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Immigration, Crime, and Crime (Mis)Perceptions

Migration Unit

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Abstract

Does immigration affect crime or beliefs about crime? We answer this question in the context of Chile, where the foreign-born population almost tripled in five years. To identify a causal effect, we use two strategies: a two-way fixed effects model at the municipality level and a 2SLS model, which is based on immigration toward destination countries other than Chile. First, we show that immigration increases concerns about crime and public security. We then document a substantial effect on behavioral responses such as investing in home-security or adopting coordinated anti-crime measures with neighbors. Finally, we show that these concerns about crime seem ungrounded as we fail to find any significant effect on victimization. When exploring potential channels, we find suggestive evidence of the effect being driven by municipalities with a larger number of local radio stations per capita. We also find that the effect seems to be larger when the composition of immigrants is relatively low-skilled. Finally, using an index of bilateral ethnic distance to measure ethnic-related intergroup threat, we show that the genetic distance between Chileans and the nationality of immigrants does not drive any effects.

JEL classification: O15, F22, K1

Keywords: crime, immigration, crime perception, crime beliefs

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I Introduction

Immigration has recently been a critical topic for policy and academic debates. A growing literature has focused on how migration shapes the beliefs and attitudes of native populations (Alesina et al. (2018b)): migration can trigger native hostility (Hangartner et al. (2019)), changes in political preferences (Steinmayr (2020)), in preferences for redistribution (Alesina et al. (2019)), and even in risk attitudes (Ajzenman et al. (2020)). An important issue that seems to concern natives, and which could potentially explain hostility, is the potential impact of migration on crime.[1] As Fasani et al. (2019) show, not only do natives tend to overstate the size of immigrant population, but they are also prone to forming prejudices based on misperceptions about crime, instead of for example labor market considerations. In general, potential increases in crime consistently tops the list of immigration-related concerns (Bianchi et al. (2012a)).

The recent massive influx of Venezuelans and Central Americans to other Latin American countries seems to have triggered an increase in anti-migration sentiment, and crime-related concerns appear to be a natural candidate to explain this phenomenon. In Chile, for example, a nationally representative survey of urban perceptions[2] found that the main concern of Chileans regarding migration is citizen security (59%), while economic concerns rank third (46%). In Peru, a nationally representative survey showed that almost 60% of people think Venezuelans are involved in illegal activities[3]. This concern affects both the general population and likely the positions of politicians.[4]

Although the evidence is scarce and focused on Europe and the U.S., most papers have identified a mild to null effect of migration on crime (Bianchi et al. (2012a); Bell et al. (2013)). However, rigorous and systematic evidence on how migration affects crime perceptions is virtually non-existent. In this paper we aim at bridging this gap by shedding light on the causal relationship between immigration, crime, and crime-related beliefs and attitudes. We focus on Chile, one of the countries with the highest relative increases of migrants in the region since 2010, where, considering only legal visa requests, the annual influx rose from around 100,000 migrants per year in 2010, to almost 200,000 in 2015 and more than 350,000 in 2017 (see Figure I).[5]

Our analysis relies on two sources of data. We first build an immigration dataset, containing the number of valid residence permits reported by the Chilean Department of State in a given year, as well as information on the municipality of destination reported by the immigrant. We then construct a time-comparable dataset on self-reported victimization and perception data from a national victimization survey (*Encuesta Nacional Urbana de Seguridad Ciudadana*, ENUSC). ENUSC is an official cross-sectional household survey collected by the *Instituto Nacional de Estadisticas* (INE) every year between October-December. ENUSC is representative of the national urban population, and it has the advantage of containing several questions related to concerns about crime, crime expectations, and a detailed set of questions on victimization (which helps to overcome a potential problem of crime underreporting). In the Latin American context, ENUSC represents the largest effort to measure criminal activity via household victimization surveys.

[1]In the case of the US, concerns about the criminal potential of immigrants has a long history; for example, Fasani et al. (2019) describes the Immigration Act of 1882 which prohibited people with criminal histories from entering the country.

[2]See, for instance, this link

[3]See, for instance, this link

[4]See, for instance, this link for the case of Chile.

[5]For immigration statistics in Chile, see this link.

To estimate the causal effect of immigration on crime, crime-related concerns, and crime perceptions, we exploit the sudden increase in migration flows to Chile starting around 2010. Implementing two empirical approaches – a two-way fixed effects model at the municipality level and a 2SLS model based on Bianchi et al. (2012b) –, we document three systematic patterns.

First, we find a large and significant effect on crime-related concerns. People living in areas with a high influx of immigrants are more likely to report that crime is among their first or second most important concerns (a 1% increase in the immigration rate triggers a rise of 0.18pp, relative to the 2017 mean of 39%) that crime is the first or second factor affecting their personal life (a 1% increase in the immigration rate triggers a rise of 0.15pp, relative to the 2017 mean of 37%), that crime is affecting their quality of life (a 1% increase in the immigration rate triggers a rise of 0.18pp, relative to the 2017 mean of 62%) and that they feel there is a significant chance they will be a victim in the near future (a 1% increase in the immigration rate triggers a rise of 0.17pp, relative to the 2017 mean of 43%). When aggregated into an index of personal concerns, these results remain large and significant (a 1% increase in the immigration rate triggers a rise of 0.14pp, relative to the 2017 mean of 42%). The estimations from the two-way fixed effects model, although smaller in magnitude, are qualitatively very similar.

Second, we document a large effect on different measures of crime-preventive behavior, such as increasing personal security, installing an alarm, or coordinating security actions with neighbors or local authorities (we find that a 1% increase in the immigration rate triggers a rise of 0.11pp in an aggregated index, relative to the 2017 mean of 16%). We find no robust effect on outcomes related to perceptions (or expectations) of increases in the *general* crime rate (as opposed to the subjective probability of being *personally* affected by crime). Our results are robust to different definitions of migration and, although different in magnitude, they are qualitatively similar estimating the 2SLS or the two-way fixed effects model.

Finally, we find no effect of immigration on victimization rates. We analyze all relevant crimes included in the survey: robbery, larceny, burglary, theft, assault, and theft of vehicle/vehicle accessories. We also create an aggregated index (defined as the sum of all these types of crime). We fail to identify any significant effect for any of the individual types of crime or the aggregated index when estimating the 2SLS model. In the case of the two-way fixed effects model, the results are similar (including aggregated crime) with the exceptions of theft, which has a small negative and significant effect, and burglary, which has a small positive and significant effect. Altogether, our results suggest that immigration does not increase crime but triggers seemingly ungrounded crime-related concerns among the native population.

Our instrument follows Bianchi et al. (2012a)'s approach. We build a shift-share, Bartik-like instrument that exploits the supply-push component of migration by nationality as a plausibly exogenous variation driving "shifts" in the immigrant population across municipalities, and interact it with the "share" of immigrants settled in each municipality in the initial period of analysis. The "shift" component exploits (presumably exogeneous) events in origin countries that increase the propensity to emigrate; that is, events that are potentially relevant for determining migration outflows from the origin country but independent of across-municipality differences of immigration inflows within Chile. More specifically, our measure of exogenous supply-push factors is based on bilateral migration flows from the country of origin to destination countries that are not Chile. Hence, the predicted change in the inflows of nationality-specific immigrants incoming to a given municipality (that is, variations in its total immigration rate), will not be triggered by changes in the local conditions of that particular municipality (demand-pull factors) but by variations in the conditions in other locations outside of Chile (supply-push factors).

As Goldsmith-Pinkham et al. (2020) show, Bartik-type instruments, such as the one used in this paper, are numerically equivalent to GMM where the exogeneity of the instrument relies on the exogeneity of the (pre-shock) country shares by municipality. The empirical strategy is an "exposure" research design, where the shares measure the differential exogenous exposure to the common shock (international migration). The main identification threat is thus that the shares predict outcomes (for instance, crime perceptions) through channels other than migration. Following the recommendations by Goldsmith-Pinkham et al. (2020), we show that there are parallel trends in the relevant outcomes before the shock started. Our results are also robust to different definitions of immigration and the inclusion of different types of controls.

Exposure to immigration could trigger prejudice, fear, and eventually crime concerns through different channels. We present exploratory/suggestive evidence analyzing three potential mechanisms underlying our main effects, often emphasized in the literature of economics and political science.[6] First, we explore the role of intergroup threat Allport et al. (1954). Outgroup individuals could be perceived as threatening, and interactions with foreign outgroups could thus foster anxiety and concerns for physical safety (Cottrell and Neuberg, 2005; Maner et al., 2005). We use a measure of bilateral ethnic/genetic distance constructed by Spolaore and Wacziarg (2018) to compute the average distance between Chileans and immigrants arriving at different municipalities at different times. We then show that our results do not vary by the level of ethnic/genetic distance, which suggests that ethnic-related intergroup threat does not play a major role.

Second, we explore how the composition of immigration in terms of education could trigger different reactions. When dividing immigrants into low-skill (up to primary school completed) versus high-skill, we find that our main effects may be driven by the arrival of low-skill migrants. While the null effect on victimization holds for both groups, the effects on crime-related concerns and behavioral reactions seem to be more significant when immigrants are less educated. These results, which seem to be consistent with other papers in the literature (Mayda et al. (2016)), could be explained by the perception that low-skilled immigrants are relatively unlikely to be integrated in the labor market and thus more likely to eventually commit crime. Alternatively, lower levels of educational attainment could correlate with other characteristics (such as poverty) that could by themselves trigger a sentiment of threat.

Third, we analyze the role of local media as a potential mediator. As Couttenier et al. (2019) show, crimes perpetrated by immigrants could be over-represented in the news. If so, even when immigrants did not trigger crime, their crimes would be more salient. We show that, while the effect of immigration on victimization seems to be null in municipalities with a high or low number of local radio stations, the effects on both crime-related concerns and behavioral reactions are only significant in municipalities in which there is a relatively large number of local radio stations per capita.

Our paper relates to several strands of the literature. First, it is closely related to a growing literature focusing on how mass migration shapes natives' beliefs and attitudes. Exploiting data from the recent refugee crisis in Austria, Steinmayr (2020) finds that in "passing through" municipalities, the vote share of far-right parties increased (probably as a result of an increase in hostility towards foreigners), while it decreased in municipalities where refugees settled, a result in line with other studies (Mayda et al. (2016); Becker et al. (2016); Halla et al. (2017); Dustmann et al. (2017, 2019); Edo et al. (2019), and Rozo and Vargas (2019), among others). Consistent with these results, Ajzenman et al. (2020) focus on localities exposed to transit migration of Syrian refugees passing through the Eastern Mediterranean Route and document a significant increase in native hostility towards immigrants, a significant drop in

[6] The exploration of channels is conducted using the 2WFE models, as we could not find acceptable first stages in the IV models when including interactions.

their institutional trust, and a decrease in their willingness to take risks and in their propensity to start new business. In a similar context, but analyzing the case of Greece, Hangartner et al. (2019) show that the exposure of islanders to a massive influx of Syrian refugees triggered a significant change in the attitudes of natives towards migrants. Also with a focus on Europe, Alesina et al. (2019) document a negative association between support for redistribution and the share of immigrants in a given local region.

