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DISCUSSION PAPER SERIES

IZA DP No. 14087

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ABSTRACT

Immigration, Crime, and Crime (Mis)Perceptions*

This paper studies the effects of immigration on crime and crime perceptions in Chile, where the foreign-born population more than doubled in the last decade. By using individual-level victimization data, we document null effects of immigration on crime but positive and significant effects on crime-related concerns, which in turn triggered preventive behavioral responses, such as investing in home-security. Our results are robust across a two-way fixed effects model and an IV strategy based on a shift-share instrument that exploits immigration inflows towards destination countries other than Chile. On mechanisms, we examine data on crime-related news on TV and in newspapers, and find a disproportionate coverage of immigrant-perpetrated homicides as well as a larger effect of immigration on crime perceptions in municipalities with a stronger media presence. These effects might explain the widening gap between actual crime trends and public perceptions of crime.

JEL Classification: O15, F22, K1
Keywords: crime, immigration, crime perception, media, crime beliefs

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I Introduction

Immigration is a critical topic in contemporary policy and academic debates. A growing literature has focused on how immigration shapes the beliefs and attitudes of native populations (Alesina et al. (2018b)). Immigration can change political preferences (Steinmayr (2020)), preferences for redistribution (Alesina et al. (2019)), or risk attitudes (Ajzenman et al. (2020)), but it can also trigger hostility (Hangartner et al. (2019)). Such animosity may be explained by a perceived link between migrants and crime.[1] As Fasani et al. (2019) show, natives not only tend to overstate the size of the immigrant population, but are also prone to forming prejudices based on misperceptions about crime. Indeed, consistently topping the list of immigration-related concerns is a potential increase in crime (Bianchi et al. (2012a)).

The recent massive influx of Venezuelans and Central Americans to other Latin American countries has provoked a rise in anti-immigrant sentiment. Crime-related fears seem to offer an explanation. In Chile, for example, a nationally representative survey of urban perceptions found that natives' main concern regarding immigration is citizen security (59%), with economic concerns ranking third (46%) (Espacio Público (2018)). In Peru, a nationally representative survey showed that almost 60% of people think Venezuelans are involved in illegal activities (IOP-PUCP (2019)). Such beliefs likely also affect the positions of politicians.[2]

Yet, most papers– albeit the evidence is scarce and largely focuses on Europe and the U.S.– have identified a mild to null effect of immigration on crime (Bianchi et al. (2012a); Bell et al. (2013)). Meanwhile, there is virtually no rigorous or systematic evidence on how immigration affects crime perceptions and investment in crime prevention. Our study aims to fill this gap by shedding light on the causal effect of immigration on crime, crime-related concerns, and crime-preventive behavior. We explore this question in Chile, one of the most popular destinations for recent Latin American immigrants. With a population of around 18 million, Chile is currently near an all-time high in terms of the proportion of foreign-born residents. Considering only legal visa requests, the annual influx rose from around 100,000 migrants per year in 2010, to

[1] In the US, concerns about the criminal potential of immigrants has a long history. For example, the Immigration Act of 1882 prohibited people with criminal histories from entering the country.

[2] Examples of anti-immigration rhetoric among politicians abound. For instance, the Chilean president publicly declared that "Gangs in Chile are mostly led by immigrants" (see this link). Likewise, the chief of the Chilean Immigration Office said "The pious paternalistic attitude that favors transforming Chile into a rehabilitation center for delinquent immigrants is not helpful" (link).

almost 200,000 in 2015, and more than 350,000 in 2017.[3,4]

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

To estimate the causal effect of immigration on crime, crime-related concerns, and crime-preventive behavior, we exploit the sudden increase in immigration flows to Chile that began around the year 2010. We implement two empirical approaches: a two-way fixed effects model at the municipality level and an IV strategy that closely follows Bianchi et al. (2012a)'s approach. Specifically, we build a shift-share, Bartik-like instrument that exploits the supply-push component of immigration 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, i.e., events that are potentially relevant for determining migration outflows from the origin country but are independent of across-municipality differences in immigration inflows within Chile. More precisely, our measure of exogenous supply-push factors is based on bilateral migration flows from the country of origin to destination countries other than Chile. The

[3]The growth rates of immigrants by region have been far from uniform. Figures I, II, and III depict these patterns over the last 20 years. We observe a sharp change in the share of the overall immigrant population rising from around 1-2 percent of the population between 2002 and 2012, to 4 percent in the most recent years. In addition, the composition of immigrants arriving in Chile shifted in 2016-2017 with the arrival of a large number of people from Venezuela and Haiti.

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

predicted change in the incoming flows of nationality-specific immigrants to a given municipality (i.e., variations in its total immigration rate) will thus 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).

We document several 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 (i) crime is their first or second most important concern (the 2SLS estimates reveal that a 1% increase in the immigration rate triggers a rise of 0.18pp, relative to the mean of 36%); (ii) 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 mean of 35%); (iii) crime affects their quality of life (a 1% increase in the immigration rate triggers a rise of 0.18pp, relative to the mean of 63%); and (iv) 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 mean of 44%). 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 mean of 39%).

Second, we observe 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. The 2SLS estimates show that a 1% increase in the immigration rate triggers a rise of 0.11pp in an aggregated index, relative to the mean of 16%.

Yet, 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 – and observe no 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 exception 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 while immigration does not actually increase crime, it does trigger seemingly ungrounded crime-related concerns among the native population. The results are robust to different definitions of immigration and the inclusion of various types of controls. The estimations from the two-way fixed effects model, although different in magnitude, are qualitatively similar to those identified in the 2SLS model. Note that our IV empirical strategy is an "exposure" research design, where the shares of immigrants per municipality measure the differential exogenous exposure to a common shock (international migration). As Goldsmith-Pinkham et al. (2020) show, the exogeneity of Bartik-type instruments like ours relies on the exogeneity of the (pre-shock) country shares by municipality. The main identification threat is thus that the shares predict our outcomes (for instance, crime perceptions) through channels other than immigration. We accordingly closely follow the authors' recommendations and show that there are parallel trends in the relevant outcomes before the immigration shock began, such that the identification assumptions are well met in our design.

Exposure to immigration may provoke prejudice, fear, and resultant crime concerns through a variety of channels. We explore three potential mechanisms underlying our main effects, often emphasized in the economics and political science literature.[5] First, we assess the role of ethnic-related intergroup threats (Allport et al. (1954)). Specifically, foreign outgroups could be perceived as threatening, such that interactions with them 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 in different municipalities at different times. Our results do not vary by the level of ethnic/genetic distance, suggesting that an ethnic-related intergroup threat is not a major factor.

Second, we investigate whether immigration composition, based on education level (high vs. low), triggers wariness of migrants. We find that our main effects may, in fact, be driven by the arrival of low-skilled immigrants (up to primary school completed) . While the null effect on victimization holds for both the high and low-skilled groups, the effects on crime-related concerns and crime-preventive behavioral reactions seem to be more significant when immigrants are less educated. These results are consistent with other papers in the literature (e.g., Mayda et al. (2016)), and are perhaps explained by the perception that low-skilled immigrants are relatively unlikely to be integrated into the labor market and are thus more likely to commit crime. Alternatively, lower levels of educational attainment could correlate with other characteristics (e.g., poverty), which could themselves provoke a sentiment of threat.

[5]We do so using the 2WFE models, as we could not find acceptable first stages in the IV models when including interactions.

Third, we analyze the role of local media as a potential mediator. As Couttenier et al. (2019) show, crimes perpetrated by immigrants can be over-represented in the news. Thus, even if immigrants do not commit more crime than natives, their offences may comparatively be more salient. We show that, while the effect of immigration on victimization seems to be null in all municipalities independent of whether they have a high or low number of local radio stations per capita, the effects on both crime-related concerns and crime-preventive behaviors are only significant in municipalities with a relatively large number of local radio stations per capita. In addition, we study the frequency of crime-related news on TV and in newspapers. Using daily data on crime-related articles and the TV captions of Chile's main national media outlets, matched with a database containing daily homicides, we show that the frequency of media coverage is systematically higher when an homicide is perpetrated by an immigrant compared to when committed by a Chilean. The latter suggest that media bias might play a key role in the widening gap between actual crime trends and public perceptions of crime.

Our paper relates to several strands of the literature of economics of immigration, including a growing body of work focusing on how mass immigration shapes natives' beliefs and attitudes. Exploiting data from the recent refugee crisis in Austria, Steinmayr (2020) shows that exposure to refugees "passing through" a municipality increased the share of votes for far-right parties (likely due to a rise in hostility towards foreigners). Conversely, in municipalities where refugees ultimately settled, far-right votes decreased, a finding 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). In a similar vein, Ajzenman et al. (2020) look at localities exposed to transit migration of Syrian refugees via the Eastern Mediterranean route and document an increase in native hostility towards immigrants, together with drops in institutional trust, willingness to take risks, and propensity to start a new business. Analyzing the case of Greece, Hangartner et al. (2019) show that islanders' exposure to a massive influx of Syrian refugees triggered a significant change in natives' attitudes towards migrants. Again with a focus on Europe, Alesina et al. (2019) find a negative association between support for redistribution and the share of immigrants in a given local region.

The novelty of our contribution is two-fold. First, while previous studies on immigration effects concentrate mainly on beliefs related to hostility, prejudice, risk attitudes, and political or redistribution preferences, we study the effect of immigration on crime perceptions, crime-related concerns, and crime-preventive behavioral reactions. Although potentially connected to the aforementioned beliefs (e.g., increases in crime-related concerns could be a plausible mediator of the effect on political preferences), these outcomes have, to date, been little explored. The closest paper to ours is Nunziata (2015), who uses the European Social Survey to examine the relationship between the immigration inflows into western European countries that took place in the 2000s and the "fear of crime" of European natives[6]. Our paper expands the literature by jointly examining the effect of immigration on victimization as well as on a battery of crime-related concerns and investment in crime prevention, and it provides novel evidence on the role played by media bias, ethnic distance, and educational composition of immigrants on the immigration-crime perceptions nexus. This is something that, to the best of our knowledge, it has not yet been explored. Second, while most studies examine the European context, particularly the recent refugee crisis, ours is one of the first to explore how Latin American migration fosters significant changes in the beliefs and attitudes of native residents.

