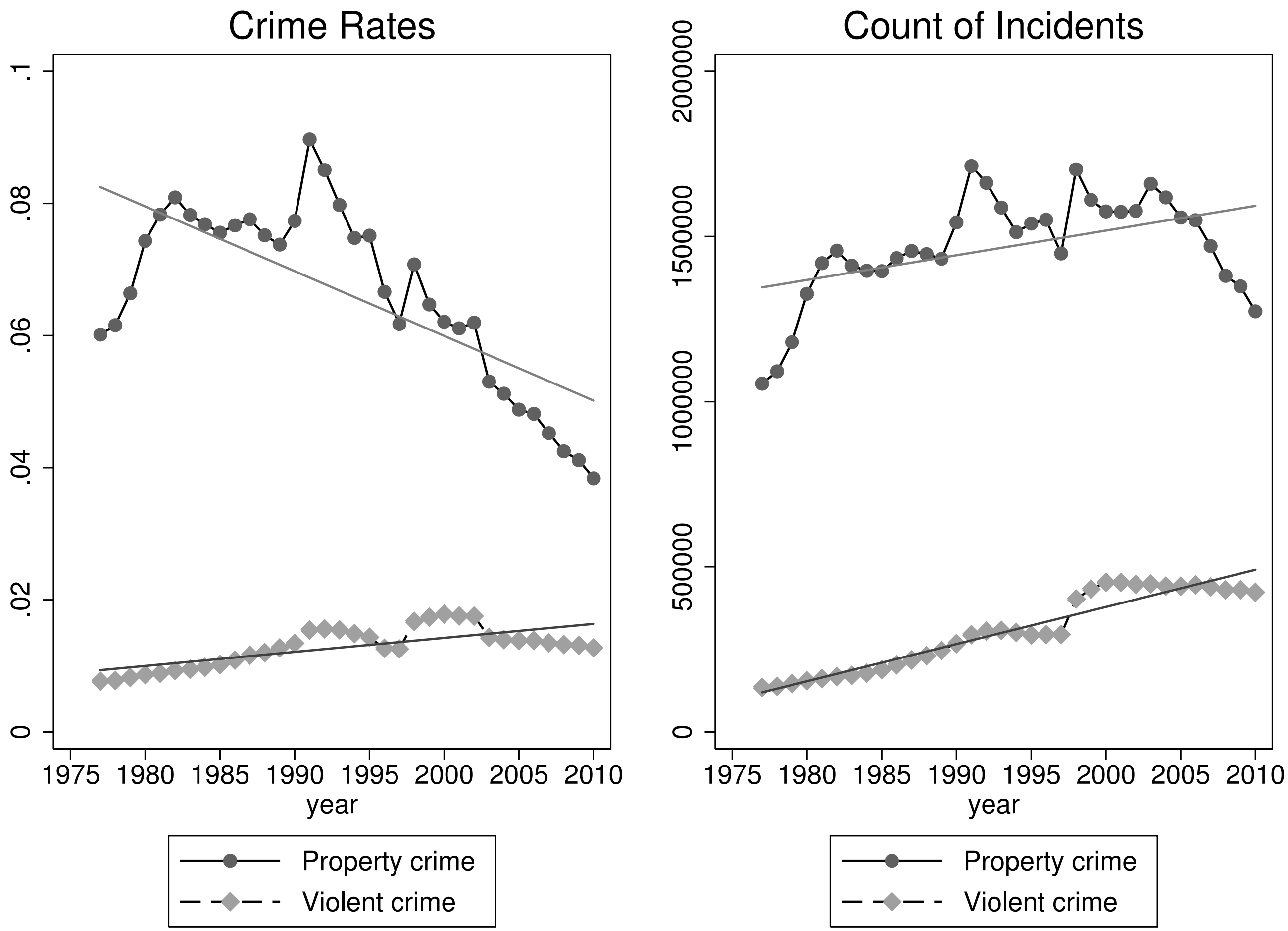


Table 1: Summary Statistics for CD Level Variables

	Number of Observations (1)	Mean (2)	Standard Deviation (3)	Min (4)	Max (5)
UCR variables					
Property crime rate	1374	5.6	2.3	0.3	30.3
Violent crime rate	1374	1.2	0.8	0.0	17.3
Clearance rate (violent crime)	1374	47.8	11.2	18.0	97.7
Immigrant share					
All immigrant	1374	17.7	14.0	0.2	50.0
New immigrant (0-5)	1374	2.6	2.8	0.0	11.2
Recent immigrant (5-10)	1374	2.5	2.6	0.0	9.9
Aggregated subgroups					
African (0-10)	1374	0.4	0.5	0.0	2.8
Asian (0-10)	1374	2.5	3.4	0.0	12.0
European (0-10)	1374	1.1	0.9	0.0	3.7
South/Central American (0-10)	1374	0.6	0.8	0.0	3.5
Other characteristics					
Female	1374	50.8	0.9	45.0	52.9
Married	1374	48.1	2.9	31.8	58.7
Rural population	1374	21.4	23.1	0.0	100.0
Less than high school educated	1374	35.8	10.7	15.3	75.1
High school educated	1374	23.2	3.4	6.7	32.3
Unemployment rate (less educated)	1374	11.1	5.1	2.0	52.4
Hourly wage (less educated, 2002 $)	1374	16.3	1.4	10.3	24.1
0 <Gini coefficient< 1	1374	0.4	0.04	0.22	0.53
Age group share					
Age 15-19	1374	7.0	0.8	4.4	11.8
Age 20-24	1374	7.2	1.3	3.1	14.4
Age 25-29	1374	7.5	1.7	3.0	12.9
Age 30-34	1374	7.9	1.4	3.7	12.4
Age 35-39	1374	8.2	1.0	4.2	11.8
Age 40-44	1374	7.9	1.0	3.8	10.6
Age 45-49	1374	7.0	1.3	3.3	10.2
Age 50-54	1374	6.1	1.2	2.8	10.1
Age 55-59	1374	5.2	1.1	2.0	10.1
Age 60-64	1374	4.5	0.9	1.1	9.1
Age 65-69	1374	3.8	0.8	0.6	9.1
Age 70-above	1374	7.8	2.4	0.9	18.5