Our contribution here is twofold. First, while this literature has focused mainly on beliefs related to hostility, prejudice, risk attitudes, and political or redistribution preferences, our paper studies the effect on crime perceptions, crime-related concerns, and behavioral reactions to perceived crime. Although these outcomes are potentially connected to the former (e.g., increases in crime-related concerns could be a plausible mediator of the effect on political preferences), our focus is on a set of outcomes which are not yet fully explored. Second, while most of these papers are focused on Europe and usually on the recent refugee crisis, ours is one of the first papers focusing on how Latin American migration fosters significant changes in the beliefs and attitudes of native residents. To the best of our knowledge, there is only one paper focusing on immigration and fear of crime (Nunziata (2015), focusing on Europe). Besides the contextual/regional differences, our dataset allows us to complement his results by conducting a more extensive analysis: we not only reveal an effect on fear of crime but also study how immigration affects perceptions about crime trends and, more importantly, how these effects translate into behavioral reactions.

Our paper also relates to a set of studies examining the impact of immigration on crime. Although the evidence varies by the context and the composition of the immigrant population most studies find null or very small effects. Bianchi et al. (2012a) uses an instrumental variables approach to find no aggregated effect of immigration on crime in Italy (a small positive effect on robberies), Bell et al. (2013) find positive and negative effects of two different massive waves of immigrants arriving to the UK (asylum seekers in the late 90's and the inflow of EU citizens after the accession), suggesting that the sign and magnitude of the effect depends on the labor market opportunities of the immigrants (Mastrobuoni and Pinotti (2015), Pinotti (2017), Freedman et al. (2018), Baker (2015), and Fasani (2018)). Spenkuch (2013) uses county panel data from the US to show a small effect of migration on property crime only (motivated by financial gain, which again highlights the importance of the labor market channel).[7] In the case of the Mexican immigration to the US, Chalfin (2014) relies on two different instruments to identify the causal effect of immigration on crime. Similar to Bianchi et al. (2012b) and others, Chalfin (2014) exploits persistence in regional Mexico-US migration networks, comparing the results to an additional strategy that leverages temporal variation in rainfall across regions, finding no link between changes in Mexican migration and changes in US criminal activity. More recently, Ozden et al. (2017) show a negative effect of migration on crime in Malaysia, interpreted as an improvement triggered by a positive effect of migration on economic activity. On the other hand, Piopiunik and Ruhose (2017) finds a positive and significant effect of immigration on crime examining an episode in which ethnic Germans from the USSR were relocated to Germany after the collapse of the Soviet Union and were allowed to live and work only in specific counties, severely restricting labor mobility. Our paper adds another piece of evidence to this literature by showing a zero effect of migration on total crime in the case of Chile.

Finally, our results are also related to a scarce but growing literature on the determinants of crime misperception. Esberg and Mummolo (2018) analyze different potential explanations for

[7] In the case of Latin American countries evidence on the relationship between immigration and crime is still scarce, and much of the work has been focused on the link between conflict and internal migration. A salient example is a set of papers based on Colombia such as Lozano-Gracia et al. (2010) and Ibáñez and Vélez (2008)

the growing gap between crime and crime perception in the US and find suggestive evidence that continuous exposure to news of episodic crime events may have widened the gap. Consistent with this, Mastrorocco and Minale (2018) exploit a natural experiment in Italy - the staggered introduction of the Digital TV signal - to identify a media persuasion effect on crime perceptions. Our paper contributes to this literature by examining an insofar unexplored determinant, which is the exposure to a sudden inflow of immigrants.[8]

From a policy point of view, our results contribute to the current public debate on immigration and crime. Latin America is amidst a severe migration crisis. According to the United Nations Refugee Agency (UNHCR)[9], as of June 2019 approximately 4 million Venezuelans were living abroad, considerably more than the 556,641 in 2010 and 700,000 in 2015, with Colombia (1.3 M), Peru (0.7 M), the US (0.35 M), Spain (0.32 M), and Chile (0.29 M) the main destination countries. This Venezuelan exodus is on top of other big migration flows in the region, such as the northern triangle migration to North America, the recent growth of Haitian migration to South America (especially Chile), and the more stable internal migration flows in South America.

Studying Chile is key as it is one of the most popular destinations for immigrants to Latin American. With a population of around 18 million, Chile is near all-time highs in the proportion of foreign-born residents. Migrants represented more than 1.5% of the population in 2019, while immigrants were already more than 4% of population in the 2017 census, one of the highest levels in the region[10]. Moreover, the growth rate of immigrants by region has been far from uniform. Figures I, II, and III provide a description over the last 20 years combining data from the annual census and the Chilean Department of State. First, Figure I and III show a sharp change in the share of the overall immigrant population from around 1-2 percent of the population between 2002 and 2012 to 4 percent over the most recent years. In addition, Figures II, and III show that the composition of immigrants arriving to Chile changed in 2016-2017 with the arrival of a large amount of immigrants from Venezuela and Haiti.

We show that the growing concerns of citizens and governments on the potential effect of immigration and crime in Latin America seem to be unfounded, as the effect of immigrants, at least in the case of Chile, seemed to have no effect on crime. Moreover, our results document formally what anecdotal and survey evidence suggests: at least part of the widening in the crime-perceptions gap in the region can be attributed to the recent migration shock.

The paper is structured as follows. Section II describes the data. Section III presents the empirical models, discusses the validity of the instrument in this context, and displays the main results and several robustness checks. Finally, Section IV concludes.

II Data

Our main variables come from two sources of data: official immigration data and a rich annual victimization survey (ENUSC) which includes information on crime victimization and crime-related concerns, behavior, and beliefs. In both cases we restricted the analysis to the period 2008-2017.

[8]Our results are not totally surprising, given that crimes perpetuated by immigrants are disproportionately covered by the media Couttenier et al. (2019).

[9]See this link.

[10]For geographical reasons, Colombia and Peru have recently been the main destination countries in absolute terms, especially for Venezuelans. However, in Colombia, for instance, less than 3% of the population is foreign-born, similar to Peru. See IOM estimates here.

1. **Immigration**: We obtained individual-level data on all visa and permanent residence permits granted by the Chilean Department of State (Extranjería). This data includes basic demographic statistics such as date of birth, nationality, municipality of intended residence at time of application[11], gender, and self-reported variables dealing with education and labor market experience. Information on municipality populations for each year was obtained directly from INE (the National Institute of Statistics) estimates using projections from census data, so that for each year we can calculate the rate of immigration by municipality. During the period of analysis, the database includes more than 2 million individuals. As shown in Table I, immigration grew considerably within our period of analysis, but the growth rate varied substantially by region. While in 2008 no region was receiving more than 2 percent of their population as new immigrants per year, at least five regions were above this level in 2017, mostly comprised of immigrations from other Latin America countries. Figures I and III describe the composition of the immigrant group during our sample period by country of origin.

2. **Victimization**: We harmonized a set of variables dealing with crime perceptions, behavior related to adoption of security measures, and victimization included in the ENUSC survey (National Urban Survey of Citizen Security). ENUSC is an annual household survey, covering the period 2008-2017, and the field work takes place between October and December of each year[12]. Relative to other sources of crime data such as police reports, victimization surveys are particularly well suited for this study since they are less subject to reporting bias, a potentially relevant problem in the case of immigration. Although ENUSC covers a subset of municipalities (101 out of 346 municipalities in Chile, with a focus on the largest urban areas), it represents approximately 80% of the national population, a proportion that is even larger (around 95 percent) for the immigrant population who are more likely to live in large urban areas.

   Table II shows descriptive statistics for some of the variables used in our analysis.

3. **Additional Controls**: For robustness purposes, in some of our regressions we include controls at the municipality level that we take from CASEN, a bi-annual national household survey. This survey covers the entire country and includes standard questions related to demographics, labor market outcomes, income, and education, among others. The survey was conducted in 2017, 2015, 2013, 2011, 2009 and 2007 (considering only the years relevant for our study).

Using the ENUSC dataset, we define different outcomes which we classify into the following groups:

Victimization. ENUSC contains detailed information on self-reported episodes of crime by type. We consider all the crimes included in the questionnaire and focus on the following question: "During the last 12 months, have you or a member of your household suffered from X?", with X being eight specific crime categories, including robbery, larceny/theft, vehicle (or their accessories) theft, assaults, aggravated assaults, and burglary. We create a variable for each type of crime that takes a value of one if the answer to the question was positive and 0 otherwise. We report the results of an aggregated measure of crime, defined as the simple

[11] Applicants have to declare a specific municipality within Chile where they will move to once the permit is approved.

[12] There are previous editions of the ENUSC but the methodology underwent a series of changes in 2008 and thus it is not recommended to compare data pre and post-2008. The survey was also conducted in 2018, but for the first time the municipality codes were not available to researchers.

average of all the types of crime (it is thus defined on a scale from 0%, no crime, to 100%, universal victimization across all types of crime).

Crime-related personal concerns. This category includes all the crime perception questions focused on personal concerns (that is, crime potentially affecting the individual directly). We report results for five outcomes. **”Crime as 1st or 2nd concern”)** takes a value of one if the individual answered ”crime” as the first or second option to the question ”Which of the following problems do you think is the most important nowadays? (the list of options includes ten categories, including economic situation, health, education, unemployment, poverty, and inequality, among other social concerns)”. The outcome **”Crime as 1st or 2nd factor affecting personal life”)** takes a value of one if the individual answered ”crime” as the first or second option to the question ”Which of the following problems affects you personally the most? (the list includes the aforementioned categories)”. The outcome **”Crime affecting quality of life”)** takes a value of one if the individual answered positively (”a lot” or ”much”, the two highest categories) to the question ”According to your personal experience, how much does crime affects your quality of life?” (other categories are “not much” or “nothing”). The outcome **”Feeling Unsafe”** takes a value of one if the individual felt at least some fear when walking alone in their neighborhood, while alone at home, or while waiting for public transportation. The outcome **”Will be a victim”**, takes a value of one if the individual said she thinks she will be a victim of a crime in the following 12 months. Finally, we aggregate these results by taking the first component of a principal component analysis **“Principal Component - Summary Index”, as reported in the tables**, and normalize it to a 0-1 scale.

Beliefs about crime trends. We complement the previous subjective measures with three outcomes measuring beliefs on how aggregated patterns of crime will evolve. Although these variables are likely connected to personal concerns, they are of a different nature and they may move in different directions: an individual could think crime will rise but it will not affect her personal life; or feel that crime will not grow on average but her life will be nevertheless affected.[13]. This category includes three variables which measure the same belief at different geographical levels. The variables **”Crime is rising (N, M, C)”** take a value of one if the individuals answered positively to the question ”Would you say that during the last 12 months crime has increased in your neighborhood (N), municipality (M) or country (C)?”.