Our paper also builds on a set of studies examining the impact of immigration on crime. Although the evidence varies by context and composition of the immigrant population, most studies find null or very small effects. Bianchi et al. (2012a) uses an instrumental variables approach to demonstrate no aggregated effect of immigration on crime in Italy (with the exception of a small positive effect on robberies). Bell et al. (2013) observe positive and negative effects of two different large waves of immigration to the UK (asylum seekers in the late 90's and then an inflow of EU citizens after the accession), and suggest that the sign and magnitude of the effect depends on the immigrants' labor market opportunities, a result that is similarly highlighted by Spenkuch (2013), Baker (2015), Mastrobuoni and Pinotti (2015), Pinotti (2017), Freedman et al. (2018), and Fasani (2018). In examining the case of Mexican migration 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, he exploits persistence in regional Mexico-US migration networks, and compares the results to an additional strategy that leverages temporal variation in rainfall across regions, finding no

[6] A limitation of this study is that the very single crime perception variable the study examines is a dummy variable constructed based on whether the respondent feel unsafe or very unsafe when walking alone in local areas after dark. This is arguably a narrow indicator of "fear of crime", which in turn represents just one single aspect among the multiple dimensions underlying crime perceptions.

link between changes in Mexican migration and shifts in US criminal activity. More recently, however, Ozden et al. (2017) show a negative effect of immigration on crime in Malaysia, which they interpret as triggered by a positive effect of immigration on economic activity. Conversely, Piopiunik and Ruhose (2017) find a positive and significant effect of immigration on crime in the context of the relocation of individuals of German ancestry from the USSR to Germany after the collapse of the Soviet Union. Our paper adds another piece of evidence to this literature by showing a zero effect of immigration on total crime in the case of Chile.[7]

Finally, our results contribute to a scarce but growing literature on the determinants of crime misperceptions. Esberg and Mummolo (2018), for example, analyze different potential explanations for the growing divide between actual crime and crime perception in the US and find suggestive evidence that continuous exposure to news of episodic crime events has widened this gap. Consistent with this finding, 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 adds to this literature by examining an insofar unexplored determinant: exposure to a sudden inflow of immigrants.

Our findings are also relevant from a policy standpoint, particularly as this concerns contemporary public debate on immigration and crime. Latin America is currently experiencing a severe migration crisis. According to the United Nations Refugee Agency (IOM (2019)), as of June 2019 approximately 4 million Venezuelans were living abroad, considerably more than the 550,000 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) being the main destination countries. This Venezuelan exodus is in addition to other large migration flows already present in the region, including the northern triangle migration to North America, the recent growth in Haitian migration to South America (especially Chile), and the more stable internal migration flows throughout the continent. We contribute to this debate by showing that the growing concerns of citizens and governments over the potential effect of immigration on crime seems, at least in Chile, to be unfounded. Moreover, our results document formally that already suggested by anecdotal and

[7]Few studies have been conducted on the relationship between immigration and crime in Latin America, prioritizing instead the link between conflict and internal migration. A salient example is a set of papers based on Colombia, including Lozano-Gracia et al. (2010) and Ibáñez and Vélez (2008). More recently, Leiva et al. (2020) uses a dynamic Spatial Durbin Model and find no relationship between immigration and crime rate in Chile.

survey evidence: at least part of the region's widening crime-perceptions gap can be attributed to the recent immigration shock.

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

II Data

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

Immigration Data. We obtained individual-level data on all visa and permanent residence permits granted by the Chilean Department of State. This data includes basic demographic statistics such as date of birth, nationality, municipality of intended residence at time of application[8], gender, and self-reported variables on education and labor market experience. Information on population comes from INE (*National Institute of Statistics*) estimates using projections from census data, which allows to calculate the rate of immigration by municipality for each year. For the 2008-2017 period, the database includes more than 2 million individuals. As shown in Table I, immigration rose considerably within our study years, though growth rates vary substantially by region. While in 2008, none of the regions received 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 migrants from other Latin America countries. Figures I and III describe the immigrant composition during our sample period by country of origin.

Victimization Data. We harmonized a set of variables dealing with crime perceptions, behavior related to the adoption of security measures, and victimization included in the ENUSC survey. As mentioned, this is an annual household survey covering the period 2008-2017, for

[8]Once the permit is approved, applicants must declare a specific municipality within Chile where they plan to arrive.

which the field work took place between October and December of each year.[9] Relative to other sources of crime data (e.g., police reports), victimization surveys are particularly well suited for this study since they are less subject to reporting bias. Although the ENUSC covers a subset of municipalities (101 out of 346 municipalities in Chile), 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 presents descriptive statistics for some of the variables used in our analysis.

Additional Controls. For robustness purposes, in some of our regressions we include controls at the municipality level taken from the Chile National Socioeconomic Characterization Survey (CASEN). This household survey covers the entire country and includes standard questions related to demographics, labor market outcomes, income, and education. During the analysis period, it was conducted in 2007, 2009, 2011, 2013, 2015, and 2017.

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

Victimization. ENUSC contains detailed information on self-reported episodes of crime by type. We consider all the different types through 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, assault, aggravated assault, and burglary. We create a variable for each type of crime, which takes a value of one if the answer to the question is positive and zero otherwise. We report the results of an aggregated measure of crime, defined as the simple average of all the types (on a scale of 0%, i.e., no crime, to 100%, i.e., victimization across all types of crime).

Crime-related personal concerns. This group includes all the crime perception questions related to personal concerns, i.e., feelings or opinions reflecting individual's subjective views on crime. We report results for the following 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?"* (in addition to crime, the list includes another 9 options, e.g., economic situation, health,

[9]There do exist previous editions of the ENUSC, but the methodology underwent a series of changes in 2008, thus making comparison of the pre- and post-2008 data is not recommendable. The survey was also conducted in 2018 but, unlike previous years, the municipality codes were not made available to researchers.

education, unemployment, poverty, 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 options). The outcome **"Crime affecting quality of life"** takes a value of one if the individual answered positively (i.e., "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 options are "not much" or "not at all"). The outcome **"Feeling unsafe"** takes a value of one if the individual has 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 says 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"**), 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. We classify the same belief at different geographical levels. The question is first asked relative to the neighborhood level: *"Would you say that during the last 12 months crime has increased in your neighborhood (N)?"*. It is then replicated relative to the municipality (M) and then the country (C) level in separate questions. The variables **"Crime is rising (N, M, C)"** take a value of one if the individual answered positively to the corresponding question. Note that although these variables are likely connected to personal concerns, they are of a distinct nature and may shift in different directions. For example, an individual could think that crime will rise, but that it will not affect her personal life. Or she may feel that crime will not increase on average, but that her life will nevertheless be affected.[10]

Crime-preventive 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 people may take in order to increase their personal security. We first create an **"Investment in Home**

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

Security Index," defined as the proportion of positive answers to the following 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 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. We then create a **"Neighborhood Security System Index,"** 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 system to monitor entry into the neighborhood, g) coordinated security measures with the police, h) coordinated security measures with municipal officers, h) an agreement with the neighbors to call the police any time we see something suspicious. Third, we report the dummy variable **"Owns a weapon,"** which takes a value of one if the individual answers positively. Finally, we aggregate these results by taking the first component of a principal component analysis –**"Principal Component - Summary Index"**– and normalize it to a 0-1 scale. Table II presents the descriptive statistics of the outcomes.

III Empirical Analysis

To estimate a causal effect of immigration on crime, crime-related concerns, crime beliefs, and crime-preventive behaviors, we implement two different types of models: a two-way fixed effects model at the municipality and year level and a 2SLS model using a shift-share instrument inspired by Bianchi et al. (2012a). In the following subsections, we present the models and describe the results.

III.1 Two-way fixed effects model

We estimate 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:

$$y_{imt} = \beta log(imm)_{mt} + \eta_m + \eta_t + \gamma X_{imt} + \epsilon_{imt} \quad (1)$$

Where y_{imt} are the different outcomes (victimization, crime-related concerns, crime beliefs, and crime-preventive 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; and X_{imt} is a set of control variables representing observed characteristics of the individual i residing in municipality m during the year t (e.g., gender, age).[11]

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 crime-preventive behaviors, we analyze the effects on both the individual outcomes, as well as on the different aggregated indexes.

Table III presents the regression results. Panel A displays the findings on crime-related concerns. In three out of the four categories available in the survey, we find that concern about crime rises among residents living in municipalities where the immigrant population has increased. This pattern is consistent with a positive increase in the principal component index, which summarizes all four dimensions. Panel B shows a positive relationship with respondent beliefs about the perceived crime trajectory at different geographical levels, and the increase is significant for views on municipality-level crime. Panel C shows a positive relationship between immigrant population at the municipality level and crime-preventive behavioral reactions associated with public security. For example, we observe that following a rise in immigration, respondents are more likely to invest in protecting their houses and to coordinate actions with their neighbors.

[11] Our results are robust to excluding control variables and using alternative definitions of immigration, as is shown in the results section.

Finally, Panel D in Table III shows the effect of immigration on crime victimization. In contrast to the previous three panels, the 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 that observed for each crime type: while in some cases we see a positive relationship, in others we find a negative effect. Indeed, 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 a growing immigrant population –over time and across municipalities– does not, in fact, correspond to a discernible change in criminal activity. It has, however, had an impact on crime-related concerns and citizens' preventive behavioral responses, widening the gap between actual crime and crime perceptions.

III.2 2SLS Approach

In order for our two-way fixed effects model to identify a causal effect, we must assume that, in the absence of immigration shocks, the trends of the outcomes would have been similar in municipalities with different levels of immigration. That is, 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 attract both migrants and criminals, thus biasing our estimates upwards. In addition, changes in crime rates across municipalities could have a direct effect on immigrants' location decisions.