Source: UCR and Census of Canada (1986, 1991, 1996, 2001, 2006)

Note: Summary statistics are for aggregated CD level variables. Means are weighted by CD population. Because 1981 census is used for IV construction, dependent variables and control variables are obtained from the last five censuses (1986, 1991, 1996, 2001, 2006). Other than hourly wage and Gini coefficient, all variables are expressed as a percentage value.

Table 2: Summary Statistics for GSS Variables

	Immigrants		Natives	
	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)
Any contact with police in last 12 months				
Contact as a victim	0.081	0.274	0.098	0.297
Contact as a witness	0.047	0.211	0.070	0.255
Immigrant groups				
New immigrant (less than 5)	0.111	0.315		
Recent immigrant (5-10)	0.145	0.352		
Education variables				
University or above	0.337	0.473	0.198	0.398
Diploma below bachelor	0.245	0.430	0.266	0.442
Some university or college	0.133	0.339	0.158	0.365
High school diploma	0.126	0.332	0.152	0.359
Below high school	0.159	0.366	0.226	0.418
Age variables				
Age 15-29	0.187	0.390	0.272	0.445
Age 30-44	0.300	0.458	0.279	0.448
Age 45-49	0.275	0.447	0.250	0.433
Other characteristics				
Female	0.503	0.500	0.508	0.500
Married	0.685	0.464	0.608	0.488
CMA	0.927	0.260	0.767	0.422
Number of observations	7,498		35,401	

Source: General Social Survey (cycle 13 and cycle 23)

Note: Summary statistics are for individual level variables and are weighted using survey weights.

Table 3: Census Divisions' 1981 Shares of National Total Immigrants from Various Regions

Source Regions	Mean	Standard Deviation	Maximum	CD of Maximum	National % Change 1981 to 2006
	(1)	(2)	(3)	(4)	(5)
South America	0.056	0.123	0.436	Toronto	194%
Central America	0.030	0.047	0.132	Montréal	781%
Eastern Africa	0.047	0.083	0.277	Toronto	269%
Northern Africa	0.055	0.135	0.516	Montral	263%
Western and Middle Africa	0.049	0.092	0.320	Toronto	1158%
Southern Africa	0.044	0.086	0.295	Toronto	116%
Northern America	0.023	0.029	0.092	Toronto	-3%
Caribbean	0.060	0.127	0.430	Toronto	91%
Eastern Asia	0.051	0.101	0.298	Toronto	381%
Southern Asia	0.044	0.078	0.261	Toronto	547%
South-Eastern Asia	0.042	0.068	0.224	Toronto	287 %
Southern Europe	0.051	0.102	0.348	Toronto	-3%
Australia and New Zealand	0.033	0.059	0.238	Greater Vancouver	50%
Oceania	0.044	0.143	0.659	Greater Vancouver	144%
Central and Western Asia	0.051	0.092	0.263	Toronto	346%
Eastern Europe	0.039	0.067	0.231	Toronto	23%
Northern Europe	0.031	0.049	0.166	Toronto	-29%
Western Europe	0.026	0.033	0.098	Toronto	-1%

Source: Census of Canada, 1981, Master File

Note: The statistics are for variables $\tau_{i,1981,g}$, the share of national total immigrants from source region g among all immigrants that come from the same source region g in 1981. They are CD level variables. Means are weighted by CD population. There are 281 observations for each source region. Column (5) is calculated by $(\text{Population}_{2006} - \text{Population}_{1981})/\text{Population}_{1981}$.