Behavioral reactions. As the subjective evaluation of crime worsens, we expect individuals to take actions to protect themselves from criminal experiences. The ENUSC survey includes several questions directly related to concrete measures that individuals could have taken in order to increase their personal security. First, we create an index (**“Investment in Home Security Index”**, as reported in the tables), that is defined as the proportion of positive answers to the following questions: “Do you have the following security items at home?”: a) an animal to protect your dwelling, b) an alarm or panic button, c) a surveillance camera, d) window or door security bars, e) an electric fence or perimeter wall for your dwelling, f) a non-electric fence or perimeter wall for your dwelling, g) a chain lock or double locking doors, h) alterations to the infrastructure of your property to make it safer, i) light or motor sensors. Second, we create an index (**“Neighborhood Security System Index”**, as reported in the tables) defined as the proportion of positive answers to the question “Which of the following measures have you adopted jointly with your neighbors in order to feel safer?”: a) exchanged phone numbers, b) a surveillance system among the neighbors, c) a community alarm system, d) a guard to watch over our dwellings, e) a private surveillance system, f) an access control

[13] This could happen for a variety of reasons. For instance, even if crime rates do not increase, the composition of crime could change and thereby affect personal concerns (the type of crime, the severity of crime, the type of victims).

system to monitor entry into the neighborhood, g) coordinated security measures with police, h) coordinated security measures with municipal officers, h) reached an agreement with the neighbors to call the police every time we see any neighbor at risk. Third, we report a dummy variable (**"Owns a weapon"**) that takes a value of one if the individual said that she owns a weapon. Finally, we aggregate these results by taking the first component of a principal component analysis **"Principal Component - Summary Index", as reported in the tables**, and normalize it to a 0-1 scale. We present the descriptive statistics of the outcomes in Table II.

III Empirical Analysis

To estimate a causal effect of immigration on crime, crime-related concerns, and behavioral reactions, we use implement two different types of models: a two-way fixed effects model at the municipality and year level and a 2SLS model using an instrument inspired by Bianchi et al. (2012a). In the following sections, we present the models, describe the results, and discuss the identifications of each.

III.1 Two-way fixed effects model

We first examine how immigration affects crime victimization and perceptions about crime by estimating a two-way fixed effects model at the municipality-year level. To do so, we combine the respondent-level data with the municipality-year immigration dataset and the pooled cross-sectional ENUSC surveys for the period 2008-2017, as described in the Data section.

More specifically, we estimate the following linear regression model:

$$y_{imt} = \beta log(imm)_{mt} + \eta_m + \eta_t + \gamma X_{imt} + \phi(\eta_t \times \bar{y}_{m_{2008}}) + \epsilon_{imt} \tag{1}$$

Where y_{imt} are the different outcomes (victimization, crime-related concerns, and behavioral reactions) of an individual i residing in municipality m in year t; $log(imm)_{mt}$ represents the log of the immigrant population stock ratio in municipality m for year t; η_m and η_t are municipality and year fixed effects that capture year-specific or municipality-specific shocks. X_{imt} is a set of control variables representing observed characteristics of the individual t residing in municipality m during the year t, such as gender and age. Finally, the immigrant population in a given year could be influenced by the characteristics of local populations in each municipality in previous years, which may well be correlated with the previous and actual determinants of crime rates. Thus, in our preferred specification, we also control for the interaction of each outcome (municipality average at baseline) and each period effect.[14]

Our parameter of interest is β, which represents the average effect of increasing the number of migrants (per 100.000 inhabitants) by one percent on our set of outcomes. We estimate the same equation for each type of crime individually and for an aggregate measure of criminal activity. Likewise, when analyzing the effects of immigration inflows on crime-related concerns and behavioral reactions, we analyze the effects on individual outcomes, as well as on different aggregated indexes.

Table III displays the results of estimating equation 1 in terms of different aspects of beliefs about crime and crime victimization. In Panel A we display results on crime-related

[14] In a different section, we show that our results are very similar when excluding all controls or using other definitions of immigration.

concerns that ENUSC respondents have consistently reported every year during the 2008-2017 period. In three out of the four categories available in the survey, we find that concerns regarding crime increase among residents living in municipalities where immigrant populations rise. This pattern is consistent with a positive increase in the principal component index that summarizes all four dimensions. Panel B shows a positive relationship between respondent beliefs and the perceived crime trajectory at different geographical levels, and the increase is significant when they were asked about the trajectory at the municipality level. Panel C shows a positive relationship between the immigrant population at the municipality level and behavioral reactions associated with public security. For example, we observe that following immigration respondents are more likely to invest in protecting their houses and to coordinate actions with their neighbors.

Panel D in Table III shows the effect of immigration on crime victimization. Relative to the previous three panels, these coefficients do not depict a clear relationship between immigration and criminal activity. The aggregate effect of immigration on total victimization is small and not significant at conventional levels. This pattern is consistent with what we observe for each crime type: in some cases we observe a positive relationship while in others we find a negative effect. The effect in most crime categories is not significant, with the exceptions of theft and burglary which point in opposite directions. Overall, these results indicate that the change in immigrant populations over time and across municipalities does not correspond with a discernible change in criminal activity.

III.2 2SLS Approach

For our two-way fixed effects model to identify a causal effect, we must assume that, in the absence of migration shocks, the trends of the outcomes would have been similar in municipalities with different levels of migration, i.e, that the distribution of the immigrant population across municipalities and over time is uncorrelated with the error term. Such an assumption might not hold in practice. For instance, a vigorous labor market in a particular municipality during a given year could simultaneously attract immigrants and decrease crime, generating a downwards bias in our estimates. Likewise, a growing city could simultaneously attract migrants and criminals, thus biasing our estimates upwards. In addition, changes in crime rates across municipalities could have a direct effect on the location decisions of immigrants.

We thus follow Bianchi et al. (2012a)'s approach and build a shift-share, Bartik-like instrument that exploits the supply-push component of migration by nationality as a plausibly exogenous variation driving "shifts" in the immigrant population across municipalities, and interact it with the "share" of immigrants settled in each municipality in the initial period of analysis[15]. The "share" component provides predictive power to the instrument as it exploits the fact that new immigrants of a given nationality tend to settle into the same areas as previous immigrants from the same country. The "shift" component exploits (presumably exogeneous) events in origin countries that increase the propensity to emigrate; that is, events that are potentially relevant for determining migration outflows from the origin country but independent of across-municipality differences of immigration inflows within Chile. Since these types of events are relevant for migration outflows but orthogonal to regional differences within the host country, they could in principle be used as a source of exogenous variation in the distribution of the immigrant population in Chile.

[15]Similar shift-share instruments have been used in multiple papers estimating immigration effects, for instance Munshi (2003), Jaeger (2006), and McKenzie and Rapoport (2007). For a list of all papers in this category, see the thorough work of Jaeger et al. (2018).

Nonetheless, total inflows of immigrants by nationality could be correlated with local demand-pull factors. This would potentially violate the excludability assumption related to immigration shocks[16]. Therefore, our measure of exogenous supply-push factors is based on bilateral migration flows from the country of origin to destination countries other than Chile. Hence, the predicted change in the inflows of nationality-specific immigrants to a given municipality (that is, variations in its total immigration rate), will not be triggered by changes in the local conditions of that particular municipality (demand-pull factors) but by variations in the conditions in other locations outside Chile (supply-push factors).

An important point to emphasize is that the empirical strategy in our model is based on an "exposure" research design, where the shares measure the differential exogenous exposure to the common shock (international migration). The main identification threat is thus that the shares predict outcomes (for instance, crime perceptions) through channels other than migration. The shares will thus play a crucial role in identifying a causal effect. As Goldsmith-Pinkham et al. (2020) remark, for this empirical strategy to be valid we require that the differential exposure to common immigration shocks does not lead to differential changes in the outcome (for instance, crime), an assumption that we would typically assume in a difference-in-differences setup. Indeed, we closely follow Goldsmith-Pinkham et al. (2020)'s suggestions in this regard to support the claim of internal validity for our identification strategy.

III.2.1 Building the shift-share instrument

With the sample period 2017-2008, we first take within-municipality differences of equation 1 and decompose $\Delta migr_{mt} = migr_{m,2017} - migr_{m,2008}$ as

$$\Delta migr_{mt} \approx \sum_{n} \theta^{n}_{m,2008} \times \Delta lnMIGR^{n}_{mt} - \Delta pop_{mt} \tag{2}$$

where $\Delta lnMIGR^{n}_{mt}$ is the log change of the stock of immigrants from country of origin n in municipality m between 2008 and 2017, Δpop_{mt} is the log change of municipality population between 2008 and 2017, and $\theta^{n}_{m,2008}$ is the share of immigrants from country of origin n over the total immigrants residing in municipality m in 2008, i.e.,

$$\theta^{n}_{m,2008} = \frac{\sum_{n} MIGR^{n}_{m,2008}}{\sum_{n'} MIGR^{n'}_{m,2008}} \tag{3}$$

where n represents nationalities other than Chile.

Note that the first term on equation 2 is the weighted sum of the log changes of immigrants of each nationality into each destination municipality m, and these depend both on supply-push factors in each origin country (a common shock to all municipalities), as well as on demand-pull factors corresponding to each particular municipality. Hence, we substitute $\Delta lnMIGR^{n}_{mt}$ with the log change of immigrants of nationality n in destination countries other than Chile, $\Delta lnMIGR^{n}_{t}$, where the variation in this term is by construction orthogonal to demand-pull factors embedded in municipality m. To do so, we use migration data from the United Nations Population Division. The data contains annual data for 45 countries on the bilateral flows of international migrants, and for most countries the coverage goes, at least, from 1990 to 2015. The data presents both inflows and outflows according to place of birth, citizenship, and place

[16] In an extreme case where all immigrants from a given nationality moved to the same municipality it would be impossible to disentangle push and pull factors based on total inflows by country of origin. Hence, for this shift-share instrument to work, enough variation is required in the spatial (municipality) distribution of immigrant allocations.

of previous/next residence both for foreigners and nationals. Though coverage is limited to the most relevant origin-destination cells, we were able to build the 2008-2017 (log) changes for 11 countries (that collectively represent 87% and 94% of residence permits in 2008 and 2017, respectively). The list of countries includes Argentina, Bolivia, Brasil, China, Colombia, Ecuador, Haiti, Peru, Spain, USA, and Venezuela.

We define the predicted log change in the immigrant to population ratio in each municipality as

$$\Delta\widehat{migr}_{mt} = \sum_n \theta^n_{m,2008} \times \Delta lnMIGR^n_t \tag{4}$$

Since demand-pull factors in destination countries other than Chile are plausibly exogenous to variation in crime across Chilean municipalities, the correlation between $\Delta migr_{mt}$ and $\Delta\widehat{migr}_{mt}$ must be due solely to supply-push factors in origin countries and/or to demand-pull factors from locations outside Chile. As previously stated, for this approach to estimate a causal effect, we must assume that crime rates in municipalities with a large initial share of immigrants from a given nationality would have evolved in a similar way relative to those with a low initial share. In Subsection III.3 we discuss the plausibility of this assumption for our context.

III.2.2 2SLS Estimation

We use $\Delta\widehat{migr}_{mt}$ as an instrument to estimate the causal effects of the change of migration on victimization, crime-related concerns, crime beliefs, and behavioral reactions. Since the instrument is available as a cross section of changes between 2008 and 2017, we run all regressions on the within-municipality differences over the same period. For the sake of comparability between OLS and IV, the first column of each table reports OLS estimates on the equation in first-differences, which are broadly consistent with the 2WFE models using all years. The second column reports the reduced form regression of (the log-changes of) each outcome on the instrument (that is, the supply-push component of immigration growth weighted by the beginning-of-period share of immigrants), while the third column shows the 2SLS estimates and its respective first-stage results. As controls, all regressions include the average age and the proportion of women in each municipality during 2017. In Table VIII we show that all the results presented below are robust to the exclusion of control variables in the regression analysis, as well as to the use of different measures of immigration. Moreover, in every case, the first stage is strong enough (F-stat above 17).