We consequently follow Bianchi et al. (2012a)'s approach and build a shift-share, Bartik-like instrument that exploits the supply-push component of immigration by nationality as a plausibly exogenous variation driving "shifts" in the immigrant population across municipalities. We interact this with the "share" of immigrants settled in each municipality in the initial period of analysis.[12] The "share" component provides predictive power to the instrument, as it exploits the fact that new immigrants of a given nationality tend to settle

[12]Similar shift-share instruments have been used in a number of papers estimating immigration effects, including Munshi (2003), Jaeger (2006), and McKenzie and Rapoport (2007). For a thorough list of studies of this type, see Jaeger et al. (2018).

into the same areas as previous migrants from the same country. The "shift" component (presumably exogeneous) exploits 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 are independent of across-municipality differences in immigration inflows within Chile. Since these types of events are relevant for migration outflows but orthogonal to regional differences within the host country, they can arguably be used as a source of exogenous variation in the distribution of the immigrant population in Chile.

Nonetheless, total inflows of immigrants by nationality could still be correlated with local demand-pull factors. This would potentially violate the excludability assumption related to immigration shocks.[13] Our measure of exogenous supply-push factors is therefore based on bilateral migration flows from the country of origin to destination countries other than Chile. In other words, rather than being triggered by changes in the local conditions of that particular municipality (demand-pull factors), the predicted change in the inflows of nationality-specific immigrants to a given municipality (i.e., variations in its total immigration rate) is driven by variations in the conditions in locations outside of Chile (supply-push factors).

Importantly, 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). This means that the shares play a crucial role in identifying a causal effect. An identification threat is then that the shares predict outcomes (for instance, crime perceptions) through channels other than immigration. 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 (e.g., crime). This would be a typical assumption in a difference-in-differences setup. Indeed, we closely follow Goldsmith-Pinkham et al. (2020)'s suggestions in this regard, allowing to support the claim of internal validity for our identification strategy.

[13] 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. Thus, for the shift-share instrument to work, a certain degree of variation in the spatial (municipality) distribution of immigrant allocations is necessary.

III.2.1 Building the shift-share instrument

With the sample period 2008-2017, we first take within-municipality differences in 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 number of 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 Chilean.

Note that the first term in equation 2 is the weighted sum of the log changes of immigrants of each nationality into each destination municipality m. These depend on both supply-push factors in each origin country (a common shock to all municipalities), as well as 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 this end, we use UN Population Division migration data for 45 countries on the bilateral flows of international migrants. For most nations, information is available from, at least, 1990 to 2015, and includes both inflows and outflows according to place of birth, citizenship, and place 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: Argentina, Bolivia, Brazil, China, Colombia, Ecuador, Haiti, Peru, Spain, USA, and Venezuela. Collectively, these cells represent 87% and 94% of residence permits in 2008 and 2017, respectively.

We thus define our shift-share instrument as the predicted log change in the immigrant to population ratio in each municipality:

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

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 $\widehat{\Delta migr}_{mt}$ must be due solely to supply-push factors in origin countries and/or to demand-pull factors from locations outside Chile. As suggested by Goldsmith-Pinkham et al. (2020), for this instrument to estimate a causal effect, we must assume that crime rates (or any other outcome of interest) in municipalities with a large initial share of immigrants of 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 $\widehat{\Delta migr}_{mt}$, i.e., the supply-push component of immigration growth weighted by the beginning-of-period share of immigrants, as an instrument to estimate the causal effects of the change in immigration on (the log-change of) victimization, crime-related concerns, crime beliefs, and crime-preventive behavioral reactions. Since the instrument is available as a cross section of changes between 2008 and 2017, we run all regressions on the 2017-2008 within-municipality differences. Results are presented in Tables IV through VII. For the sake of comparability between the OLS and 2SLS estimates, 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 each outcome on the instrument, while the third column shows the 2SLS estimates and the respective first-stage results. As controls, all regressions include the average age and proportion of women in each municipality in 2017.[14]. Finally, a summary of the 2SLS point estimates for each outcome is graphically depicted in Figure IV.

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

[14] As is shown in subsection III.4, 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.

captures the effects on victimization at the individual level. Second, for IV regressions, we consistently find a null causal effect of immigration on victimization in each outcome separately as well as on total crime. Moreover, the 2SLS estimates are broadly comparable with their OLS counterparts. As pointed out by Bianchi et al. (2012a), the fact that the estimated coefficient associated with the reduced form regression against the instrument (Model (2)) is never significant could be due either to a lack of causal effect, or because 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).[15] 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 OLS estimates 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 immigration causes a 0.14 percentage point rise in the aggregated measure of personal crime-related concerns. Doubling immigration would thus increase these concerns by 14%. This is a sizeable effect, considering an across years mean of 39%. In Table VIII we show that these results are not driven by the inclusion of controls.

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 latter we find a significant effect on the perception of crime trends at the municipal level, which becomes insignificant in the 2SLS model). While all the point estimates are positive, 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 somewhat larger in the case of the 2SLS models, meaning that the OLS parameter estimates were likely biased downwards.

Effects on crime-preventive behavior. Table VII shows the effects on citizens' crime-

[15] 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, which reinforces the internal validity of our results. Our partial R^2 is 0.104, which is well above the inverse of the number of observations ($1/101 = 0.0099$).

preventive behavior. The results are qualitatively similar to those of the 2WFE model. The point estimates are positive and all 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. Specifically, as a consequence of their exposure to immigration, people are significantly more likely to increase home security and to coordinate preventive actions with their neighbors. Moreover, the magnitudes are sizeable: a one percent rise in immigration causes a 0.11 percentage point increase in the aggregated measure of crime-preventive behavior. Therefore, doubling immigration would increase crime-prevention by 11%. This is a large effect, considering that the average value of the outcome across years 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 Bartik 2SLS 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.[16] 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 relies on the exogeneity of shares. Indeed, in settings where the researcher has a pre-period, this empirical strategy is equivalent to a difference-in-differences. Thus, testing whether the differential exposure to common shocks leads to differential changes in the outcome becomes central to assessing the internal validity of the identification strategy.

In our research design, the 2008 immigration shares measure the differential exposure to the post-2008 common immigration shock. Yet, the immigration effects found in the 2008-2017

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

period may in part be driven by changes that occurred in the period prior to the analysis. For our empirical strategy to be valid, we thus require that the differential exposure to common immigration shocks (the "shares") does not lead to differential changes in crime – necessary so that these changes are not driven by pre-period, endogenous mechanisms affecting both the composition of immigrants within municipalities and local crime. This same logic similarly applies for the other outcomes of the study. In order to verify the plausibility of this assumption, Goldsmith-Pinkham et al. (2020) suggest testing for parallel trends. This test helps to alleviate the concern that our results are driven by differential pre-existing trends in our outcomes in municipalities with different shares of immigrants (and hence, with differing exposure to the post-2008 shock).

We thus proceed following their proposed steps. First, we calculate the Rotemberg Weights (RWs) for each country-specific instrument. We 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.[17,18] The RWs 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 RWs, and the mean of the full set of countries.

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 each case, we collapse the data at the municipality-year level so as to have exactly the same structure as the 2SLS models. We then convert the growth rates to levels and index them to 0 in 2005. Figures V and VI present the results.

Generally, we find no evidence of statistically significant pre-trends. The differential shares of Peruvian immigrants do not statistically or economically predict higher crime rates in pre-shock years. Moreover, the evidence is consistent when analyzing outcomes related to crime

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

[18] The ENUSC survey methodology was altered in 2008. Indeed, many of our outcomes were not present in various waves conducted before that year. We are therefore only able to implement the parallel pre-trends test for a limited number of outcomes.

concerns or crime-preventive behavioral reactions. Given how relevant Peru is in terms of its RW, it is not surprising that the aggregate instrument looks like this country. Overall, the evidence indicates the absence of pre-existing trends in the outcomes of interest. This supports our identification assumption that the pre-shock shares do not predict outcomes through channels other than the post-2008 immigration shock.

III.4 Robustness

In what follows, we test for whether our results are robust to the exclusion of controls and the use of other measures of immigration. Table VIII shows different robustness checks for victimization (Total Crime), crime-related concerns (Summary Index), and crime-preventive behavior (Summary Index).

First, we show five columns for the 2SLS model ("2SLS in Differences"): 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 correction to account for a potential correlation of residuals across regions with similar shares. Second, we re-estimate the same models but instead of using the IV specification in differences (equation 2), we estimate a 2SLS in levels ("2SLS in Levels"). Unfortunately, we do not have reliable yearly data for the common shock (international migration flows to countries other than Chile). The official data compiled by the UN is by periods of five years (e.g., 2000, 2005, 2010, 2015). We thus linearly interpolate each year in-between. We again show five columns: 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, finally, the baseline result adding the interaction between the baseline outcome and a time period as a control.[19] Third, we 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. Finally, we further complement this analysis by showing the results of our 2SLS model including Anderson et al. (1949)'s confidence intervals (see Table IX).

[19] 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. The interaction helps to alleviate this problem.

The results remain insignificant in all robustness specifications for victimization and significant for the crime perception and crime-preventive outcomes, with the exception of some results when using Adao et al. (2019)'s correction, where the p-values are slightly above the conventional level of statistical confidence.

III.5 Potential channels

Exposure to immigration could trigger prejudice and fear – and in turn crime concerns – through different channels. In this section, we present suggestive evidence on three potential mechanisms through which our main results may operate: educational composition of immigrants, ethnic prejudice, and media bias effects.[20] These mechanisms have frequently been emphasized in the economics and political science literature (see, for instance Alesina et al. (2018a), Mayda et al. (2018), or Couttenier et al. (2019)).

Educational Composition. The level of education of immigrant populations has shown to be an important determinant of immigration effects (Ottaviano and Peri (2006), Card (2009), Ottaviano and Peri (2012), Mayda et al. (2018)). For a variety of reasons, low-skilled immigrants could trigger different reactions in terms of crime concerns compared to high-skilled immigrants. First, they are relatively less likely to integrate into the labor market, and thus may be perceived as more prone to engaging in criminal activities. Second, an immigrant's educational attainment could be related to other characteristics, such as poverty, that appear as threatening. As suggested by Cortina (2017), natives may seemingly reject immigrants for xenophobic or racist reasons, when in reality it is not their condition as foreigners but mostly their being poor that provokes discrimination. Immigrants may also affect the transmission of social norms in destination countries (Alesina and Giuliano (2011)). Low-skilled immigrants who have difficulty integrating into local markets could thus represent 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 level collected by the Department of State, proceeding as follows. First, we classify each immigrant according

[20]When endeavoring to conduct the following analysis using the IV approach, we failed to find relevant instruments for either interaction term or the immigration variable. We thus only report results derived from the 2WFE models.

to their self-reported education level, classifying as low-skilled those migrants who completed at most primary school. Second, we compute the proportion of low- and high-skilled immigrants per municipality and year, excluding the missing values. Finally, we create two independent variables, each of which multiplies the immigration stock (which is the independent variable in our baseline model) by 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 immigration.