Table 4: Effect of Immigrant Share on Property Crime Rates, OLS

	(1)	(2)	(3)	(4)	(5)	(6)
Δ New immigrant	0.253	0.206	0.164	0.144	0.194	0.175
(0-5 years)	(0.056)***	(0.065)***	(0.066)**	(0.075)*	(0.068)***	(0.076)**
Δ Recent immigrant	-0.218	-0.199	-0.200	-0.197	-0.179	-0.173
(5-10 years)	(0.070)***	(0.063)***	(0.060)***	(0.063)***	(0.061)***	(0.063)***
Δ Established immigrant	-0.183	-0.164	-0.156	-0.156	-0.110	-0.104
(10 years above)	(0.051)***	(0.046)***	(0.049)***	(0.051)***	(0.054)**	(0.055)*
Δ Log population	-0.013	-0.014	-0.013	-0.013	-0.013	-0.013
density	(0.009)	(0.008)*	(0.007)*	(0.007)*	(0.007)*	(0.007)*
Δ Female		0.173	0.120	0.109	0.187	0.185
		(0.193)	(0.192)	(0.192)	(0.187)	(0.183)
Δ Married		-0.275	-0.265	-0.284	-0.301	-0.328
		(0.087)***	(0.087)***	(0.090)***	(0.098)***	(0.101)***
Δ Rural		0.011	0.004	0.006	0.007	0.009
		(0.020)	(0.019)	(0.019)	(0.018)	(0.018)
Δ Less than high school			0.200	0.205	0.213	0.220
			(0.047)***	(0.047)***	(0.048)***	(0.049)***
Δ High school			0.111	0.112	0.117	0.118
			(0.030)***	(0.030)***	(0.033)***	(0.032)***
Δ Unemployment rate					-0.031	-0.034
for less educated					(0.029)	(0.030)
Δ Hourly wage					0.008	0.011
for less educated					(0.016)	(0.016)
Δ Gini coefficient					-0.048	-0.055
					(0.024)**	(0.024)**
Δ Clearance rate				-0.011		-0.013
for violent crime				(0.007)*		(0.007)*
Age groups share	√	√	√	√	√	√
Year dummies	√	√	√	√	√	√
Observations	1048	1048	1048	1048	1048	1048
R-squared	0.37	0.38	0.41	0.41	0.41	0.42

Dependent variable: property crime rates $\Delta Crime_{it}/Pop_{it}$

Standard errors are in parentheses and are clustered on the CD level. Regressions are weighed by cell size.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Effect of Immigrant Share on Property Crime Rates, IV

	(1)	(2)	(3)	(4)	(5)	(6)
Δ New immigrant	0.159	0.075	0.052	0.025	0.096	0.077
(0-5 years)	(0.053)***	(0.069)	(0.068)	(0.078)	(0.083)	(0.089)
Δ Recent immigrant	-0.338	-0.310	-0.287	-0.281	-0.267	-0.256
(5-10 years)	(0.106)***	(0.097)***	(0.086)***	(0.092)***	(0.086)***	(0.089) ***
Δ Established immigrant	-0.225	-0.212	-0.195	-0.196	-0.157	-0.149
(10 years above)	(0.059)***	(0.051)***	(0.053)***	(0.054)***	(0.062)**	(0.062) **
Δ Log population density	-0.009	-0.009	-0.009	-0.008	-0.010	-0.009
	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Δ Female		0.079	0.038	0.021	0.101	0.100
		(0.207)	(0.206)	(0.205)	(0.200)	(0.193)
Δ Married		-0.325	-0.306	-0.331	-0.322	-0.351
		(0.094)***	(0.093)***	(0.095)***	(0.105)***	(0.109) ***
Δ Rural		0.012	0.004	0.006	0.006	0.008
		(0.020)	(0.019)	(0.019)	(0.018)	(0.018)
Δ Less than high school			0.216	0.223	0.221	0.229
			(0.047)***	(0.047)***	(0.048)***	(0.048) ***
Δ High school			0.119	0.120	0.122	0.122
			(0.031)***	(0.030)***	(0.032)***	(0.032) ***
Δ Unemployment rate					-0.022	-0.026
for less educated					(0.030)	0.031
Δ Hourly wage					0.005	(0.009)
for less educated					(0.017)	0.017
Δ Gini coefficient					-0.032	-(0.039)
					(0.030)	0.031
Δ Clearance rate				-0.013		-0.014
for violent crime				(0.007)*		(0.007) **
Age groups share	√	√	√	√	√	√
Year dummies	√	√	√	√	√	√
First Stage						
New immigrant	0.987	0.947	0.934	0.921	0.926	0.917
	(0.081)***	(0.078)***	(0.076)***	(0.083)***	(0.091)***	(0.096) ***
t-value	12.18	12.13	12.24	11.07	10.2	9.53
Shea's partial R^2	0.47	0.44	0.44	0.43	0.38	0.37
Recent immigrant	0.902	0.908	0.913	0.915	0.905	0.906
	(0.111)***	(0.112)***	(0.110)***	(0.111)***	(0.120)***	(0.121) ***
t-value	8.12	8.11	8.27	8.22	7.54	7.48
Shea's partial R^2	0.42	0.43	0.44	0.44	0.41	0.41
Observations	1048	1048	1048	1048	1048	1048

Dependent variable: property crime rates $\Delta Crime_{it}/Pop_{it}$

Standard errors are in parentheses and are clustered on the CD level. Regressions are weighed by cell size.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: This specification has two instrumental variables: $\frac{\widehat{Imm}^N_{i,t}}{Pop_{it}}$ and $\frac{\widehat{Imm}^R_{i,t}}{Pop_{it}}$. $\frac{Imm^O_{i,t}}{Pop_{it}}$ is included as a control.