Effects on Victimization. The results are shown in Table IV. The OLS estimates from model (1) are qualitatively similar to the estimates of the 2WFE model analyzed in the previous section, suggesting that taking averages and first-differences at the municipality level accurately captures the effects on victimization at the individual level. Moreover, the 2SLS estimates are broadly comparable with their OLS counterparts. We consistently find a null causal effect of immigration on victimization in each outcome separately as well as on total crime.

The estimated coefficient associated with the reduced form regression against the instrument (Model (2)) is never significant. As pointed out by Bianchi et al. (2012a), this could be due either to lack of causal effect or to the fact that the correlation between actual and predicted changes in immigration is too low. In our case, the latter is unlikely given that our instrument is strong enough (F=17.35).[17].

[17]Nelson and Startz (1990) suggest that an instrument is likely to be weak if the bias-corrected partial R^2 falls short of the inverse of the sample size. We find no statistical support for this in our sample, all of which reinforces the internal validity of our results. Our partial $R^2 = 0.104$, which is well above the inverse of the

Overall, our results are generally in line with a large literature showing that immigration does not cause crime (see Bianchi et al. (2012a) for a summary).

Effects on crime-related concerns. Table V shows the results. The results are qualitatively similar to those of the 2WFE models. The magnitudes are naturally larger in the case of the 2SLS models, meaning that the OLS parameters were likely biased downwards. We find significant results (at the conventional levels of 1%, 5% or 10%) for almost all the outcomes. A one percent increase in migration caused an increase of 0.13 percentage points in the aggregated measure of personal crime-related concerns. Therefore, doubling migration would increase concerns by 13%. A sizeable effect, considering that the average of the outcome was 41% in the last period of our sample. In Table VIII we show that these results are not driven by the inclusion of controls. The first stage is highly significant (F-stat above 17) and thus the instrument is strong.

Effects on beliefs about crime trends. In Table VI we show the results on citizen beliefs about crime trends. The results are qualitatively similar to those of the 2WFE models (although in the 2WFE model we find a significant effect on the perception of crime trends at the municipal level, which becomes insignificant in the 2SLS model). All the point estimates are positive, although we do not identify significant effects at conventional levels for the individual outcomes (in the case of "crime rising in the neighborhood" the p-value is slightly above 0.10). The magnitudes are naturally larger in the case of the 2SLS models, meaning that the OLS parameter estimates were likely biased downwards.

Effects on behavioral reactions. See Table VII. We show effects on citizen behavioral reactions regarding protection against crime. The results are qualitatively similar to those of the 2WFE model. The point estimates are positive and all are highly significant with the exception of "owns a weapon". The magnitudes are naturally larger in the case of the 2SLS models, meaning that the OLS parameter estimates were likely biased downwards. As a consequence of exposure to migration, people are significantly more likely to increase the protection of their houses and to coordinate actions with their neighbors. Moreover, the magnitudes are sizeable: a one percent increase in migration caused an increase of 0.11 percentage points in the aggregated measure of behavioral reactions. Therefore, doubling migration would increase concerns by 11%. A large effect, considering that the average value of the outcome during the last year of our sample was 16%.

III.3 Internal Validity and the GPSS Test

Goldsmith-Pinkham et al. (2020) show that the Bartik-type 2SLS estimator is numerically equivalent to a generalized method of moments (GMM) estimator. In particular, they build on Rotemberg (1983) and decompose the estimator into a weighted sum of the just-identified instrumental variable estimators that use each entity-specific share as a separate instrument; that is, the local shares play the role of instruments and the growth shocks play the role of a weight matrix that "shifts" the "share" effects. The statistical implication of this result is that the exogeneity condition (and thus the consistency of the estimator) should be interpreted in terms of the shares[18]. Goldsmith-Pinkham et al. (2020) argue that whenever the econometrician describes her research design as reflecting differential exogenous exposure to common shocks (as in our case), identification through shares is effectively being relied on. Moreover, in settings where the researcher has a pre-period, this empirical strategy is just difference-in-differences,

number of observations, $1/101 = 0.0099$.

[18] In contrast, Borusyak et al. (2018) emphasize that under some assumptions the consistency of the estimator can also come from the shocks, and they also provide a motivating numerical equivalence result.

and thus testing whether the differential exposure to common shocks leads to differential changes in the outcome becomes central to assess the internal validity of the identification strategy.

While we are not exploiting a sharp change in immigration over time to assess the effects of immigration on crime and crime beliefs (as is typically the case of difference-in-difference designs), the immigration effects found in the 2008-2017 period may still be driven by changes that occurred in the period prior to the analysis. In our research design the immigration shares of 2008 measure the differential exposure to the post-2008 common immigration shock. Hence, for our empirical strategy to be valid we require that the differential exposure to common immigration shocks (the "shares") does not lead to differential changes in crime and crime beliefs, so that these changes are not driven by pre-period, endogenous mechanisms affecting both the composition of immigrants within municipalities and local crime. The recommended way to test the plausibility of this assumption is to test for parallel trends (Goldsmith-Pinkham et al. (2020)). This test helps to alleviate any concerns related to the possibility of our results being driven by differential pre-existing trends in our outcomes in municipalities with different shares of migrants (and thus, with different exposure to the post-2008 shock).

We proceed following the steps proposed by Goldsmith-Pinkham et al. (2020). First, we calculate the Rotemberg weights for each country-specific instrument and then test for parallel trends by plotting the reduced form effect of each nationality-share on our outcomes for the pre-periods 2005, 2006, and 2008[19]. The Rotemberg weights indicate which country-specific exposure design gets a larger weight in the overall Bartik-2SLS estimate, and thus which nationality-share effects are worth testing. In our data, Peru has by far the highest weight (RW= 2.225), followed by Bolivia (0.484), Ecuador (0.092), China (0.087), and Brazil (0.0091). We show graphical analyses for Peru, the mean of the top 5 Rotemberg weights, and the mean of the full set of countries.

The methodology of the ENUSC survey was altered in 2008. This not only means that the results before and after 2008 are not comparable but also that many of our outcomes were not present in many of the waves conducted before that year. Therefore, we are only able to implement the parallel pre-trends test for a limited number of outcomes.

We regress the outcome of interest against the nationality-shares in each year interacted with each year fixed effect, controlling for municipality fixed effects, year fixed effects, and year fixed effects interacted with the set of control variables (age and gender by municipality). In every case, we collapse the data at the municipality-year level to have exactly the same structure as the 2SLS models. We then convert the growth rates to levels and index the levels in 2005 to 0. Figures IV and V present the results.

First, we generally find no evidence of statistically significant pre-trends. The differential shares of Peruvian immigrants do not statistically or economically predict larger crime rates in pre-shock years, and the evidence is consistent when analyzing outcomes related to crime-related concerns or behavioral reactions. Given how relevant Peru is in terms of its weight, it is not surprising that the aggregate instrument looks like Peru. Overall, our evidence supports the identification assumption that the pre-existing trends in our outcomes are orthogonal to the future changes in the same outcomes. This gives support to the identification assumption that the pre-shock shares do not predict outcomes through channels other than the post-2008 migration shock.

[19] Goldsmith-Pinkham et al. (2020) provides a code in R (available at this link) that allows to straightforward calculation of the Rotemberg weights.

III.4 Robustness

We finally show that our results are robust to the exclusion of controls and to the use of other measures of immigration. We re-estimate our baseline 2SLS and 2WFE models using the main outcomes. In Table VIII we show the results for victimization (total crime), crime-related concerns (the Summary Index), and behavioral reactions (the Summary Index). For each outcome we first show five columns for the 2SLS model: the baseline model, the baseline with no controls, the baseline using only "Work Visas" as the measure of immigration, the baseline model using "Work Permits" as the measure of immigration, and the baseline model adjusting the standard errors using Adao et al. (2019)'s to account for a potential correlation of residuals across regions with similar shares. We then show the same models using the 2WFE specification (with the exception of Adao et al. (2019)'s correction, which is only valid for Bartik-type instruments).

The results remain insignificant in any specification for the case of victimization and remains significant in almost all robustness specifications for every outcome. The only exception is the index of behavioral reaction when using Adao et al. (2019)'s correction, where the p-value is 0.15, slightly above the conventional level of statistical confidence.

III.5 Potential channels

Exposure to immigration could trigger prejudice, fear, and eventually crime concerns through different channels. In this section, we present suggestive evidence analyzing three potential mechanisms underlying our main results, often emphasized in the literature of economics and political science (see, for instance Alesina et al. (2018a), Mayda et al. (2018), or Couttenier et al. (2019)): ethnic prejudice, socioeconomic differences, and media-induced fears[20]

Educational Composition. A first potential channel, widely explored in the migration literature, is related to the educational composition of immigrants (Ottaviano and Peri (2006), Card (2009), Ottaviano and Peri (2012), Mayda et al. (2018)). Low-skilled immigrants could trigger different reactions in terms of crime concerns compared to high-skilled immigrants for a variety of reasons. First, low-skilled immigrants are relatively less likely to integrate into the labor market and thus could be potentially perceived as more prone to engaging in criminal activities. Second, the educational attainment of an immigrant could be related to other characteristics that trigger a sentiment of rejection, like poverty. As such, natives may use xenophobia or racism to reject immigrants when in reality they are discriminated against not for their condition as foreigners but mostly for being poor, as suggested by Cortina (2017). Likewise, immigrants can affect the transmission of social norms in destination countries (Alesina and Giuliano (2011)), and thus low-skill immigrants with difficulties integrating within local markets could become a threat for native citizens who aim to preserve the stability of predominant cultural values.

To analyze this, we exploit individual information on immigrants' education provided by the Department of State. We proceed as follows. First, we classify each migrant according to their self-reported skill level, with low-skilled migrants those who completed at most primary school or less. We then compute the proportion of low and high skilled immigrants per municipality and year, excluding the missing values. We then create two dependent variables, each of which multiplies the immigration stock (which is the dependent variable in our baseline model) by

[20]When trying to conduct the following analysis using the IV approach, we failed to find relevant instruments for both the interaction terms and the migration variable. We thus report only results derived from 2WFE models.

the proportion of low(high)-skilled immigrants in each municipality-year, and re-estimate the 2WFE model of Equation 1 including the *horse race* between high and low skill migration.

The results are presented in Table IX (Panel A). For crime-related concerns, the effect is mostly driven by low-skilled immigrants. The immigration parameter is highly significant and roughly four times larger relative to the case of high-skilled immigration. For behavioral reactions, the pattern is somewhat similar in that the effect size for low-skilled immigration is almost double its high-skilled counterpart. Finally, the effect of immigration on victimization is indistinguishable from zero regardless of the skill level of immigrants. Overall, our results suggest that the educational composition of immigrants does matter for the widening gap between crime and crime perceptions.

Ethnic Distance. A second potential channel, largely explored in the social and cognitive psychology literature, could be related to an intergroup threat motivated by ingroup bias Allport et al. (1954). Outgroup individuals may be perceived as threatening, and interactions with foreign outgroups could thus foster anxiety and concerns about physical safety (Cottrell and Neuberg, 2005; Maner et al., 2005).