The results are presented in Table X (Panel A). We observe that the effect on crime-related concerns is mostly driven by low-skilled immigrants. The immigration parameter is highly significant and five times larger relative to that for high-skilled immigration. A somewhat similar pattern appears for crime-preventive behavior, in that the effect size for low-skilled immigration is double that for its high-skilled counterpart. Finally, the effect of immigration on victimization is indistinguishable from zero regardless of immigrant skill level. These findings suggest that the educational composition of immigrants does matter for the widening gap between crime and crime perceptions.

Ethnic Distance. A second potential channel, extensively investigated in the social and cognitive psychology literature, consists of an intergroup threat motivated by ingroup bias (Allport et al. (1954)). Specifically, outgroup individuals may be perceived as threatening; in our case, interactions with foreign outgroups could foster anxiety and concerns about physical safety (Cottrell and Neuberg, 2005; Maner et al., 2005).

Although the cleavages that divide the ingroup and outgroup could be related to various dimensions, ethnic/genetic differences are certainly one of the most salient, especially for people that are not directly related to immigrants.[21] A plausible hypothesis is thus that, the farther the ethnic distance between natives and immigrants, the greater the prejudice and fear. To measure ethnic bilateral relatedness, we employ the genetic distance between two countries using the approached developed by Spolaore and Wacziarg (2009, 2018). Their work is, in turn, based on the bilateral genetic distances between populations calculated by Cavalli-Sforza

[21]Cultural distance represents another important dimension. However, as Spolaore and Wacziarg (2018) explain, cultural traits and habits are similarly passed on from one generation to the next; thus genetic distance represents a summary statistic for a wide array of cultural traits transmitted intergenerationally. While linguistic distance could also be potentially relevant, in our context the vast majority of immigrants in Chile speak Spanish as their mother tongue, and thus this variability is minimal.

et al. (1994) and then extended by Pemberton et al. (2013).

Cavalli-Sforza et al. (1994) provide measures of genetic distance between populations using classic genetic markers, based on data for 42 representative populations (i.e., aggregates of sufficiently similar sub-populations). Pemberton et al. (2013)'s extension covers 267 populations around the world. Both studies offer data on bilateral distance calculated at the population level. Meanwhile, Spolaore and Wacziarg (2009, 2018) match populations to countries using ethnic composition information from Alesina et al. (2003). Specifically, they construct a measure of bilateral ethnic distance by matching each of their 1,120 country-ethnic group categories to Pemberton et al. (2013)'s genetic groups. The authors provide two indices: one based on the largest group of each country (i.e., the distance between the plurality groups of each country in a pair; defined as the group with the largest share of the country's population) and another based on 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, where scholars have endeavored to investigate international migrant selection (Krieger et al. (2018)), explore the relationship between ethnicity and culture (Desmet et al. (2017)), predict or study conflict between countries (Spolaore and Wacziarg (2016)) or within societies (Arbatlı et al. (2020)), or understand the effect of board diversity on corporate performance (Delis et al. (2017)), among others.

Here, we use the bilateral index between Chile and other countries to construct a weighted average ethnic distance between incoming migrants and Chileans. The weights are given by the proportion of immigration from each country, in each period, and in each municipality. We then classify the observations as either "high distance" (above the median ethnic distance) or "low distance" (below the median), and re-estimate Equation 1 (2WFE) including a "high distance" dummy and its interaction with the immigration variable. Table X (Panel B) presents the results. For all outcomes (crime-related concerns, crime-preventive behavior, and victimization), we find very similar effects above or below the median of ethnic distance, implying that an ethnic-related intergroup threat does not drive our results.

Media Effects. In order to better understand the gap between crime and crime perceptions, we also explore the potential role of local media. Indeed, media may affect individual perceptions and consequently trigger specific behavioral responses, particularly when certain news are made more salient. For example, Mastrorocco and Minale (2018) find an increase in concerns about crime among individuals who were more exposed to TV channels that have more crime-related content. Meanwhile, Couttenier et al. (2019) show that disproportionate news coverage of migrant criminality affected vote shares in a referendum that took place during an aggressive political campaign seeking to link immigration with terrorism and violence.

Ferraz and Finan (2011) and Larreguy et al. (2020) instead focus on the presence of local media, finding differential effects across districts with high and low access to local media in the electoral accountability of local governments and voter behavior, respectively. Following these authors, we similarly build a measure of local media. Using data on local radio at the municipality level provided by the Chilean Department of Telecommunications (SUBTEL), we divide municipalities into two groups: "low media," where the number of local radio stations per capita is below the median, and "high media" otherwise. A potential concern could be that municipalities with a larger media presence are also more urbanized. In our context, however, this is unlikely given that our study is based on a survey (ENUSC) that covers only the 101 (out of 346) most urbanized municipalities in the country. There is thus little variation in urbanization rates between our municipalities.

Panel C in Table X compares coefficients for separate regressions based on the set of "high-media" and "low-media" municipalities included in the sample. For both crime-related concerns and crime-preventive behavior, we observe a significant effect only in "high media" municipalities, suggesting that the 2WFE estimates are driven by that which occurs in places with a strong local media presence. Note that we observe no effect of immigration on total crime for either type of municipality. These correlations jointly suggest that the presence of local media is an important factor in explaining the gap between the perceived immigration-crime link, and the actual effect of immigration on crime.

To further analyze this channel, we also compare the evolution of crime-related news concerning homicides allegedly perpetrated by native and foreign offenders. Specifically, we examine whether the frequency of crime-related news varies systematically after a crime is perpetrated by a local *versus* by a foreigner. We focus on homicides for two reasons. First, the largest proportion of people are arrested for this crime, meaning that we can identify the country of origin of the suspected perpetrator. In addition, this striking offence is much more likely to be reported in the media.

We use arrest-level data from the Chilean police (*Carabineros de Chile*) for all homicides committed between 2010 and 2015, which includes the nationality of the perpetrator as well as the exact day when the crime took place. We match this information with crime-related news reported in newspapers and on T.V. This allows us to compare the frequency of crime-related news (reported between 2010 and 2015) relative to two types of events: (i) when the arrested suspect is Chilean and (ii) when the arrested suspect is foreign.

First, we present a visual inspection of the data and compare the average daily frequency of crime-related news before/after a homicide perpetrated by a Chilean *versus* by an immigrant. Both time series display different levels of volatility, reflecting the frequency of each type of event. In our database, foreigners represent only 2 percent of the homicides where there is an identified suspect. Importantly, Figure VII shows that prior to the event, a similar average number of crime-related news reports are dedicated to both types of incidents. This suggests that there are no systematic differences in the average frequency of crime-related news *before* a homicide is perpetrated by a national or an immigrant. However, the frequency of crime-related news does seem to be much greater after an homicide committed by an immigrant, as opposed to by a Chilean.

To explore this relationship in a more systematic way, we run the following difference-in-differences regression:

$$Y_{it} = \alpha Imm_i + \beta Post_t + \delta Post_t \times Imm_i + \eta_{dow(t)} + \phi_{month(t)} + \psi_{year(t)} + \epsilon_{it} \tag{5}$$

where i refers to a homicide where a suspected perpetrator is arrested by the Chilean police, and the dependent variable measures the frequency of crime-related news relative to the day t when the event-type i took place. $Post_t$ takes a value of zero or one before or after an event i took place, and Imm_i indicates whether or not the suspected perpetrator i is a foreigner. We also include a set of fixed effects by day of the week, year, and month. Our coefficient of interest is δ, which captures the systematic difference in crime-related news associated to events where the suspected perpetrator is a foreigner, relative to those where he/she is Chilean.

The results are presented in Table XI. We document a systematic disparity by nationality of the arrested perpetrator in the frequency of crime-related news after the event takes place. Our results suggest that the effects are mostly driven by TV news. We include several window days relative to the exact day when the homicide took place. For instance, with a 15-day window, the estimated difference between Chilean- versus immigrant-perpetrated homicide is 1.8 news reports (compared to a mean of 36 news reports). With regard to TV, the effect is 1.4 news reports (compared to a mean of 16). The effect becomes smaller as the window widens, implying that there is an immediate impact that then fades with time.

Finally, using a machine-learning classification algorithm, we analyze the share of crime-related reports in newspapers and TV captions covering immigrants during the years of our sample. As Figure VIII shows, less than 3% of newspaper articles are about crime, but this figure rises to roughly 20% in the case of TV captions. This is consistent with TV news driving the results presented in Table XI.

While our results relative to these potential channels are exploratory, they do highlight interesting patterns that could be driving the widening gap between crime and crime-related concerns documented in this paper. overall, an intergroup threat seems an unlikely explanation (at least in relation to ethnic distance), but the role of local media as a plausible amplifier of migrant crime news as well as the differential perception of high- versus low-skilled immigrants are more promising candidates.

Alternative Hypotheses. Finally, a plausible alternative hypothesis is that, in the absence of the endogenous crime-preventive behavioral reactions, the immigration shock did have an impact on crime. Although a formal test is not possible, we nonetheless explore this idea, and provide suggestive evidence of its unlikelihood.

Specifically, a possible story to rationalize our results is that, as a consequence of immigration, an initial spike in crime did, in fact, occur. This in turn triggered a preventive behavioral reaction (i.e., people felt scared and thus decided to invest in protection), which stopped further increases in crime. If so, the average effect of immigration on crime during the entire period would be rather small and statistically indistinguishable from 0. We would, however, expect to see some suggestive evidence of crime rising *before* observing a behavioral change in crime-preventive measures.

We examine this by estimating the 2-way fixed effects model for victimization and the aggregated index of crime-preventive behavioral reactions, adding an interaction between immigration and the period effects. We plot the results, by year, in Figure IX. The effects on victimization are never different from zero. Although possible that individuals increased their investment in personal protection in anticipation of a potential rise in crime before it actually happened, the consistently null effect on crime suggests that the preventive measures were not adopted as a response to an observed early spike in crime rates. Indeed, Figure IX, Panel (b) shows that the strongest effect on behavioral reactions began in the last years of our sample, coinciding with the largest increase in immigration rates.