Table 6: Effect of Immigrant Share on $t + x$ Property Crime Rates

	t+1		t+2		t+3		t+4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OLS								
Δ New immigrant share	0.098	0.078	-0.074	-0.076	-0.178	-0.176	-0.214	-0.221
	(0.053)*	(0.060)	(0.074)	(0.076)	(0.080)**	(0.080)**	(0.080)***	(0.080)***
Δ Recent immigrant share	-0.098	-0.092	-0.134	-0.133	-0.134	-0.134	-0.244	-0.242
	(0.051)*	(0.049)*	(0.052)**	(0.053)**	(0.055)**	(0.055)**	(0.088)***	(0.087)***
Δ Established immigrant share	-0.133	-0.127	-0.159	-0.158	-0.201	-0.201	-0.196	-0.194
	(0.063)**	(0.065)*	(0.105)	(0.106)	(0.120)*	(0.120)*	(0.136)	(0.137)
R-squared	0.43	0.44	0.30	0.30	0.26	0.26	0.24	0.24
IV								
Δ New immigrant share	-0.031	-0.051	-0.298	-0.304	-0.336	-0.337	-0.443	-0.452
	(0.086)	(0.089)	(0.097)***	(0.103)***	(0.095)***	(0.096)***	(0.095)***	(0.095)***
Δ Recent immigrant share	-0.163	-0.152	-0.312	-0.309	-0.284	-0.283	-0.480	-0.475
	(0.078)**	(0.066)**	(0.084)***	(0.082)***	(0.068)***	(0.069)***	(0.116)***	(0.113)***
Δ Established immigrant share	-0.188	-0.180	-0.264	-0.262	-0.279	-0.279	-0.313	-0.309
	(0.072)***	(0.073)**	(0.104)***	(0.105)**	(0.119)**	(0.121)**	(0.134)**	(0.135)**
First Stage								
Δ New immigrant share	0.925	0.915	0.925	0.916	0.925	0.916	0.925	0.916
	(0.091)***	(0.096)***	(0.091)***	(0.096)***	(0.091)***	(0.097)***	(0.091)***	(0.096)***
T-value	10.2	9.5	10.2	9.5	10.2	9.5	10.2	9.5
Shea's partial R	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.39
Δ Recent immigrant share	0.904	0.905	0.904	0.905	0.904	0.905	0.904	0.905
	(0.120)***	(0.122)***	(0.120)***	(0.122)***	(0.121)***	(0.122)***	(0.120)***	(0.122)***
T-value	7.5	7.5	7.5	7.4	7.5	7.4	7.5	7.5
Shea's partial R	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42
Log population density	√	√	√	√	√	√	√	√
Age groups	√	√	√	√	√	√	√	√
Female, married, rural	√	√	√	√	√	√	√	√
Less educated	√	√	√	√	√	√	√	√
Economic variables	√	√	√	√	√	√	√	√
Clearance rate	√	√	√	√	√	√	√	√
Year dummies	√	√	√	√	√	√	√	√
CD dummies	√	√	√	√	√	√	√	√
Number of observations	1042	1039	1044	1041	1041	1038	1041	1038

Dependent variable: property crime rates $\Delta Crime_{it}/Pop_{it}$, year $t + x$ UCR matched with year t census, where$x$ takes value 1 to 4.
Standard errors are in parentheses and are clustered on the CD level. Regressions are weighed by cell size.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Effect of Immigrant Share on $t - x$ Property Crime Rates

	t-1		t-2		t-3		t-4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OLS								
Δ New immigrant share	0.162	0.143	0.086	0.061	0.063	0.047	0.057	0.055
	(0.065)**	(0.070)**	(0.050)*	(0.049)	(0.057)	(0.056)	(0.055)	(0.056)
Δ Recent immigrant share	-0.115	-0.109	-0.060	-0.052	0.037	0.042	0.219	0.220
	(0.045)**	(0.046)**	(0.048)	(0.053)	(0.061)	(0.067)	(0.046)***	(0.046)***
Δ Established immigrant share	-0.060	-0.053	-0.020	-0.012	0.008	0.013	0.001	0.002
	(0.047)	(0.045)	(0.056)	(0.051)	(0.057)	(0.055)	(0.049)	(0.049)
R-squared	0.23	0.24	0.20	0.22	0.24	0.25	0.40	0.40
IV								
Δ New immigrant share	0.133	0.115	0.041	0.017	0.037	0.021	0.011	0.009
	(0.071)*	(0.076)	(0.067)	(0.072)	(0.065)	(0.070)	(0.078)	(0.081)
Δ Recent immigrant share	-0.127	-0.116	-0.103	-0.089	-0.060	-0.051	0.067	0.069
	(0.089)	(0.090)	(0.099)	(0.107)	(0.116)	(0.122)	(0.085)	(0.085)
Δ Established immigrant share	-0.071	-0.064	-0.042	-0.033	-0.017	-0.011	-0.039	-0.038
	(0.052)	(0.050)	(0.064)	(0.061)	(0.064)	(0.063)	(0.052)	(0.053)
First Stage								
Δ New immigrant share	0.926	0.917	0.926	0.917	0.926	0.917	0.926	0.917
	(0.091)***	(0.096)***	(0.091)***	(0.096)***	(0.091)***	(0.096)***	(0.091)***	(0.096)***
T-value	10.2	9.5	10.2	9.5	10.2	9.5	10.2	9.5
Shea's partial R	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.39
Δ Recent immigrant share	0.905	0.906	0.905	0.906	0.905	0.906	0.905	0.906
	(0.120)***	(0.121)***	(0.120)***	(0.121)***	(0.120)***	(0.121)***	(0.120)***	(0.121)***
T-value	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5
Shea's partial R	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42
Log population density	√	√	√	√	√	√	√	√
Age groups	√	√	√	√	√	√	√	√
Female, married, rural	√	√	√	√	√	√	√	√
Less educated	√	√	√	√	√	√	√	√
Economic variables	√	√	√	√	√	√	√	√
Clearance rate	√	√	√	√	√	√	√	√
Year dummies	√	√	√	√	√	√	√	√
CD dummies	√	√	√	√	√	√	√	√
Number of observations	1044	1048	1046	1043	1046	1043	1044	1041