Although the group cleavages that divide ingroup and outgroup could be related to different dimensions, the ethnic/genetic differences are certainly one of the most salient, especially so for people that are not directly related to immigrants.[21] A plausible hypothesis is thus that, the longer the ethnic distance between natives and immigrants, the larger the prejudice and fear. To measure ethnic bilateral relatedness, we use the genetic distance between two countries using the approached developed by (Spolaore and Wacziarg, 2009, 2018), which is based on the bilateral genetic distances between populations initially calculated by Cavalli-Sforza et al. (1994) and then extended by Pemberton et al. (2013).

The data produced by Cavalli-Sforza et al. (1994) provides measures of genetic distance between populations using classic genetic markers, for which they use 42 representative populations (which are a result of aggregating sufficiently similar sub-populations), while Pemberton et al. (2013)'s extension covers 267 worldwide populations. Both papers provide data on bilateral distance calculated at the population level. (Spolaore and Wacziarg, 2009, 2018) match populations to countries using ethnic composition data by country from Alesina et al. (2003). They match each of the 1,120 country-ethnic group categories to the genetic groups of Pemberton et al. (2013) to construct an index of bilateral ethnic distance by country. The authors provide two indexes: one based on the largest group of each country (that is, the distance between the plurality groups of each country in a pair, defined as the groups with the largest shares of each country's population) and the second is a weighted average distance, where the weights are the shares of each population in every country. This, or similar measures, have been widely used in a variety of domains in economics, such as explaining international migrant selection (Krieger et al. (2018)), exploring the relationship between ethnicity and culture (Desmet et al. (2017)), predicting conflict between countries (Spolaore and Wacziarg (2016)), intersocietal conflicts (Arbatlı et al. (2020)), and studying the effect of diversity in corporate boards on corporate performance (Delis et al. (2017)), among others.

Using the bilateral index between Chile and other countries, we construct a weighted average distance of migration. The weights are given by the proportion of migration from each country in each period and municipality. We then classify each observation as "high distance" (above the median) or "low distance" (above the median). We then re-estimate Equation 1) (2WFE) including a "high distance" dummy and its interaction with the migration variable. The results

[21] Another important dimension is the cultural distance. However, as Spolaore and Wacziarg (2018) explain, cultural traits and habits are similarly transmitted across generations and thus genetic distance represents a summary statistic for a wide array of cultural traits transmitted between generations.

are presented in Table IX (Panel B). In every case (crime-related concerns, behavioral reactions, and victimization), we find very similar effects above or below the median of ethnic distance. Ethnic-related intergroup threat does not seem to drive our results.

Media Effects. Finally, in order to understand the gap between crime and crime perceptions we explore the role of local media as a mediator of our main results. Media may affect individual perceptions and it may trigger specific behavioral responses which can be related to those perceptions. Among the specific ways through which media can alter individual perceptions, we can hypothesize its role in modifying the salience of a particular set of news. For example, in the case of individual perceptions, Mastrorocco and Minale (2018) find an increase in concerns about crime among individuals who were more exposed to TV channels which reported more crime-related content. On the other hand, in terms of voting behavior, Couttenier et al. (2019) show that disproportionate news coverage of migrant criminality affected the share of votes in a referendum that took place during an aggressive campaign of connecting immigration with terrorism and violence.

In our case, we build a measure of local media presence following the previous work of Ferraz and Finan (2011) and Larreguy et al. (2020), who use the presence of local media to find differential effects in the electoral accountability of local governments and voter behavior, respectively. We divide Chilean municipalities into two groups: "low media", where the number of local radio stations per capita is below the median, and "high media" otherwise (Ajzenman et al., 2020). We use data on local radio at the municipality level provided by the Chilean Department of Telecommunications (*Subsecretaría de Telecomunicaciones*, SUBTEL).

Panel C in Table IX reproduces the results of Table III by comparing coefficients for separate regressions based on the set of municipalities included in the sample. In the case of the indexes for both crime concerns and behavioral reactions, we observe a significant effect only in "high media" municipalities. This suggests that the Table III results are driven by what happens in municipalities where local media has a strong presence. Again, we observe no effect of migration on total crime for both types of municipalities. These results jointly suggest that the presence of local media is an important factor in explaining the differences between the relationship between immigration and crime on the one hand, and immigration and crime perceptions on the other.

Our results related to potential channels are exploratory. However, they provide interesting patterns related to what could be driving the widening in the gap between crime and crime-related concerns documented in this paper. While intergroup threat seems to be an unlikely explanation (at least in relation to ethnic distance), the role of local media as a plausible amplifier of crime news related to migrants and the differential perception of high versus low skilled migrants seem to be more promising candidates.

IV Conclusion

Does immigration affect crime or beliefs about crime? We examine this question in the context of Chile, a country that tripled its foreign-born population in a period of approximately five years. We show that this massive influx of immigrants caused no effects whatsoever on victimization (a result that is aligned with papers finding similar conclusions in other contexts, such as Bianchi et al. (2012b)), but a large increase in crime-related concerns and behavioral responses associated with those concerns. Given the precisely estimated null effect on victimization, our results indicate that the impact on crime-related concerns cannot be explained by a similar increase in crime rates, suggesting that immigration triggers the formation of misperceptions related to crime.

We explore multiple mechanisms that could rationalize the widening of the gap between crime and perceptions and find suggestive evidence related to two potential channels. First, the media seems to have an important role: municipalities with a larger local media presence seem to drive the effects. Second, the differential composition of migration in terms of the educational attainment of immigrants seems to be relevant. Low-skilled newcomers seem to generate larger increases in crime-related concerns and, to a lower extent, on behavioral reactions. Finally, we are not able to detect any heterogeneous effect by the ethnic proximity of immigrants in relation to the natives. This suggests that intergroup threat (e.g., a threat mostly triggered by those perceived as ethnically more distant) is not an important channel underlying the main effects documented in this paper.

Misperceptions are likely to affect other outcomes that are potentially critical from a policy point of view. For instance, this effect could be one plausible mechanism to explain the shifts in political preferences (toward more conservative parties) as documented by a recent literature in different contexts (Dustmann et al. (2019), Steinmayr (2020), Rozo and Vargas (2019)). Not only could misperceptions affect the demand for policies, but also could be one of the factors underlying the growth in hostility and prejudice also identified in several concurrent studies (Ajzenman et al. (2020); Hangartner et al. (2019)).

Our results should be interpreted in the context of Latin America, a region that has been amidst a severe migration crisis in recent years. The ongoing Venezuelan crisis in addition to other large migration flows in the region, such as the northern triangle migration to North America and the recent growth of Haitian migration to South America (especially Chile). In such a context, understanding the real impact of immigration on crime and how it shapes beliefs about crime becomes crucial for the design of non-discriminatory, well-balanced immigration policies.

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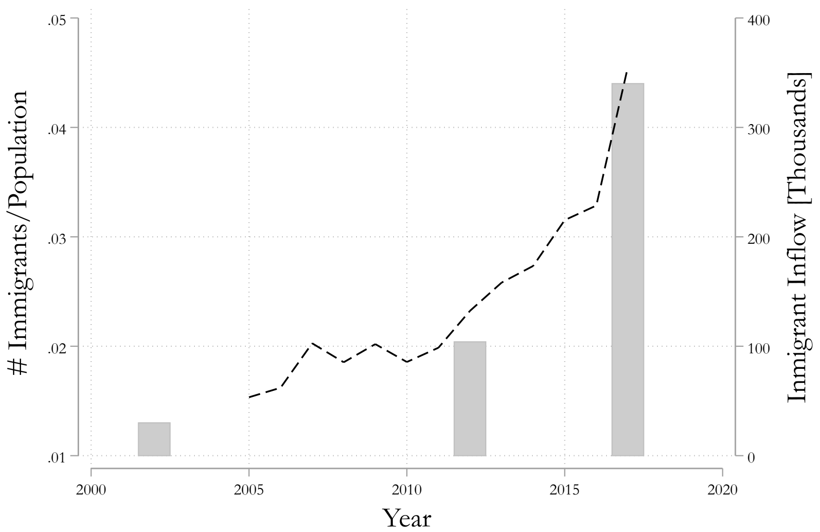
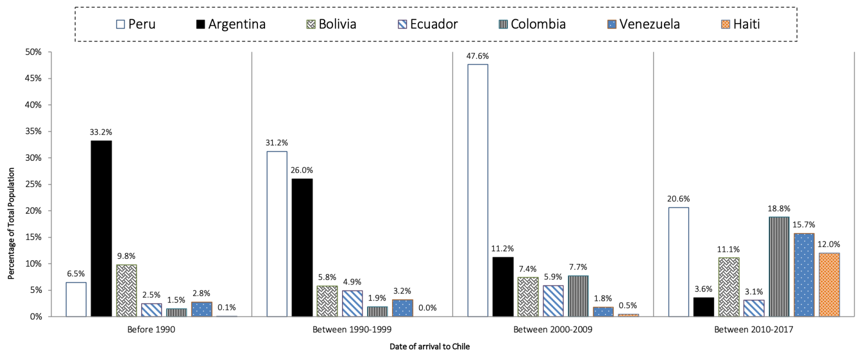
V Tables and Figures

Figure I. Immigrant inflows and the percentage of immigrants in Chile: 2005-2017



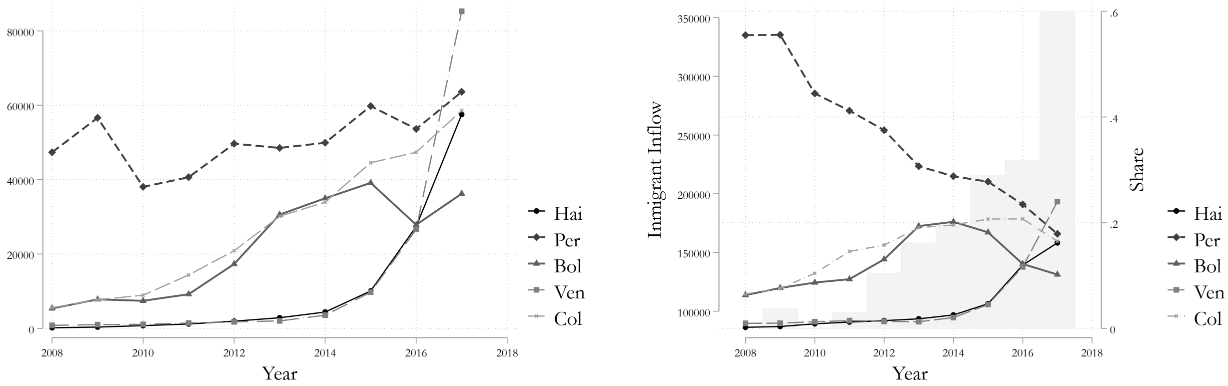
Notes: Bars represent the percentage of immigrants as reported by national Census years 2002, 2012, and 2017. Values for CENSUS data are indicated by the left vertical axis. The 2012 estimation corresponds to unofficial statistics. Inflow represents the number of residential permits and visas granted per year, and values are indicated by the right vertical axis. Inflow data is collected by the Chilean Department of State (Extranjería and INE)

Figure II. Percentage of foreign-born population by country of origin and period of arrival



Source: INE based on 2017 CENSUS.