IV Conclusion

Does immigration affect crime or this is just an illusory correlation? We examine this question in the context of Chile, where the foreign-born population more than doubled in the last decade. We show that this massive influx of immigrants had no impact on victimization (a result that aligns with papers in other contexts, such as Bianchi et al. (2012b)), but did significantly increase both crime-related concerns and crime-preventive behaviors. Given the precisely estimated null effect on victimization, our findings indicate that the influence on crime-related concerns is not explained by a rise in immigrant-perpetrated crime rates. Indeed, it seems that immigration itself triggers the formation of misperceptions related to crime.

We explore multiple mechanisms that could underlie the widening gap between actual crime and crime perceptions and find suggestive evidence for two potential channels. First, the media arguably plays an important role: municipalities with a stronger local media presence drive the effects. Second, the differential composition of immigrants in terms of educational attainment appears to be relevant. Low-skilled newcomers generate larger increases in crime-related concerns and, to a lesser extent, crime-preventive behavioral reactions. We were not, however, able to detect any heterogeneous effect by the ethnic proximity of immigrants in relation to Chileans. This suggests that an intergroup threat (i.e., a danger mostly triggered by those perceived as ethnically more distant) is not a relevant channel underlying the crime-perception gap.

Such misperceptions likely affect other outcomes that are potentially critical from a policy point of view. For instance, the crime-perception gap could be one plausible mechanism behind shifts in political preferences toward more conservative parties, as documented in a recent literature across different contexts (Dustmann et al. (2019), Steinmayr (2020), Rozo and Vargas (2019)). Crime misperceptions may affect not only the demand for anti-immigration policies, but could also be one of the factors behind the growth in hostility and prejudice against migrants (as argued by Ajzenman et al. (2020); Hangartner et al. (2019)).

Our results should be interpreted in the context of Latin America, a region currently experiencing a severe migration crisis, with significant movement due to the ongoing Venezuelan situation, northern triangle migration to North America, and the recent growth in Haitian migration to South America (especially Chile). In this setting, understanding the real impact of immigration on crime and how it shape crime beliefs is crucial for the design of non-discriminatory, well-balanced immigration policies.

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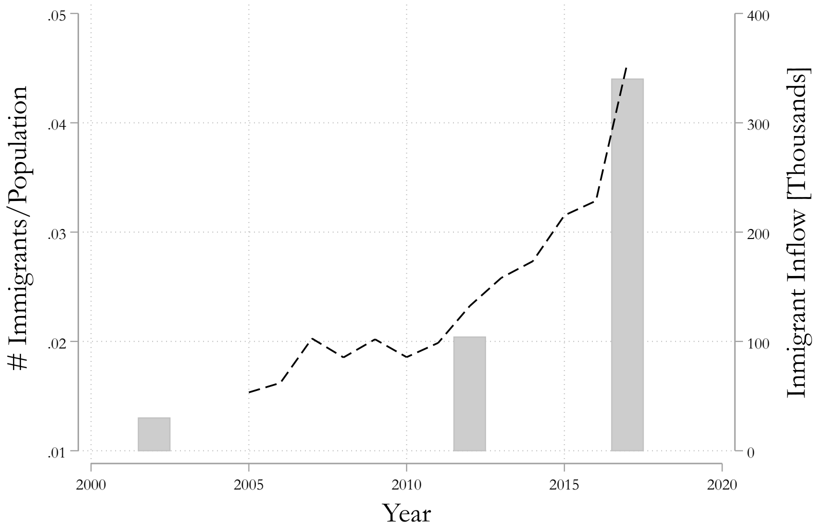
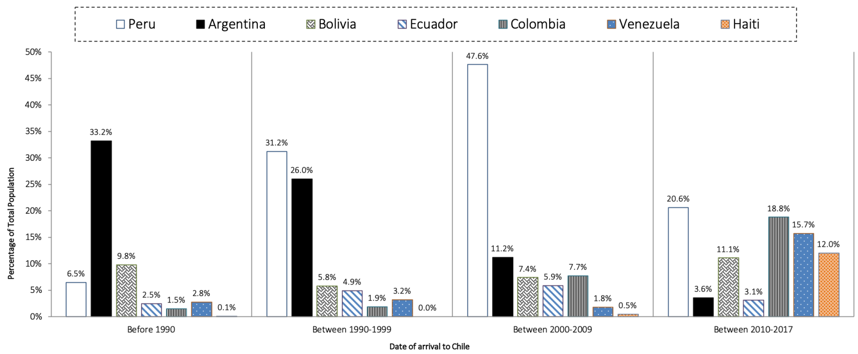
V Tables and Figures

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



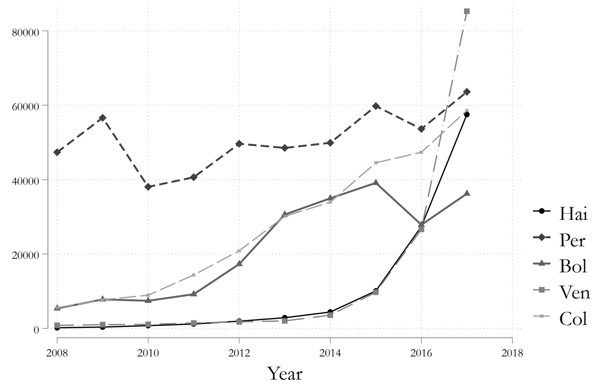
Notes: Bars represent the percentage of immigrants as reported by the National Census, years 2002, 2012, and 2017. Values for the Census data are indicated by the left vertical axis. The 2012 estimation corresponds to unofficial statistics. Inflow represents the number of residential permits and visas 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

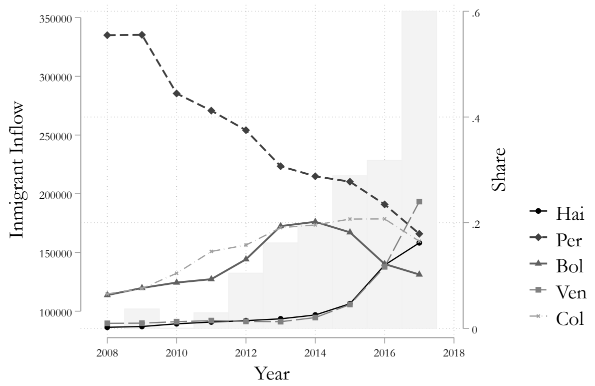


Source: INE based on 2017 CENSUS.

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).

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-related Personal Concerns

	Crime as a 1st or 2nd Concern	Crime as Impacting Pers.Life	Crime Affecting Qual-Life	Feeling Unsafe	Will be Victim	Principal Component Summary Index
Log Imm Rate	0.02	0.04***	0.04*	0.03**	0.02	0.03**
	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)
Observations	242,539	232,570	243,449	213,203	214,375	180,039
R-squared	0.02	0.02	0.04	0.05	0.03	0.05
Mean DV	0.36	0.35	0.63	0.17	0.44	0.39

Panel B: Beliefs about Crime Trends

	Crime is rising at:		
	Village	Munic	Country
Log Imm Rate	0.03	0.03	-0.00
	(0.02)	(0.02)	(0.01)
Observations	235,815	236,760	241,219
R-squared	0.05	0.06	0.07
Mean DV	0.4	0.65	0.79

Panel C: Crime-preventive Behavioral Reactions

	Investment in Home Security	Neighbors Security System	Owns a Weapon	Principal Component Summary Index
Log Imm Rate	0.01	0.02***	0.01***	0.02***
	(0.01)	(0.01)	(0.00)	(0.01)
Observations	243,786	243,993	243,408	243,096
R-squared	0.07	0.05	0.01	0.07
Mean DV	0.23	0.13	0.05	0.16

Panel D: Victimization

	Total	Robbery	Larceny	Burglary	Theft	Assault	MV Theft
Log Imm Rate	0.00	0.00	0.00	0.01**	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Observations	244,115	244,084	244,079	244,103	244,052	244,095	244,115
R-squared	0.03	0.02	0.02	0.01	0.01	0.01	0.00
Mean DV	0.04	0.04	0.05	0.05	0.09	0.02	0.01

Notes: Results of a two-way fixed effects model 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 victim of a crime in the last 12 months. First column, "Total", is defined as the number of crime types that the individual reported to have suffered over the total possible crime types that individuals could suffer. All regressions include individual-level controls (age and gender), and year and municipality fixed effects 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)
$\Delta migr_{mt}$	0.01		0.00	-0.00		-0.01	0.00		-0.01	0.02***		0.01	0.00		0.02	0.00		0.03	0.01		0.01
	(0.01)		(0.04)	(0.01)		(0.03)	(0.00)		(0.01)	(0.01)		(0.02)	(0.01)		(0.02)	(0.01)		(0.02)	(0.00)		(0.01)
$\widehat{\Delta migr}_{mt}$		0.02			-0.04			-0.07			0.08			0.13			0.21			0.05	
		(0.25)			(0.21)			(0.05)			(0.13)			(0.11)			(0.14)			(0.09)	
Obs.	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101	101
Mean DV	0.08	0.08	0.08	0.02	0.02	0.02	0.01	0.01	0.01	0.05	0.05	0.05	0.04	0.04	0.04	0.05	0.05	0.05	0.21	0.21	0.21
First Stage Regressions																					
$\widehat{\Delta migr}_{mt}$			6.81***			6.81***			6.81***			6.81***			6.81***			6.81***			6.81***
			(1.64)			(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			17.35
Part. R^2			0.10			0.10			0.10			0.10			0.10			0.10			0.10

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
$\Delta migr_{mt}$	0.04**		0.19***	0.05***		0.15**	0.04**		0.19***	0.06***		0.05	0.07**		0.17*	0.06***		0.14**
	(0.02)		(0.07)	(0.02)		(0.07)	(0.02)		(0.07)	(0.02)		(0.07)	(0.03)		(0.09)	(0.02)		(0.05)
$\widehat{\Delta migr_{mt}}$		1.27***			1.02**			1.27***			0.33			1.15*			0.93**	
		(0.40)			(0.47)			(0.40)			(0.46)			(0.62)			(0.37)	
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			0.10			0.10			0.10			0.10			0.10			0.10