Dependent variable: property crime rates $\Delta Crime_{it}/Pop_{it}$, year $t + x$ UCR matched with year t census, where$x$ takes value -1 to -4.
Standard errors are in parentheses and are clustered on the CD level. Regressions are weighed by cell size.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: Effect of Immigrant Share on Property Crime Rates, IV Robustness Check I

	(1)	(2)	(3)	(4)	(5)	(6)
Δ New immigrant share	0.059	-0.017	-0.035	-0.065	-0.079	-0.098
	(0.103)	(0.106)	(0.105)	(0.114)	(0.221)	(0.226)
Δ Recent immigrant share	-0.352	-0.327	-0.305	-0.299	-0.325	-0.316
	(0.121)***	(0.113)***	(0.099)***	(0.106)***	(0.141)**	(0.144)**
Δ Established immigrant share	-0.417	-0.411	-0.395	-0.402	-0.449	-0.445
	(0.133)***	(0.121)***	(0.136)***	(0.137)***	(0.271)*	(0.272)
First Stage						
Δ New immigrant share	1.095	1.044	1.029	1.016	1.028	1.016
	(0.075)***	(0.082)***	(0.084)***	(0.088)***	(0.091)***	(0.095)***
t-value	14.5	12.7	12.3	11.6	11.3	10.7
Shea's partial R^2	0.26	0.28	0.27	0.27	0.11	0.11
Δ Recent immigrant share	0.941	0.945	0.948	0.950	0.945	0.946
	(0.122)***	(0.122)***	(0.121)***	(0.122)***	(0.130)***	(0.131)***
t-value	7.7	7.8	7.9	7.8	7.3	7.2
Shea's partial R^2	0.41	0.42	0.41	0.42	0.28	0.28
Δ Established immigrant share	0.446	0.445	0.404	0.404	0.336	0.335
	(0.082)***	(0.077)***	(0.083)***	(0.084)***	(0.082)***	(0.083)***
t-value	5.4	5.8	4.9	4.8	4.1	4.1
Shea's partial R^2	0.15	0.16	0.14	0.14	0.06	0.06
Log population density	√	√	√	√	√	√
Age groups	√	√	√	√	√	√
Female, married, rural		√	√	√	√	√
Less educated			√	√	√	√
Economic variables					√	√
Clearance rate				√		√
Year dummies	√	√	√	√	√	√
Number of observations	1048	1048	1048	1048	1048	1048

Dependent variable: property crime rates $\Delta Crime_{it}/Pop_{it}$

Standard errors are in parentheses and are clustered on the CD level. Regressions are weighed by cell size.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: This specification uses three instrumental variables: $\frac{\widehat{Imm}^{N}_{i,t}}{Pop_{it}}$, $\frac{\widehat{Imm}^{R}_{i,t}}{Pop_{it}}$, $\frac{\widehat{Imm}^{O}_{i,t}}{Pop_{it}}$ for the three immigrant groups.

Table 9: Effect of Immigrant Share on Property Crime Rates, IV Robustness Check II

	(1)	(2)	(3)	(4)	(5)	(6)
Δ New immigrant share	0.158	0.074	0.051	0.025	0.092	0.074
	(0.053)***	(0.069)	(0.068)	(0.079)	(0.083)	(0.089)
Δ Recent immigrant share	-0.342	-0.315	-0.292	-0.283	-0.277	-0.265
	(0.108)***	(0.099)***	(0.089)***	(0.094)***	(0.088)***	(0.091)***
Δ Established immigrant share	-0.226	-0.213	-0.196	-0.196	-0.159	-0.152
	(0.059)***	(0.051)***	(0.053)***	(0.054)***	(0.061)***	(0.062)**
First Stage						
Δ New immigrant share	0.986	0.945	0.933	0.921	0.929	0.920
	(0.084)***	(0.083)***	(0.081)***	(0.087)***	(0.095)***	(0.100)***
t-value	11.8	11.4	11.6	10.6	9.7	9.2
Shea's partial R	0.49	0.46	0.46	0.45	0.41	0.40
Δ Recent immigrant share	0.858	0.860	0.864	0.866	0.859	0.860
	(0.103)***	(0.104)***	(0.102)***	(0.103)***	(0.111)***	(0.112)***
t-value	8.3	8.3	8.4	8.4	7.7	7.7
Shea's partial R	0.47	0.48	0.48	0.48	0.46	0.47
Log population density	√	√	√	√	√	√
Age groups	√	√	√	√	√	√
Female, married, rural		√	√	√	√	√
Less educated			√	√	√	√
Economic variables					√	√
Clearance rate				√		√
Year dummies	√	√	√	√	√	√
Number of observations	1048	1048	1048	1048	1048	1048

Dependent variable: property crime rates $\Delta Crime_{it}/Pop_{it}$

Standard errors are in parentheses and are clustered on the CD level. Regressions are weighed by cell size.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Recent immigrant share is instrumented using lagged new immigrant share. Established immigrant share is included as a control variable.