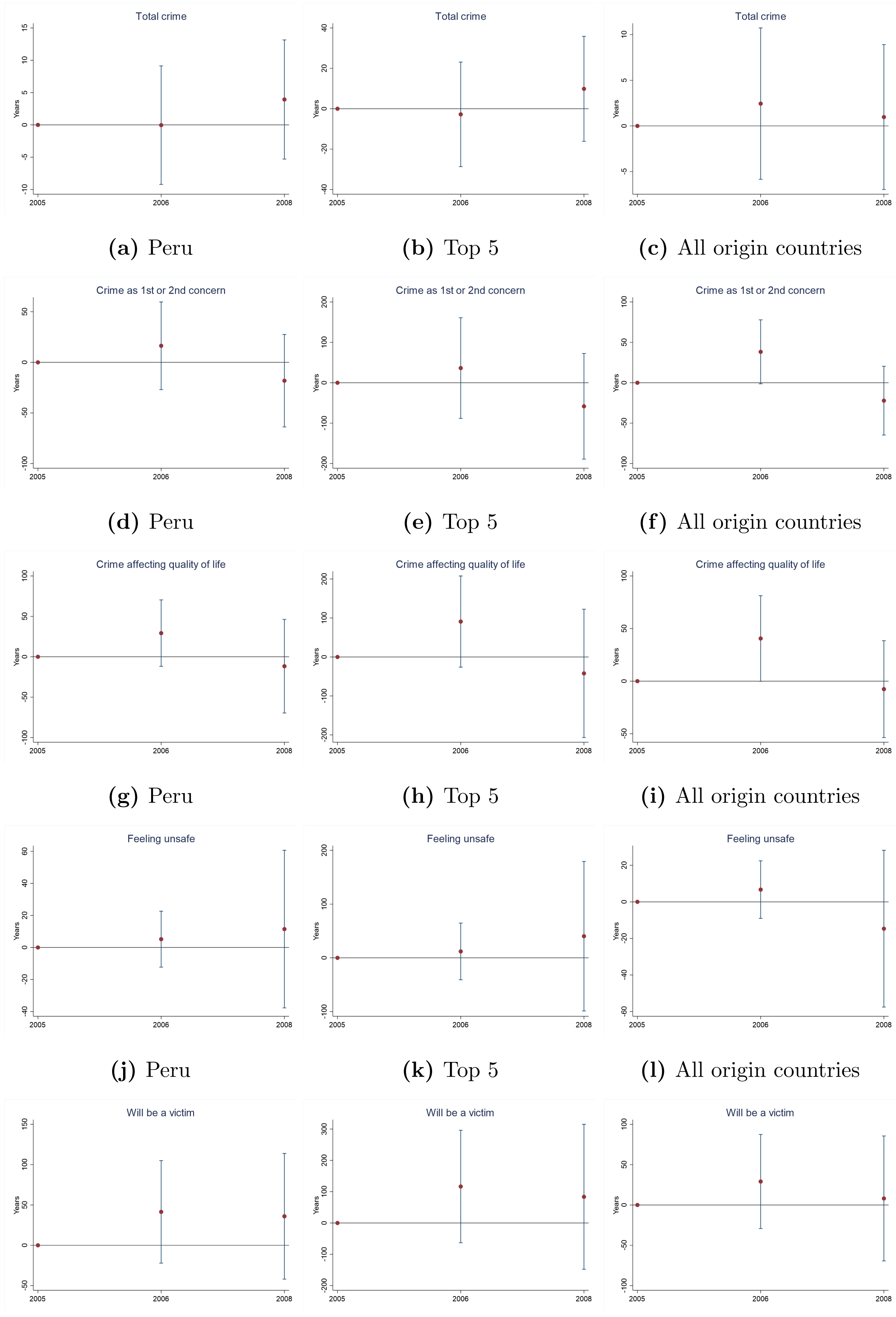
Figure III. Immigrant inflow evolution by country of origin: 2008-2017



(a) Annual inflow **(b)** Share of total inflow

Note: Panel (a) shows the number of immigrants (inflow) by country of origin and year of arrival. Each line in Panel (b) plots the share of immigrants by country of origin and year of arrival. Bars represent the total number of immigrants (inflow) per year of arrival. Inflow represents the number of residential permits and visas granted per year. Source: Chilean Department of State (Extranjería).

Figure IV. Pre-trends for high Rotemberg weight countries and all together



(a) Peru **(b)** Top 5 **(c)** All origin countries

(d) Peru **(e)** Top 5 **(f)** All origin countries

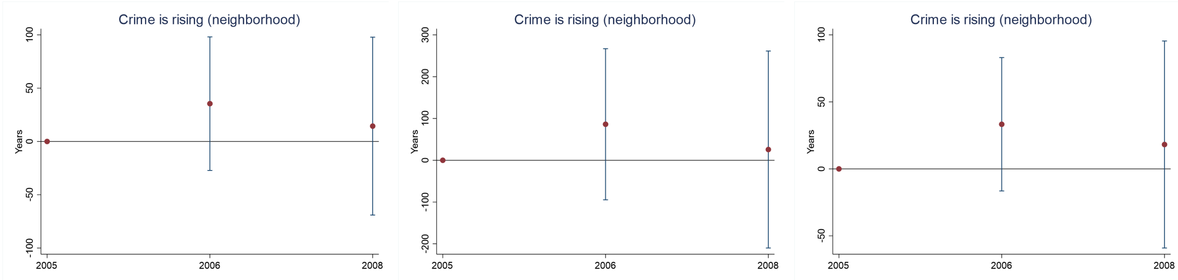
(g) Peru **(h)** Top 5 **(i)** All origin countries

(j) Peru **(k)** Top 5 **(l)** All origin countries

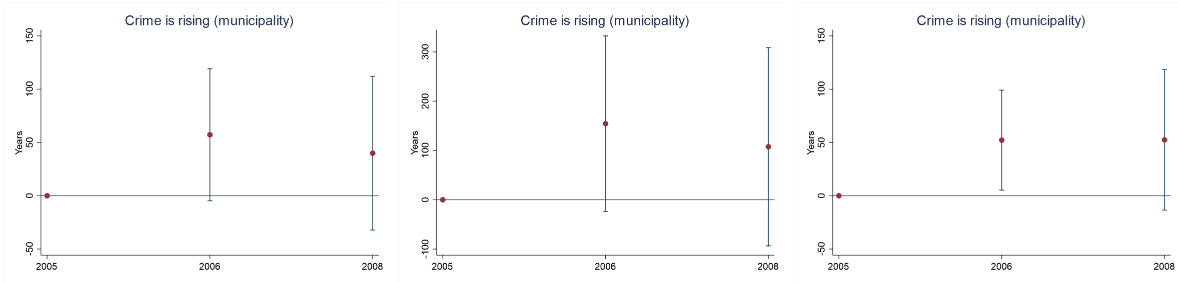
(m) Peru **(n)** Top 5 **(o)** All origin countries

Note: We regress the outcome of interest against the nationality-shares in each year interacted with year fixed effects, controlling for municipality fixed effects, year fixed effects, and years fixed effects interacted with our set of control variables (mean age and share of men). Point estimates reflect the differential effect of nationality-specific shares relative to 2005, our baseline year. We convert the growth rates to levels and index the levels in 2005 to 0. The top 5 Rotemberg weight countries are Peru, Bolivia, Ecuador, China, and Brazil.

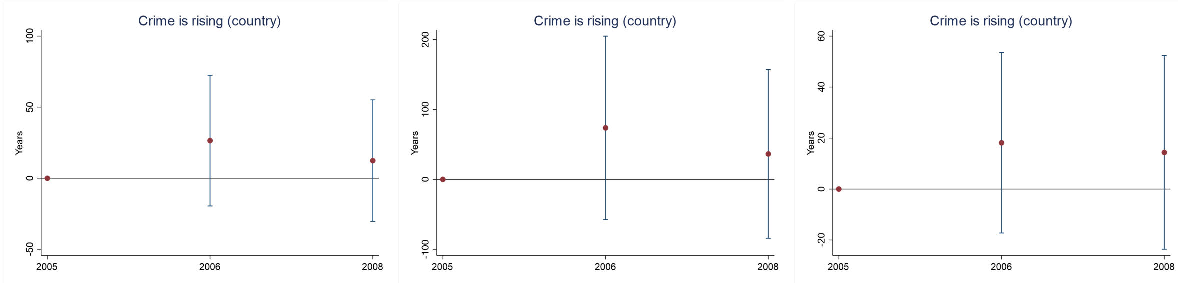
Figure V. Pre-trends for high Rotemberg weight countries and all together (cont.)



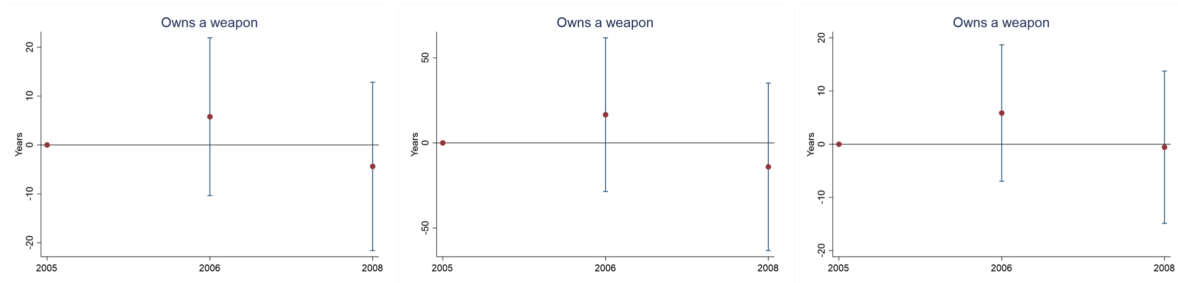
(a) Peru **(b)** Top 5 **(c)** All origin countries



(d) Peru **(e)** Top 5 **(f)** All origin countries



(g) Peru **(h)** Top 5 **(i)** All origin countries



(j) Peru **(k)** Top 5 **(l)** All origin countries

Note: We regress the outcome of interest against the nationality-shares in each year interacted with year fixed effects, controlling for municipality fixed effects, year fixed effects, and years fixed effects interacted with our set of control variables (mean age and share of men). Point estimates reflect the differential effect of nationality-specific shares relative to 2005, our baseline year. We convert the growth rates to levels and index the levels in 2005 to 0. The top 5 Rotemberg weight countries are Peru, Bolivia, Ecuador, China, and Brazil.

TABLE I. Immigrant inflow rate by year and region

Region	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Arica	1,145	1,522	1,025	1,144	1,714	1,919	2,096	2,205	1,870	2,667
Tarapacá	2,222	2,817	1,993	2,337	3,360	3,462	4,344	4,493	3,239	4,591
Antofagasta	1,129	1,611	1,630	2,055	2,859	4,975	4,569	6,262	4,800	5,538
Atacama	349	425	396	543	807	1,533	1,703	1,829	1,344	2,377
Coquimbo	183	229	239	267	404	485	530	588	690	970
Valparaíso	187	200	195	222	261	278	387	462	547	1,091
RM	841	981	802	907	1,217	1,342	1,485	1,884	2,227	3,432
O'Higgins	101	112	101	121	151	177	207	280	348	1,004
Maule	65	72	67	80	94	106	171	213	263	842
Biobio	82	97	96	105	121	136	151	163	183	325
Araucanía	72	76	70	78	84	85	106	137	148	324
Los Ríos	87	95	94	115	121	116	136	167	169	237
Los Lagos	119	108	103	119	135	164	200	218	225	453
Aysén	198	163	178	265	285	265	383	358	432	783
Magallanes	486	602	570	685	739	942	1,007	1,043	1,044	1,465
Total	500	597	502	578	776	927	1,016	1,262	1,339	2,082

Notes: Data shows the immigrant inflow per 100,000 inhabitants for each region and year. Source: Chilean Department of State (Extranjería).