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: Beliefs about Crime Trends

	Crime is rising (neighborhood)			Crime as rising (municipality)			Crime is rising (country)		
	OLS	OLS	IV	OLS	OLS	IV	OLS	OLS	IV
$\Delta migr_{mt}$	0.10***		0.13	0.07***		0.09	0.03**		0.02
	(0.03)		(0.08)	(0.02)		(0.09)	(0.01)		(0.05)
$\widehat{\Delta migr_{mt}}$		0.92			0.60			0.12	
		(0.58)			(0.60)			(0.33)	
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			0.10			0.10			0.10

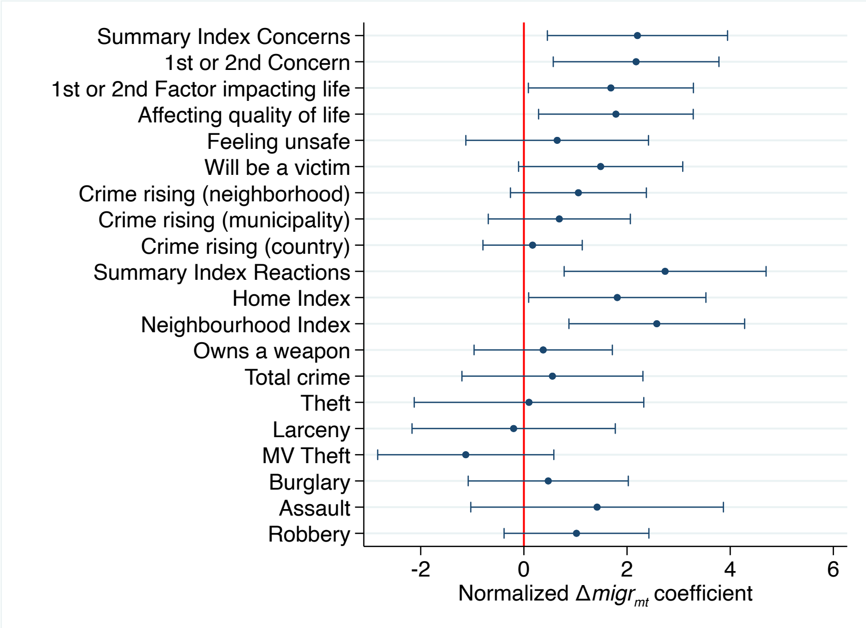
Notes: This table presents the results of OLS and IV estimates on the cross section of differences between 2008 and 2017 across 101 municipalities surveyed in ENUSC. The outcomes are defined as follows. **"Crime is rising (neighborhood)"**: one if the individual answered positively to the question"Would 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: Crime-preventive 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
$\Delta migr_{mt}$	0.02*		0.10**	0.01		0.12***	0.01		0.01	0.01		0.11***
	(0.01)		(0.05)	(0.01)		(0.04)	(0.01)		(0.02)	(0.01)		(0.04)
$\widehat{\Delta migr}_{mt}$		0.85***			1.02***			0.06			0.78***	
		(0.20)			(0.20)			(0.11)			(0.22)	
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			0.10			0.10			0.10			0.10

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

Figure IV. Summary of point estimates - 2SLS



Notes: This figure shows, for each outcome, the point estimate (in standard deviations) and a 95% confidence interval. Point estimates reflect the marginal change of increasing immigration in 100%. All the estimates are the result of the 2SLS model, as described in section III.2.2.

TABLE VIII. Robustness

Panel A: Victimization	2SLS in Differences					2WFE Panel					2SLS in Levels				
	Baseline	No Controls	Visas	Permits	Adao	Baseline	No Controls	Visas	Permits	Adao	Baseline	No Controls	Visas	Permits	Interaction
Log Imm Rate	0.01	0.01	0.01	0.00	0.01***	0.00	0.00	0.00	-0.00	0.00	0.00	0.00	0.00	-0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	101	101	101	101	101	244,115	244,115	244,115	244,115	244,115	244,115	244,115	244,115	244,115	244,115
Mean DV	-0.01	-0.01	-0.01	-0.01	-0.01	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Panel B: Crime Concerns	2SLS in Differences					2WFE Panel					2SLS in Levels				
	Baseline	No Controls	Visas	Permits	Adao	Baseline	No Controls	Visas	Permits	Adao	Baseline	No Controls	Visas	Permits	Interaction
Log Imm Rate	0.14**	0.14**	0.15**	0.07**	0.14*	0.08**	0.08**	0.08**	0.06**	0.08	0.03**	0.03**	0.03**	0.03	0.03**
	(0.05)	(0.06)	(0.06)	(0.03)	(0.00)	(0.03)	(0.03)	(0.03)	(0.03)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Observations	101	101	101	101	101	180,039	180,039	180,039	180,039	180,039	180,039	180,039	180,039	180,039	180,039
Mean DV	0.02	0.02	0.02	0.02	0.02	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.39
Panel C: Crime-prev. Behavioral Reactions	2SLS in Differences					2WFE Panel					2SLS in Levels				
	Baseline	No Controls	Visas	Permits	Adao	Baseline	No Controls	Visas	Permits	Adao	Baseline	No Controls	Visas	Permits	Interaction
Log Imm Rate	0.11***	0.12***	0.13***	0.06***	0.11	0.08***	0.08***	0.08***	0.05**	0.08	0.02***	0.02***	0.02**	0.02***	0.02**
	(0.04)	(0.05)	(0.05)	(0.02)	(0.00)	(0.03)	(0.03)	(0.03)	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	101	101	101	101	101	243,096	243,096	243,096	243,096	243,096	243,096	243,096	243,096	243,096	243,096
Mean DV	0.03	0.03	0.03	0.03	0.03	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16

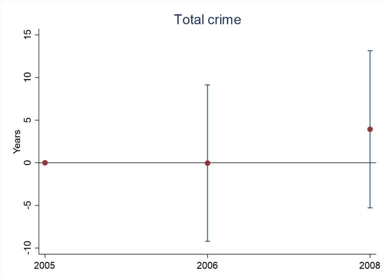
Notes: Base 2SLS: baseline 2SLS model with controls as described in Section III). Base 2SLS No controls: baseline 2SLS model as described in Section III) excluding all controls. 2SLS Visas: baseline 2SLS model with controls as described in Section III), using only visas as the measure for immigration. 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. Robustness

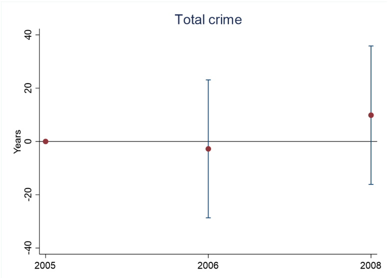
VARIABLES	(1) Total Crime	(2) Concerns Summary Index	(3) Reactions Summary Index
$\Delta migr_{mt}$	0.01	0.14**	0.11***
	(0.01)	(0.05)	(0.04)
Observations	101	101	101
AR CI	[-0.02 ; 0.04]	[0.04 ; 0.28]	[0.05 ; 0.24]
First stage F stat	17.35	17.35	17.35
Partial R sq	0.10	0.10	0.10
Mean DV	0.04	0.39	0.16

Notes: Baseline 2SLS model with controls as described in Section III), including the 95% Anderson-Rubin Confidence Interval. 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. Robust standard errors are presented in parenthesis in the 2SLS models. *** p<0.01, ** p<0.05, * p<0.1

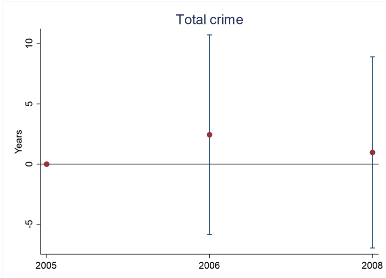
Figure V. Pre-trends for high Rotemberg weight countries and all together