Table 10: Effect of Immigrant Share on Property Crime Rates, First Difference with CD Dummies

	t	t+1	t+2	t+3	t+4	t-1	t-2	t-3	t-4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
OLS									
Δ New immigrant share	0.125	0.061	-0.071	-0.228	-0.279	0.159	0.102	0.107	0.104
	(0.130)	(0.097)	(0.137)	(0.160)	(0.153)*	(0.141)	(0.102)	(0.103)	(0.098)
Δ Recent immigrant share	-0.242	-0.147	-0.189	-0.222	-0.360	-0.114	-0.032	0.059	0.211
	(0.087)***	(0.062)**	(0.088)**	(0.091)**	(0.115)***	(0.075)	(0.079)	(0.084)	(0.058)***
Δ Established immigrant share	-0.263	-0.225	-0.225	-0.352	-0.373	-0.105	-0.021	-0.005	-0.035
	(0.097)***	(0.099)**	(0.172)	(0.203)*	(0.215)*	(0.133)	(0.113)	(0.096)	(0.097)
IV									
Δ New immigrant share	0.131	0.001	-0.267	-0.264	-0.440	0.234	0.062	0.115	-0.018
	(0.201)	(0.171)	(0.196)	(0.202)	(0.155)***	(0.177)	(0.131)	(0.131)	(0.168)
Δ Recent immigrant share	-0.184	-0.121	-0.266	-0.229	-0.449	-0.040	-0.034	0.030	0.096
	(0.132)	(0.068)*	(0.097)***	(0.095)**	(0.124)***	(0.130)	(0.117)	(0.112)	(0.097)
Δ Established immigrant share	-0.232	-0.253	-0.390	-0.380	-0.522	-0.021	-0.048	-0.013	-0.169
	(0.170)	(0.145)*	(0.192)**	(0.208)*	(0.199)***	(0.180)	(0.152)	(0.144)	(0.162)
First stage									
Δ New immigrant share	0.774	0.772	0.772	0.772	0.773	0.774	0.774	0.774	0.774
	(0.175)***	(0.175)***	(0.175)***	(0.176)***	(0.175)***	(0.175)***	(0.175)***	(0.175)***	(0.175)***
t-value	4.42	4.41	4.41	4.39	4.41	4.42	4.41	4.41	4.41
Δ Recent immigrant share	0.841	0.840	0.840	0.839	0.839	0.841	0.841	0.841	0.841
	(0.115)***	(0.115)***	(0.115)***	(0.115)***	(0.115)***	(0.115)***	(0.115)***	(0.115)***	(0.115)***
t-value	7.33	7.31	7.32	7.28	7.29	7.33	7.32	7.32	7.31
Log population density	√	√	√	√	√	√	√	√	√
Age groups	√	√	√	√	√	√	√	√	√
Female, married, rural	√	√	√	√	√	√	√	√	√
Less educated	√	√	√	√	√	√	√	√	√
Economic variables	√	√	√	√	√	√	√	√	√
Clearance rate	√	√	√	√	√	√	√	√	√
Year dummies	√	√	√	√	√	√	√	√	√
CD dummies	√	√	√	√	√	√	√	√	√
Number of observations	1045	1039	1041	1038	1038	1045	1043	1043	1041

Dependent variable: property crime rates $\Delta Crime_{it}/Pop_{it}$, year $t+x$ UCR matched with year t census, where$-4 \leq x \leq x$.
Standard errors are in parentheses and are clustered on the CD level. Regressions are weighed by cell size.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 11: Effect of Immigrant Share on Property Crime Rates, Top 65 CDs

	t	t+1	t+2	t+3	t+4	t-1	t-2	t-3	t-4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IV, with weight									
Δ New immigrant share	0.056	-0.058	-0.359	-0.394	-0.489	0.170	0.133	0.105	0.110
	(0.104)	(0.108)	(0.122)***	(0.136)***	(0.127)***	(0.088)***	(0.081)	(0.079)	(0.089)
Δ Recent immigrant share	-0.259	-0.171	-0.267	-0.260	-0.489	-0.108	-0.020	0.029	0.194
	(0.111)**	(0.074)**	(0.118)**	(0.094)***	(0.112)***	(0.095)	(0.114)	(0.140)	(0.093)**
Δ Established immigrant share	-0.191	-0.268	-0.377	-0.419	-0.453	-0.023	0.066	0.050	0.011
	(0.077)**	(0.071)***	(0.094)***	(0.113)***	(0.130)***	(0.076)	(0.091)	(0.086)	(0.074)
IV, without weight									
Δ New immigrant share	0.043	-0.008	-0.312	-0.241	-0.300	0.072	0.069	0.100	0.021
	(0.111)	(0.118)	(0.149)**	(0.143)*	(0.139)**	(0.098)	(0.098)	(0.121)	(0.097)
Δ Recent immigrant share	-0.238	-0.148	-0.299	-0.269	-0.317	-0.089	-0.033	-0.027	0.086
	(0.146)	(0.118)	(0.174)*	(0.147)*	(0.176)*	(0.154)	(0.155)	(0.183)	(0.157)
Δ Established immigrant share	-0.126	-0.165	-0.164	-0.184	-0.204	-0.085	-0.050	-0.044	-0.027
	(0.081)	(0.075)**	(0.095)*	(0.094)*	(0.096)**	(0.086)	(0.088)	(0.092)	(0.075)
Log population density	√	√	√	√	√	√	√	√	√
Age groups	√	√	√	√	√	√	√	√	√
Female, married, rural	√	√	√	√	√	√	√	√	√
Less educated	√	√	√	√	√	√	√	√	√
Economic variables	√	√	√	√	√	√	√	√	√
Clearance rate	√	√	√	√	√	√	√	√	√
Year dummies	√	√	√	√	√	√	√	√	√
CD dummies	√	√	√	√	√	√	√	√	√
Number of observations	259	258	258	257	258	259	259	259	259