TABLE II. Descriptive Statistics: Respondent Level

Variable	Obs	Mean	SD
Age	243,653	44.47	18.28
Female	243,653	0.559	0.497
Crime as a 1st or 2nd Concern	242,089	0.361	0.480
Crime as Impacting Personal Life	232,175	0.349	0.477
Crime Affecting Quality of Life	242,987	0.632	0.482
Feeling Unsafe	212,834	0.174	0.379
Will be a Victim	213,977	0.438	0.496
Crime rising: Country	241,762	0.789	0.408
Crime rising: Municipality	236,322	0.648	0.477
Crime rising: Neighborhood/Village	235,386	0.421	0.494
Investment in Home Security	243,324	0.228	0.162
Neighbors' Security System	243,531	0.132	0.154
Owns a Weapon	242,946	0.0477	0.213
Robbery	243,622	0.0444	0.206
Larceny	243,617	0.0458	0.209
Burglary	243,641	0.0475	0.213
Theft	243,591	0.0844	0.278
Assault	243,633	0.0187	0.135
Motor Vehicle Theft	243,653	0.00768	0.0873

Notes: Data collected from harmonization of annual ENUSC series 2008-2017. With the exception of age, all variables are computed as dummies. The exact definition of each of the variables can be found in Section II.

TABLE III. The effect of immigration: Two-way fixed effects model

Panel A: Crime Perceptions							
	Crime as a 1st or 2nd Concern	Crime as Impacting Pers.Life	Crime Affecting Qual-Life	Feeling Unsafe	Will be Victim	PC	
Log Imm Rate	0.0019	0.0322**	0.0380**	0.0211**	0.0259	0.0293**	
	(0.0128)	(0.0145)	(0.0173)	(0.0098)	(0.0327)	(0.0130)	
Observations	242,089	232,175	242,987	212,834	213,977	179,766	
R-squared	0.0244	0.0225	0.0409	0.0473	0.0315	0.0514	
Mean DV	0.361	0.349	0.632	0.174	0.438	0.394	
Panel B: Crime Trend							
	Crime is rising at:						
	Village	Munic	Country				
Log Imm Rate	0.0334	0.0470***	0.0010				
	(0.0236)	(0.0177)	(0.0064)				
Observations	235,386	236,322	241,762				
R-squared	0.0496	0.0652	0.0724				
Mean DV	0.421	0.648	0.789				
Panel C: Behavioral reactions							
	Investment in Home Security	Neighbors Security System	Owns a Weapon	PC			
Log Imm Rate	0.0115	0.0210***	0.0048	0.0154**			
	(0.0083)	(0.0074)	(0.0030)	(0.0060)			
Observations	243,324	243,531	242,946	242,634			
R-squared	0.0696	0.0558	0.0117	0.0731			
Mean DV	0.228	0.132	0.0477	0.164			
Panel D: Victimization							
	Total	Robbery	Larceny	Burglary	Theft	Assault	MV Theft
Log Imm Rate	0.0011	0.0033	0.0050	0.0120**	-0.0155***	-0.0021	-0.0006
	(0.0025)	(0.0036)	(0.0039)	(0.0057)	(0.0058)	(0.0020)	(0.0014)
Observations	243,653	243,622	243,617	243,641	243,591	243,633	243,653
R-squared	0.0288	0.0184	0.0173	0.0070	0.0103	0.0070	0.0048
Mean DV	0.0366	0.0444	0.0458	0.0475	0.0844	0.0187	0.00768

Notes: Results of a OLS pooled cross-section regression at the respondent level between 2008 and 2017 across 101 municipalities surveyed in ENUSC. The exact definition of each variable can be found in Section II. Panel A displays results for crime-related concerns (**"PC Index"** (PCI) is the first component of a principal component analysis (0-1 scale) of all the variables of the panel). Panel B displays results for crime trend perceptions. Panel C displays results for behavioral reactions to crime (**"PC Index"** is the first component of a principal component analysis (0-1 scale) of all the variables of the panel). Panel D displays results on crime victimization. It indicates if the respondent was the victim of a crime in the last 12 months. All regressions include individual-level controls (age and gender), year and municipality fixed effects, and a baseline interaction term as indicated in equation 1. Robust standard errors are presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

TABLE IV. 2017-2008 Difference Regressions: Victimization Disaggregated

	Theft			Larceny			MV Theft			Burglary			Assault			Robbery			Total Crime		
	OLS (1)	OLS (2)	IV (3)	OLS (1)	OLS (2)	IV (3)	OLS (1)	OLS (2)	IV (3)	OLS (1)	OLS (2)	IV (3)	OLS (1)	OLS (2)	IV (3)	OLS (1)	OLS (2)	IV (3)	OLS (1)	OLS (2)	IV (3)
$\Delta migr_{mt}$	0.0093		0.0032	-0.0003		-0.0060	0.0034		-0.0095	0.0203***		0.0113	0.0005		0.0187	0.0036		0.0309	0.0061		0.0080
	(0.0107)		(0.0356)	(0.0073)		(0.0295)	(0.0026)		(0.0071)	(0.0064)		(0.0183)	(0.0060)		(0.0159)	(0.0066)		(0.0210)	(0.0039)		(0.0125)
$\widehat{\Delta migr_{mt}}$		0.0219			-0.0410			-0.0650			0.0767			0.1272			0.2102			0.0544	
		(0.2479)			(0.2058)			(0.0457)			(0.1306)			(0.1053)			(0.1377)			(0.0870)	
Obs.	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101
Mean DV	0.0844	0.0844	0.0844	0.0187	0.0187	0.0187	0.0077	0.0077	0.0077	0.0475	0.0475	0.0475	0.0444	0.0444	0.0444	0.0458	0.0458	0.0458	0.2146	0.2146	0.2146
First Stage Regressions																					
$\widehat{\Delta migr_{mt}}$			6.8120***			6.8120***			6.8120***			6.8120***			6.8120***			6.8120***			6.8120***
			(1.6356)			(1.6356)			(1.6356)			(1.6356)			(1.6356)			(1.6356)			(1.6356)
F-stat			17.35			17.35			17.35			17.35			17.35			17.35			17.35
Part. R^2			0.104			0.104			0.104			0.104			0.104			0.104			0.104

Notes: This table presents the results of OLS and IV estimates on the cross section of differences between 2008 and 2017 across 101 municipalities surveyed in ENUSC. The dependent variable is the log change of the average self-reported victimization rate in a given municipality as reported by the 2017-2008 ENUSC. The exact definition of the outcomes can be found in Section II. The variable $\Delta migr_{mt}$ is the log change of immigrants (i.e. residence permits) divided by the municipality population. $\widehat{\Delta migr_{mt}}$ is the instrument (see equation 4). The list of countries includes Argentina, Bolivia, Brazil, China, Colombia, Ecuador, Haiti, Peru, Spain, USA, and Venezuela. 2SLS coefficients are reported in the top panel under the heading IV. Mean DV reports the across-years mean of the outcome under study for the period 2008-2017. The bottom panel reports first-stage regressions. The F-stat refers to the null hypothesis that the coefficient of the instrument is equal to zero in the first stage. The partial R^2 is the correlation between the endogenous variable and the instrument. Robust standard errors are presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

TABLE V. 2017-2008 2SLS model: Crime-related Concerns

	Crime as 1st or 2nd Concern			Crime as 1st or 2nd Factor Impacting Personal Life			Crime Affecting Quality of Life			Feeling Unsafe			Will be a Victim			Principal Component Summary Index		
	OLS	OLS	IV	OLS	OLS	IV	OLS	OLS	IV	OLS	OLS	IV	OLS	OLS	IV	OLS	OLS	IV
$\Delta migr_{mt}$	0.0408**		0.1861***	0.0539***		0.1494**	0.0408**		0.1861***	0.0627***		0.0479	0.0659**		0.1691*	0.0584***		0.1358**
	(0.0168)		(0.0679)	(0.0200)		(0.0700)	(0.0168)		(0.0679)	(0.0193)		(0.0649)	(0.0261)		(0.0892)	(0.0152)		(0.0532)
$\widehat{\Delta migr_{mt}}$		1.2679***			1.0176**			1.2679***			0.3266			1.1519*			0.9249**	
		(0.4024)			(0.4734)			(0.4024)			(0.4597)			(0.6183)			(0.3647)	
N	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101
Mean DV	0.36	0.36	0.36	0.35	0.35	0.35	0.63	0.63	0.63	0.17	0.17	0.17	0.44	0.44	0.44	0.39	0.39	0.39
First Stage Regressions																		
$\widehat{\Delta migr_{mt}}$			6.57***			6.57***			6.57***			6.57****			6.57***			6.57***
			(1.64)			(1.64)			(1.64)			(1.64)			(1.64)			(1.64)
F-stat			17.35			17.35			17.35			17.35			17.35			17.35
Par. R^2			0.104			0.104			0.104			0.104			0.104			0.104

Notes: This table presents the results of OLS and IV estimates on the cross section of differences between 2008 and 2017 across 101 municipalities surveyed in ENUSC. The outcomes are defined as follows. **"Crime as 1st or 2nd Concerns"**: one if the individual answered "crime" to the question "Which of the following problems do you think is the most important (or second most important) nowadays? (the list includes ten categories, including economic situation, health, education, unemployment, poverty, inequality, among other social concerns)". **"Crime as 1st or 2nd Factor impacting Personal Life""**: one if the individual answered "crime" to the question "Which of the following problems affects you personally the most (1st or 2nd options)? (the list includes the same aforementioned categories)". **"Crime Affecting Quality of Life"**: one if the individual answered positively ("a lot" or "much") to the question "According to your personal experience, how much does crime affects your quality of life?" (other categories are "a lot", "much", "not much", "nothing"). **"Feel Unsafe"** takes a one if the individual felt fear (at least some) when walking alone in their neighborhoods, being alone at home waiting for public transportation. **"Will be a victim"** takes a one if the individual said she thinks she will be a victim of a crime in the following 12 months. Finally, we aggregate these results by taking the first component of a principal component analysis, and normalize it to a 0-1 scale (**"Principal Component Summary Index"**). The dependent variable is the difference of the average self-reported crime perception rate in a given municipality as reported by the 2017-2008 ENUSC. The variable $\Delta migr_{mt}$ is the log change of immigrants (i.e. residence permits) divided by the municipality population; $\widehat{\Delta migr_{mt}}$ is the instrument (see equation 4). The list of countries includes Argentina, Bolivia, Brazil, China, Colombia, Ecuador, Haiti, Peru, Spain, USA, and Venezuela. As controls, all regressions include the average age and the proportion of women in each municipality during 2017. 2SLS coefficients are reported in the top panel under the heading IV. Mean DV reports the across-years mean of the outcome under study for the period 2008-2017. The bottom panel reports first-stage regressions of $\widehat{\Delta migr_{mt}}$ on $\Delta migr_{mt}$. The F-stat refers to the null hypothesis that the coefficient of the instrument equals zero in the first stage. The partial R^2 is the correlation between the endogenous variable and the instrument. Robust standard errors are presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