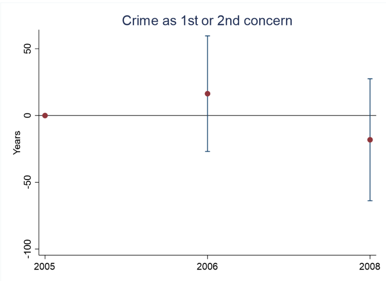
(a) Peru



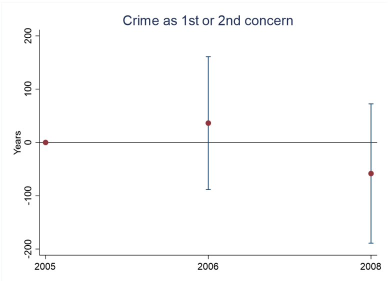
(b) Top 5



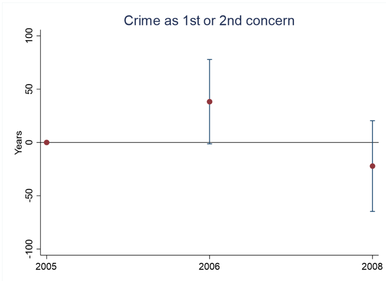
(c) All origin countries



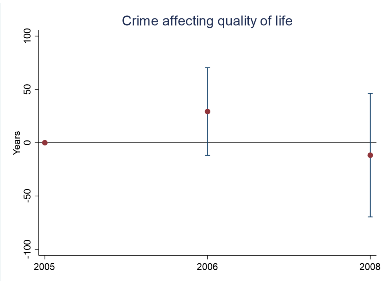
(d) Peru



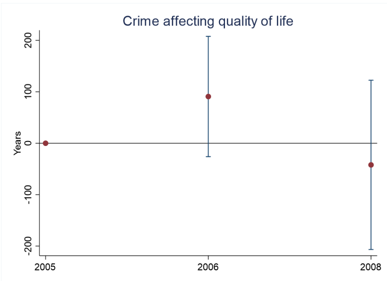
(e) Top 5



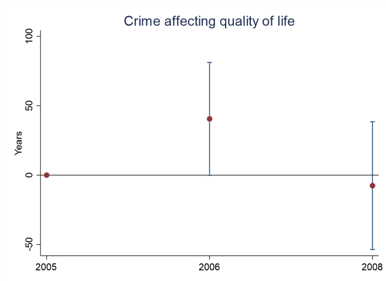
(f) All origin countries



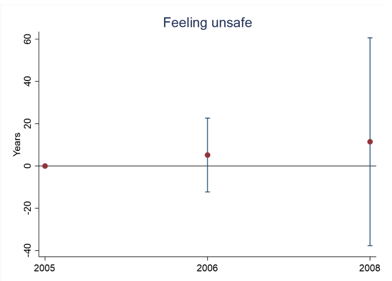
(g) Peru



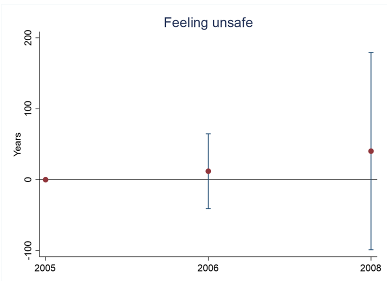
(h) Top 5



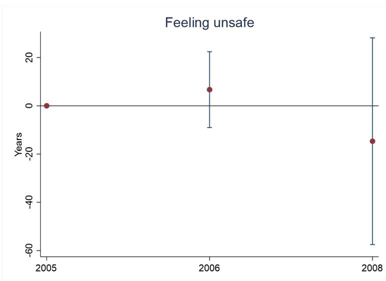
(i) All origin countries



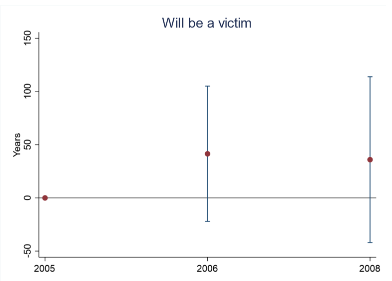
(j) Peru



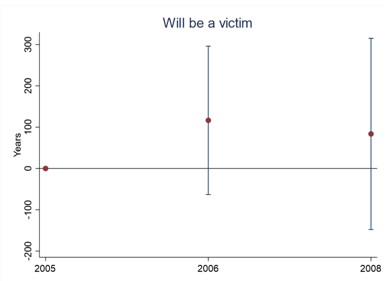
(k) Top 5



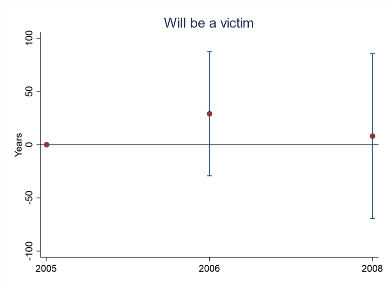
(l) All origin countries



(m) Peru



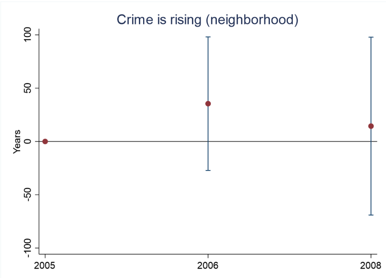
(n) Top 5



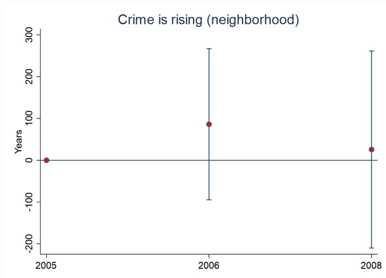
(o) All origin countries

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.

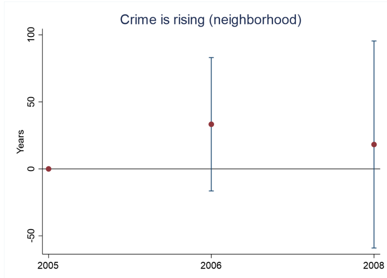
Figure VI. Pre-trends for high Rotemberg weight countries and all together (cont.)



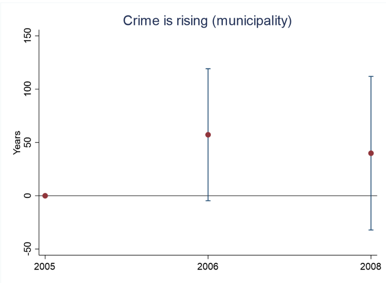
(a) Peru



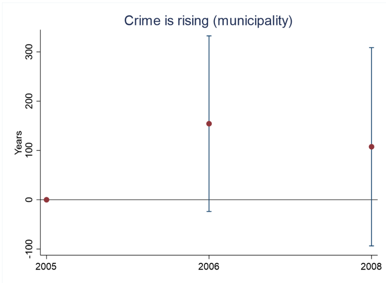
(b) Top 5



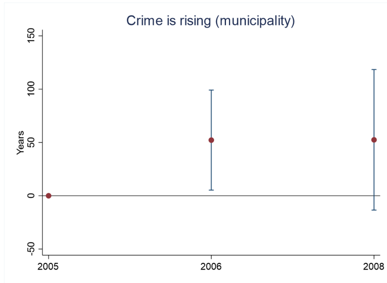
(c) All origin countries



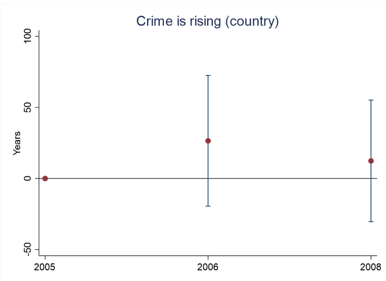
(d) Peru



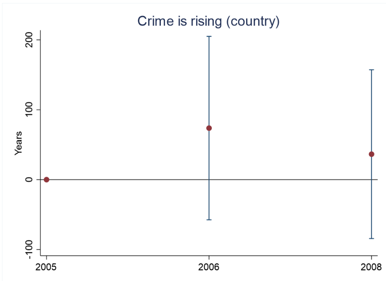
(e) Top 5



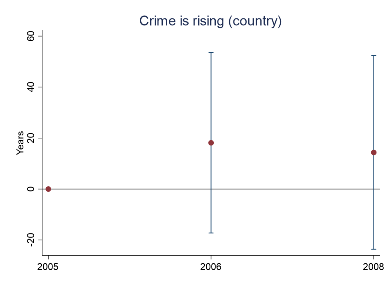
(f) All origin countries



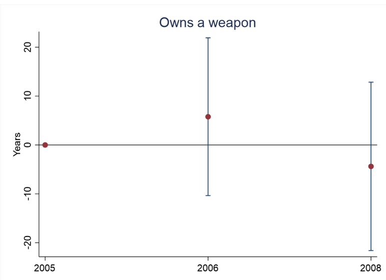
(g) Peru



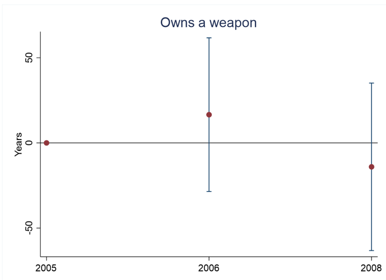
(h) Top 5



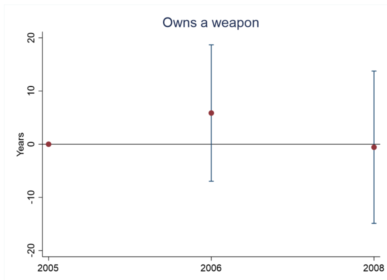
(i) All origin countries



(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 X. Exploration of Channels

Panel A: Education

	Crime-related Concerns	Crime-preventive Behavioral Reactions	Total Crime
Log Imm Rate (Low Skilled)	0.05***	0.02**	0.00
	(0.02)	(0.01)	(0.00)
Log Imm Rate (High Skilled)	0.01	0.01*	-0.00
	(0.01)	(0.01)	(0.00)
Observations	180,039	243,096	244,115

Panel B: Ethnic Distance

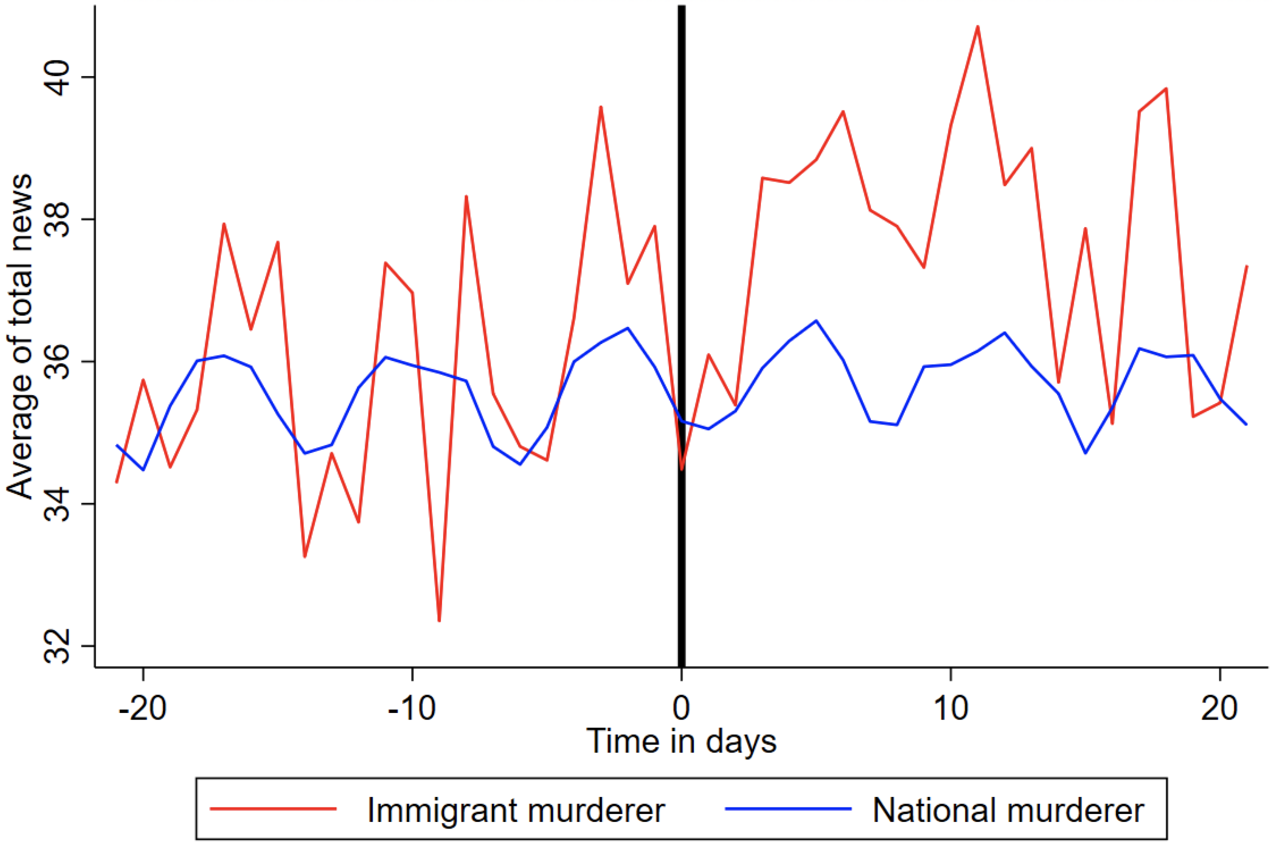
	Crime-related Concerns	Crime-preventive Behavioral Reactions	Total Crime
Log Imm Rate (Low Distance)	0.03**	0.02***	0.00
	(0.01)	(0.01)	(0.00)
Log Imm Rate*High Distance	-0.00	0.00	0.00**
	(0.00)	(0.00)	(0.00)
Log Imm Rate (High Distance)	0.03**	0.02***	0.00
	(0.01)	(0.01)	(0.00)
Observations	180,039	243,096	244,115