Dependent variable: property crime rates $\Delta Crime_{it}/Pop_{it}$, year $t+x$ UCR matched with year t census, where$x$ takes value -4 to 4.
Standard errors are in parentheses and are clustered on the CD level. First stage statistics all pass the weak IV tests, and are not reported here.
Statistics Canada defines Census Metropolitan Area as an area with a total population of at least 100,000. Sixty-five CDs in 2006 have a population over the 100,000 threshold and are included in the analysis for this table.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 12: Effect of Immigrant Share on Property Crime Rates, Interactions in Control Variables

	(1)	(2)	(3)	(4)	(5)	(6)
OLS						
Δ New immigrant share	0.175	0.193	0.097	0.181	0.168	0.129
	(0.076)**	(0.079)**	(0.074)	(0.077)**	(0.074)**	(0.075)*
Δ Recent immigrant share	-0.173	-0.025	-0.271	-0.152	-0.179	-0.056
	(0.063)***	(0.052)	(0.071)***	(0.059)**	(0.066)***	(0.055)
Δ Established immigrant share	-0.104	-0.114	-0.213	-0.116	-0.107	-0.195
	(0.055)*	(0.057)**	(0.069)***	(0.054)**	(0.057)*	(0.061)***
IV						
Δ New immigrant share	0.077	0.001	-0.009	0.102	0.071	-0.058
	(0.089)	(0.097)	(0.122)	(0.084)	(0.085)	(0.109)
Δ Recent immigrant share	-0.256	-0.122	-0.378	-0.213	-0.269	-0.132
	(0.089)***	(0.152)	(0.107)***	(0.081)***	(0.087)***	(0.117)
Δ Established immigrant share	-0.149	-0.235	-0.276	-0.152	-0.150	-0.300
	(0.062)**	(0.091)**	(0.094)***	(0.058)***	(0.062)**	(0.089)***
Controls†						
Log population density	√	√	√	√	√	√
Age groups share (separate)		√				√
Share of female, married, rural (separate)			√			√
Share of less educated (separate)				√		√
Economic variables (separate)					√	√
Clearance rate	√	√	√	√	√	√
Year dummies	√	√	√	√	√	√
Observations	1048	1048	1048	1048	1048	1048

Dependent variable: property crime rates $\Delta Crime_{it}/Pop_{it}$

Standard errors are in parentheses and are clustered on the CD level. Regressions are weighed by cell size.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

† Each column includes the whole set of controls."Y" indicates the variables are defined for immigrants and natives separately. For example, "separate married" means the share of married population enters in the regression as two variables: share of married population among immigrants, and share of married population among natives.

Table 13: Detailed Property Crime Categories

	Breaking and Entering		Motor Theft		Other Theft		Fraud	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OLS estimation								
Δ New immigrant share	0.032	0.027	0.043	0.039	0.152	0.141	-0.001	0.000
(0-5 years)	(0.021)	(0.023)	(0.017)**	(0.018)**	(0.032)***	(0.036)***	(0.006)	(0.007)
Δ Recent immigrant share	-0.030	-0.029	-0.021	-0.020	-0.076	-0.074	-0.017	-0.017
(5-10 years)	(0.022)	(0.021)	(0.014)	(0.014)	(0.033)**	(0.034)**	(0.014)	-0.014
Δ Established immigrant share	0.010	0.011	-0.045	-0.045	-0.027	-0.024	0.024	0.024
(10 years above)	(0.020)	(0.020)	(0.014)***	(0.014)***	(0.030)	(0.031)	(0.005)***	-0.005 ***
IV estimation								
Δ New immigrant share	-0.045	-0.051	0.067	0.063	0.089	0.077	0.013	0.015
(0-5 years)	(0.019)**	(0.021) **	(0.019)***	(0.019)***	(0.047)*	(0.048)	(0.010)	-0.01
Δ Recent immigrant share	-0.060	-0.057	-0.016	-0.015	-0.183	-0.177	-0.024	-0.025
(5-10 years)	(0.037)	(0.035)	(0.016)	(0.017)	(0.064)***	(0.062)***	(0.020)	-0.02
Δ Established immigrant share	-0.021	-0.019	-0.036	-0.036	-0.063	-0.061	0.028	0.028
(10 years above)	(0.021)	(0.021)	(0.016)**	(0.016)**	(0.036)*	(0.036)*	(0.006)***	-0.006 ***
Controls								
Δ Log Population	√	√	√	√	√	√	√	√
Δ Age Groups	√	√	√	√	√	√	√	√
Δ Female, married, rural	√	√	√	√	√	√	√	√
Δ Less educated	√	√	√	√	√	√	√	√
Δ Economic variables	√	√	√	√	√	√	√	√
Δ Clearance rate, violent		√		√		√		√
Year Dummies	√	√	√	√	√	√	√	√
Observations	1098	1098	1098	1098	1098	1098	1098	1098

The major theft (with value above $5,000) is not differed from the minor theft (with value below $5,000) because the value cutoff defined in the criminal code is not subject to the adjustment of Consumer Price Index (CPI), which makes the severity comparison unclear.