TABLE VI. 2017-2008 2SLS model: Crime-related Concerns

	Crime is rising (neighborhood)			Crime as rising (municipality)			Crime is rising (country)		
	OLS	OLS	IV	OLS	OLS	IV	OLS	OLS	IV
$\Delta migr_{mt}$	0.0975***		0.1344	0.0694***		0.0874	0.0273**		0.0171
	(0.0257)		(0.0827)	(0.0238)		(0.0865)	(0.0119)		(0.0482)
$\widehat{\Delta migr}_{mt}$		0.9158			0.5951			0.1168	
		(0.5750)			(0.6027)			(0.3344)	
N	101	101	101	101	101	101	101	101	101
Mean DV	0.42	0.42	0.42	0.65	0.65	0.65	0.79	0.79	0.79
First Stage Regressions									
$\widehat{\Delta migr}_{mt}$			6.57***			6.57***			6.57***
			(1.64)			(1.64)			(1.64)
F-stat			17.35			17.35			17.35
Part. R^2			0.104			0.104			0.104

Notes: This table presents the results of OLS and IV estimates on the cross section of differences between 2008 and 2017 across 101 municipalities surveyed in ENUSC. The outcomes are defined as follows. **"Crime is rising (neighborhood)"**: one if the individual answered positively to the question"Would you say that during the last 12 months crime has increased in your neighborhood". **"Crime is rising (municipality)"**: one if the individual answered positively to the question"Would you say that during the last 12 months crime has increased in your municipality". **"Crime is rising (country)"**: one if the individual answered positively to the question"Would you say that during the last 12 months crime has increased in the country". The dependent variable is the difference of the average self-reported crime perception rate in a given municipality as reported by the 2017-2008 ENUSC. The variable $\Delta migr_{mt}$ is the log change of immigrants (i.e. residence permits) divided by the municipality population; $\widehat{\Delta migr}_{mt}$ is the instrument (see equation 4). The list of countries includes Argentina, Bolivia, Brazil, China, Colombia, Ecuador, Haiti, Peru, Spain, USA, and Venezuela. As controls, all regressions include the average age and the proportion of women in each municipality during 2017. 2SLS coefficients are reported in the top panel under the heading IV. Mean DV reports the across-years mean of the outcome under study for the period 2008-2017. The bottom panel reports first-stage regressions of $\widehat{\Delta migr}_{mt}$ on $\Delta migr_{mt}$. The F-stat refers to the null hypothesis that the coefficient of the instrument equals zero in the first stage. The partial R^2 is the correlation between the endogenous variable and the instrument. Robust standard errors are presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

TABLE VII. 2017-2008 2SLS model: Behavioral reactions

	Investment in Home Security Index			Neighborhood Security System Index			Owns a weapon			Principal Component Summary Index		
	OLS	OLS	IV	OLS	OLS	IV	OLS	OLS	IV	OLS	OLS	IV
$\Delta migr_{mt}$	0.0184*		0.1003**	0.0080		0.1244***	0.0045		0.0092	0.0138		0.1144***
	(0.0109)		(0.0470)	(0.0095)		(0.0406)	(0.0075)		(0.0162)	(0.0084)		(0.0404)
$\widehat{\Delta migr_{mt}}$		0.8474***			1.0193***			0.0624			0.7790***	
		(0.2027)			(0.2028)			(0.1100)			(0.2227)	
N	101	101	101	101	101	101	101	101	101	101	101	101
Mean DV	0.23	0.23	0.23	0.13	0.13	0.13	0.05	0.05	0.05	0.16	0.16	0.16
First Stage Regressions												
$\widehat{\Delta migr_{mt}}$			6.57***			6.57***			6.57***			6.57****
			(1.64)			(1.64)			(1.64)			(1.64)
F-stat			17.35			17.35			17.35			17.35
Part. R^2			0.104			0.104			0.104			0.104

Notes: This table presents the results of OLS and IV estimates on the cross section of differences between 2008 and 2017 across 101 municipalities surveyed in ENUSC. The outcomes are defined as follows. **"Investment in Home Security Index"**: is the proportion of positive answers to the question "Do you have the following security items at home?": a) an animal to protect your dwelling, b) an alarm or panic button, c) a surveillance camera, d) window or door security bars, e) an electric fence or perimeter wall of your dwelling, f) a non-electric fence or perimeter wall off your dwelling, g) a chain lock or double locking, h) alterations to the infrastructure of your property to make it safer, i) light or motor sensors. **"Neighborhood Security System Index"**: is the proportion of positive answers to the question "Which of the following measures have you adopted, jointly with your neighbors in order to feel safer?": a) exchange phone numbers, b) we implemented a surveillance system among the neighbors, c) we have a community alarm system, d) we have hired a guard to watch over our dwellings, e) we have hired a private surveillance system, f) we have implemented an access control system to watch out the entrance of people that do not live where we live, g) we have talked with the police to coordinate security measures, h) we have talked with the municipal officers to coordinate security measures, h) we have reached an agreement with the neighbors, to call the police every time we see one of us under risk. **"Owns a weapon"**: takes a one if the individual manifested that she owns a weapon Finally, we aggregate these results by taking the first component of a principal component analysis, and normalize it to a 0-1 scale (**"Principal Component Summary Index"**). The dependent variable is the difference of the average self-reported crime perception rate in a given municipality as reported by the 2017-2008 ENUSC. The variable $\Delta migr_{mt}$ is the log change of immigrants (i.e. residence permits) divided by the municipality population; $\widehat{\Delta migr_{mt}}$ is the instrument (see equation 4). The list of countries includes Argentina, Bolivia, Brazil, China, Colombia, Ecuador, Haiti, Peru, Spain, USA, and Venezuela. As controls, all regressions include the average age and the proportion of women in each municipality during 2017. 2SLS coefficients are reported in the top panel under the heading IV. Mean DV reports the across-years mean of the outcome under study for the period 2008-2017. The bottom panel reports first-stage regressions of $\widehat{\Delta migr_{mt}}$ on $\Delta migr_{mt}$. The F-stat refers to the null hypothesis that the coefficient of the instrument equals zero in the first stage. The partial R^2 is the correlation between the endogenous variable and the instrument. Robust standard errors are presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

TABLE VIII. Robustness

Victimization (Total Crime)

	Base 2SLS	2SLS No Controls	2SLS Visas	2SLS Permits	2SLS Adao	Base2 WFE	2WFE No Controls	2WFE Visas	2WFE Permits
Log Imm Rate	0.0080	0.0086	0.0095	0.0010	0.0080	0.0011	0.0012	0.0008	0.0006
	(0.0125)	(0.0126)	(0.0139)	(0.0075)	(0.0023)	(0.0025)	(0.0024)	(0.0023)	(0.0028)
Observations	101	101	101	101	101	244,115	244,115	244,115	244,115
Mean DV	0366	0366	0366	0366	0366	0.0366	0.0366	0.0366	0.0366

Crime Concerns (Summary PCI)

	Base 2SLS	2SLS No Controls	2SLS Visas	2SLS Permits	2SLS Adao	Base2WFE	2WFE No Controls	2WFE Visas	2WFE Permits
Log Imm Rate	0.1358**	0.1391**	0.1504**	0.0687**	0.1358*	0.0291**	0.0285**	0.0261**	0.0271*
	(0.0532)	(0.0565)	(0.0619)	(0.0330)	(0.0235)	(0.0129)	(0.0131)	(0.0122)	(0.0157)
Observations	101	101	101	101	101	180,039	180,039	180,039	180,039
Mean DV	0.394	0.394	0.394	0.394	0.394	0.394	0.394	0.394	0.3942

Behavioral Reactions (Summary PCI)

	Base 2SLS	2SLS No Controls	2SLS Visas	2SLS Permits	2SLS Adao	Base2WFE	2WFE No Controls	2WFE Visas	2WFE Permits
Log Imm Rate	0.1144***	0.1239***	0.1314***	0.0635***	0.1144	0.0154**	0.0154***	0.0137**	0.0220***
	(0.0404)	(0.0446)	(0.0493)	(0.0226)	(0.0404)	(0.0060)	(0.0060)	(0.0057)	(0.0074)
Observations	101	101	101	101	101	243,096	243,096	243,096	243,096
Mean DV	0.1641	0.1641	0.1641	0.1641	0.1641	0.1641	0.1641	0.1641	0.1641

Notes: Base 2SLS: baseline 2SLS model with controls as described in Section III). Base 2SLS No controls: baseline 2SLS model as described in Section III) excluding all controls. 2SLS Visas: baseline 2SLS model with controls as described in Section III), using only visas as the measure for immigration. 2SLS Permits: baseline 2SLS model with controls as described in Section III), using only working permits as the measure for immigration. 2SLS Adao: baseline 2SLS model with controls as described in Section III), adjusting the standard errors using Adao et al. (2019)'s method. Base 2WFE: baseline 2WFE model with controls as described in Section III). Base 2WFE No controls: baseline 2WFE model as described in Section III) excluding all controls. 2WFE Visas: baseline 2WFE model with controls as described in Section III), using only visas as the measure for immigration. 2WFE Permits: baseline 2WFE model with controls as described in Section III), using only working permits as the measure for immigration. Outcomes: for victimization the outcome is total crime, for crime-related concerns it is the Summary Index (first component of a principal component analysis (0-1 scale) of all the variables in the category), and for behavioral responses it is the Summary Index (first component of a principal component analysis (0-1 scale) of all the variables in the category). The exact definition of each variable can be found in Section II. All the 2WFE models include year and municipality fixed effects (see 1). Robust standard errors are presented in parenthesis in the 2SLS models. Robust standard errors clustered at the municipality level are presented in parenthesis in the 2WFE models. *** p<0.01, ** p<0.05, * p<0.1

TABLE IX. Exploration of Channels

Panel A: Education

	Crime Concerns	Behavioral Reactions	Total Crime
Log Imm Rate (Low Skilled)	0.0504***	0.0198**	0.0026
	(0.0166)	(0.0083)	(0.0030)
Log Imm Rate (High Skilled)	0.0128	0.0120*	-0.0001
	(0.0125)	(0.0069)	(0.0025)
Observations	180,039	243,096	244,115

Panel B: Ethnic Distance

	Crime Concerns	Behavioral Reactions	Total Crime
Log Imm Rate (Low Distance)	0.0295**	0.0153***	0.0008
	(0.0127)	(0.0056)	(0.0023)
Log Imm Rate*High Distance	-0.0008	0.0036	0.0018**
	(0.0032)	(0.0024)	(0.0007)
Log Imm Rate (High Distance)	0.0286**	0.0189***	0.0026
	(0.0119)	(0.0058)	(0.0022)
Observations	180,039	243,096	244,115

Panel C: Media Presence

	Crime Concerns		Behavioral Reactions		Total Crime	
	Low Media	High Media	Low Media	High Media	Low Media	High Media
Log Imm Rate	0.0137	0.0339**	0.0054	0.0176***	-0.0015	0.0015
	(0.0161)	(0.0152)	(0.0131)	(0.0065)	(0.0035)	(0.0026)
Observations	90,528	89,511	122,259	122,837	122,942	121,173