Panel C: Media Presence

	Crime-related Concerns		Crime-preventive Behavioral Reactions		Total Crime	
	Low Media	High Media	Low Media	High Media	Low Media	High Media
Log Imm Rate	0.01	0.03**	0.01	0.02***	-0.00	0.00
	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)
Observations	90,528	89,511	122,259	122,837	122,942	121,173

Notes: Results of a 2WFE model at the respondent level between 2008 and 2017 across 101 municipalities surveyed in ENUSC. All regressions include individual-level controls (age and gender) and year and municipality fixed effects. **"Crime-related Concerns"** and **"Crime-preventive Behavioral Reactions"** are calculated as the first component of a principal component analysis (0-1 scale) of the the variables described in Section II. **"Total Crime"** is defined as the number of crime types that the individual reported to have suffered over the total possible crime types that individuals could suffer. The exact definition of each crime can be found in Section II. Panel A shows the results of estimating equation 1, but including a *horse race* between high and low skill migration. Panel B shows the results of estimating equation 1, including an interaction with **"High Distance"** (in terms of ethnicity). The regression includes the variable **"High Distance"** in levels (not reported in the table). Panel C shows the results of estimating equation 1, splitting the sample in **"Low Media"** and **"High Media"** municipalities. **"Low Skilled"** and **"High Skilled"** refer to the educational level of immigrants, **"Low Distance"**, **"High Distance"** refer to the average ethnic distance between Chile and incoming immigrants, **"Low Media"** and **"High Media"** refer to the number of local radio broadcaster. The exact definition of each variable can be found in Section III.5. Robust standard errors are presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Figure VII. Average frequency of crime-related news on TV and in newspapers: 2008-2017



Note: the graph shows the daily average count of crime-related news in the main newspapers and on TV shows (captions) in Chile. The "0" in the X-axis represents the day on which an homicide was committed.

TABLE XI. Diff-in-Diff: The impact of immigrant-commited murders on news

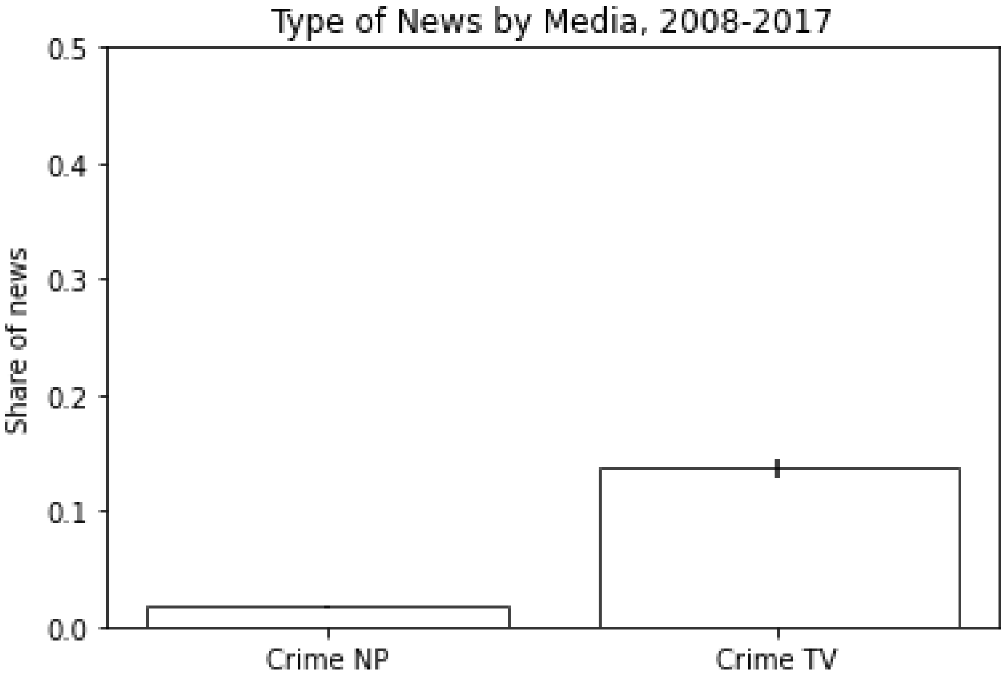
Panel A: 15 days window	Total news	TV news	Newspaper news
Immigrant	-0.65	-0.64	-0.01
	(0.54)	(0.43)	(0.26)
Post-murder	0.18	0.03	0.15**
	(0.12)	(0.09)	(0.06)
Immigrant*Post-murder	1.84**	1.40**	0.44
	(0.76)	(0.60)	(0.36)
Observations	35,991	35,991	35,991
R-squared	0.17	0.35	0.38
Mean DV	35.66	15.64	20.02

Panel B: 21 days window	Total news	TV news	Newspaper news
Immigrant	-0.59	-0.65*	0.06
	(0.45)	(0.35)	(0.22)
Post-murder	0.10	0.012	0.09*
	(0.10)	(0.08)	(0.05)
Immigrant*Post-murder	1.49**	1.39***	0.09
	(0.65)	(0.51)	(0.31)
Observations	49,923	49,923	49,923
R-squared	0.17	0.35	0.38
Mean DV	35.64	15.64	20.00

Panel C: 28 days window	Total news	TV news	Newspaper news
Immigrant	-0.52	-0.49	-0.04
	(0.64)	(0.36)	(0.36)
Post-murder	0.33**	0.11	0.22***
	(0.15)	(0.08)	(0.08)
Immigrant*Post-murder	1.50	1.19**	0.31
	(0.91)	(0.52)	(0.50)
Observations	66,177	66,177	66,177
R-squared	0.05	0.17	0.10
Mean DV	26.89	11.80	15.09

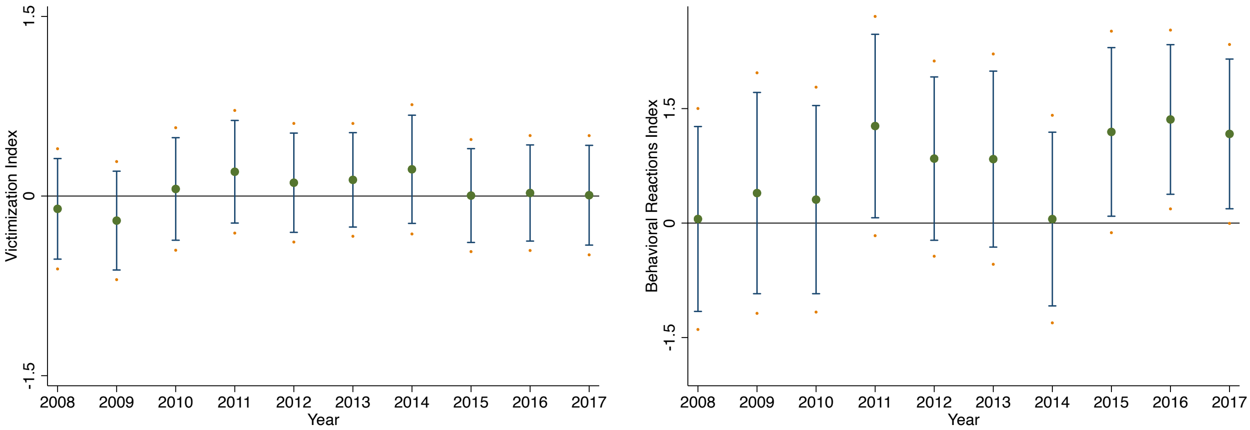
Notes: All regression control for day fixed effects at the level of day of the week, month and year. Total News s the sum of TV News and Newspaper News. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure VIII. Share of crime news by type of media: 2008-2017



Note: the graph shows the proportion of crime-related reports in each type of media (newspaper versus TV captions) including any of the following words: "migrant," "migrants," "immigrant," "immigrants," "migration," "foreign," "visa," "visas," "frontier," "migratory." The universe of news reports is 236,000+ in the case of newspapers, and 110,000+ for TV. Identification of crime-related news within these universes is through a machine-learning classification algorithm trained in an auxiliary sample of 1,000 randomly selected news reports, from which crime news were fully read and codified by hand.

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



(a) Victimization Index

(b) Crime-preventive Behavioral Reactions Index

Note: Panel (a) shows the effect of immigration on the Victimization Index. Panel (b) shows the effect of immigration on the Crime-Preventive Behavioral Reactions Index. Each point represents the estimated coefficient corresponding to each year. This is computed as the sum of the corresponding year effect and the immigration variable. The bars use 90% confidence intervals, while the small dots represent the 95% confidence intervals.