Dependent variable: crime rates $\Delta Crime_{it}/Pop_{it}$

Standard errors are in parentheses and are clustered on the CD level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 14: Impact of Immigrants by Country of Birth

	Africa		Asia		Europe		South and Central America	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OLS estimation								
Δ New immigrant share	0.645	0.476	0.344	0.322	-0.032	-0.083	0.684	0.536
(0-5 years)	(0.443)	(0.434)	(0.103)***	(0.114)***	(0.178)	(0.182)	(0.366)*	(0.368)
Δ Recent immigrant share	-1.117	-1.052	-0.206	-0.188	-0.318	-0.365	-0.790	-0.818
(5-10 years)	(0.423)***	(0.453)**	(0.080)**	(0.084)**	(0.245)	(0.249)	(0.263)***	(0.275)***
Δ Established immigrant share	-0.013	0.127	-0.073	-0.079	-0.023	-0.013	-0.255	-0.195
(10 years above)	(0.392)	(0.359)	(0.059)	(0.062)	(0.050)	(0.051)	(0.138)*	(0.123)
IV estimation								
Δ New immigrant share	2.893	2.658	0.328	0.302	-1.250	-1.559	0.902	0.603
(0-5 years)	(0.957)***	(0.964)***	(0.091)***	(0.105)***	(0.795)	(0.853)*	(0.402)**	(0.370)
Δ Recent immigrant share	-3.491	-3.130	-0.354	-0.326	-1.236	-1.381	-0.299	-0.458
(5-10 years)	(1.061)***	(1.048)***	(0.164)**	(0.164)**	(0.529)**	(0.531)***	(0.783)	(0.691)
Δ Established immigrant share	-0.860	-0.689	-0.072	-0.079	-0.092	-0.091	-0.156	-0.124
(10 years above)	(0.666)	(0.610)	(0.059)	(0.061)	(0.059)	(0.068)	(0.182)	(0.159)
Controls								
Δ Log Population	√	√	√	√	√	√	√	√
Δ Age Groups	√	√	√	√	√	√	√	√
Δ Female, married, rural	√	√	√	√	√	√	√	√
Δ Less educated	√	√	√	√	√	√	√	√
Δ Economic variables	√	√	√	√	√	√	√	√
Δ Clearance rate, violent		√		√		√		√
Year Dummies	√	√	√	√	√	√	√	√
Observations	1098	1098	1098	1098	1098	1098	1098	1098

Standard errors are in parentheses and are clustered on the CD level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 15: Probability of Contacting Police during the Previous 12 Months

	As a Victim		As a Witness	
	(1)	(2)	(3)	(4)
Linear probability model (LPM)				
New immigrants	-0.043	-0.057	-0.034	-0.048
	(0.011)***	(0.011)***	(0.010)***	(0.010)***
Recent immigrants	-0.021	-0.034	-0.019	-0.030
	(0.010)**	(0.010)***	(0.009)**	(0.009)***
Established immigrants	-0.021	-0.009	-0.031	-0.019
	(0.005)***	(0.005)*	(0.004)***	(0.004)***
Logit model: average marginal effect				
New immigrants	-0.048	-0.060	-0.038	-0.050
	(0.016)***	(0.015)***	(0.014)***	(0.014)***
Recent immigrants	-0.022	-0.032	-0.019	-0.028
	(0.011)*	(0.011)***	(0.011)*	(0.010)***
Established immigrants	-0.021	-0.009	-0.035	-0.022
	(0.005)***	(0.005)	(0.005)***	(0.005)***
Controls				
Female		√		√
Married		√		√
Age group dummies		√		√
CMA	√	√	√	√
Year dummies	√	√	√	√
Province dummies	√	√	√	√
Observations	43,909	43,522	43,903	43515
LPM R-squared	0.018	0.028	0.005	0.017

Estimation is based on the 1999 and 2009 General Social Survey (GSS). The omitted group is: natives, male, single, age 60 and above (GSS only surveyed those aged 15 and above), non-CMA, Newfoundland and Labrador, year 1999.

All the regressions are weighted using survey weight.

Robust standard errors are in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 16: Count of Inconsistent CSD/CD Definition

	Census 2006	Census 2001	Census 1996	Census 1991	Census 1986	Census 1981
Observations	6470470	6080920	6025565	5624810	5241570	5036960
1981 to 1986						79040
1986 to 1991					1303470	1274005
1991 to 1996				166625	150100	141715
1996 to 2001			1272935	1202825	1139350	1109085
2001 to 2006		859550	882905	852215	800425	782695
2006 to 2001	2600	1685	1570	1370	1305	1370
2001 to 1996	87805	82340	8640	9345	9670	22990
1996 to 1991	25165	24250	24465	1625	1860	5490
Census sub-division level influenced						
Observations	115570	967825	2190515	2234005	3406180	3416390
Percentage	1.8%	15.9%	36.4%	39.7%	65.0%	67.8%
Census division level influenced						
Observations	61	28779	57674	89770	1272134	1305520
Percentage	0.0%	0.5%	1.0%	1.6%	24.3%	25.9%

Table 17: Police-reported Count of Incidents, per 100,000 Population, 2006-2010

	Total Incidents	Total Violent	Total Property	Hate Crime
2006	7243.98	1386.45	4808.18	3.1
2007	6898.79	1352.13	4519.03	2.7
2008	6617.37	1331.52	4248.93	3.5
2009	6444.09	1318.3	4110.84	5
2010	6144.82	1282.12	3846.2	4.1

Source: Uniform Crime Reporting Survey (UCR); Dowden and Brennan [2012]