The Effect of Internal Migration on Crime and Violence: Evidence from Indonesia

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Abstract

We estimate the causal effect of internal migration on crime in Indonesia by combining detailed migration data with reports of crime and violence from over 2 million local newspapers, and from individual victimization reports from nationally representative surveys. To address endogeneity in the choice to migrate, we instrument the share of migrants in a destination with rainfall shocks at the migrant origin locations. We find that a 1 percent increase in the proportion of migrants in the population leads to a 3.9 percent increase in the number of economically-motivated crimes reported by local media. This is consistent with the existing literature on the effect of international migration to developed countries, but larger in magnitude. However, when using data on individual victimization from household surveys, we instead find that an increase in the share of migrants leads to a reduction in the probability that a person is a crime victim at the destination. The reduction in crime victimhood is particularly large for migrants and for women. We explore various reasons for these competing results, including reporting bias in newspapers as a source of increased crime coverage in areas with an influx of migrants.

JEL Classification: J61, K14, O15.

1 Introduction

Whenever immigration becomes a topic of discussion in the public sphere, one of the main concerns is the impact that it has on crime at the destination. Most of this debate and the focus of the academic literature revolves around migration from developing countries to rich nations, such as Mexican migration to the US or migration from the Middle East and Northern Africa to Western Europe (see Bianchi, Buonanno, and Pinotti, 2012 or Bell, Fasani, and Machin, 2013). Much less attention has been given to internal migration, which accounts for three quarters of total migration (Bell and Charles-Edwards, 2013; UNDESA, 2017), and its effect on crime.

Because of the lower cost of migration (both monetary and non-pecuniary), the flow of people within country borders is higher on average than that across nations, although internal migrants are more similar to natives than international migrants. As a consequence, internal migrants have been found to generate different impacts in the labor market of their destination (Boustan, Fishback, and Kantor, 2010, Kleemans and Magruder, 2018). Moreover, unlike international migrants, internal migrants enjoy the same rights to work than natives, a nontrivial difference given that (according to the existing literature) poor economic prospects is a reason behind the observed increase in property crimes following international migration. However, the impact of internal migration on crime is still largely understudied.

This paper aims to fill this gap by estimating the causal effect of internal migration on crime in Indonesia using two different sources of data: reports from over 200 thousand incidents retrieved from 2 million newspapers, and individual victimization data obtained from a nationally-representative household survey.

The fact that we focus our attention on a developing country with relatively weak institutions compared to those studied in the existing literature and the characteristics of the migrants pointed out above are likely to translate into differences in the costs and benefits on engaging in criminal activities.[1] Moreover, negative attitudes towards migrants tend to be more pronounced in developing countries than in rich nations (Kleemans and Klugman, 2009), and this is particularly salient in Indonesia, which ranked second in terms of preferences to limit or prohibit immigration. This could translate into violence towards migrants as well as limit their labor market opportunities.

On the other hand, the negative economic impact that migration produces on the native population (as documented by Kleemans and Magruder) could lead to natives engaging in criminal activities. Therefore, there is little reason to expect the same results found by previous studies.

Identification of the effects of internal migration at the destination remains a challenging issue. Not only may migrants choose to move to areas with better labor market prospects (which according

[1] Transparency International currently ranks Indonesia 96 out of 180 countries in their Corruption Perceptions Index, and its rank was lower in the previous decade. Also, Olken and Barron (2009) document more than 6,000 bribes to police officers and other officials in 304 truck trips when looking at how the number of checkpoints a driver would have to pass through influenced the amount of bribes asked in each of them.

to the recent review by Chalfin and McCrary (2017) causes a reduction in economically-motivated crime), they could also specifically target destinations with lower crime levels. This implies that estimates using OLS will be biased downward.

While most of the existing literature tries to overcome this problem by instrumenting migration with pre-existing migrant enclaves at the destination, we follow Kleemans and Magruder (2018) and combine this approach with rainfall shocks at the origin to generate exogenous variation in the number of migrants in each destination. The use of a push factor as our instrument allows us to control for unobservable conditions at the destination that could be correlated both with the decision to migrate and the existence of a migrant enclave.

In our study, OLS estimates using newspaper reports show a statistically significant positive correlation between crime rates in a given area and the share of migrants in the population. However, the magnitude of the coefficients is quite small and in line with estimates for developed countries, with a 1-point increase in the percentage of migrants at the destination associated with 0.5-1% higher crime rate. Once we instrument for the percentage of migrants at a destination, we observe a statistically significant and sizable impact of migration only on certain economically-motivated crimes. Although this in line with the existing literature in terms of the types of crime affected by migration, the magnitude of the effect is much higher. We find that a 1-point increase in the percentage of migrants leading to a rise in nonviolent crime rates of 10%, which translates to an elasticity of 4 at the mean.

On the other hand, when we use crime victimization data from a nationally-representative household survey, OLS estimates are small and statistically indistinguishable from zero. Moreover, for some crimes the estimate is negatively signed. Instead, the two-stages least squares estimates point to a large and negative effect of migration on crime: a 1 percent increase in the share of migrants reduces the probability that an individual is victim of a crime by 3% with respect to its mean. Moreover, when we disaggregate by type of crime, we find an elasticity of -4.62 for theft, and large and negative impacts for robbery (which are nevertheless indistinguishable from zero). We also observe relatively small and positive effects for fraud and rape, but we are unable rule out a null impact. When the sample is split by different demographic characteristics, we find larger reductions in crime for women and migrants.

Even though the data source and the spatial coverage are not the same across the sources of crime data used, these diverging results are surprising. A potential explanation is related to the resources devoted by media to cover criminal incidents, either in response to in-migration or due to other factors that may also be correlated with the decision of migrants on where to relocate. On the other hand, if migrants are more likely to be the target of crimes (which seems to be confirmed by the survey data), it is possible that migration decreases the probability that a person be victim of a crime while increasing the probability of reporting, conditional on a crime having occurred. That said, we do not have the necessary data to test these hypotheses.

We aim to contribute to various areas of existing research. First and foremost, it is challenging to look beyond correlations between immigration and crime rates, which tend to be positive, and study the causal effect of immigration on crime. Current papers that do identify this effect, do so with a focus in international migration to developed countries. Methodologically, our paper is similar to Chalfin (2014) who estimates the causal impact of Mexican migration to the US using a very similar instrument to ours involving weather shocks at the origin. Spenkuch (2013) also focuses on Mexican migration to the US, and like Chalfin, he finds that migration only leads to an increase in crime such as robbery and theft. In Europe, Bianchi et al. (2012) find that only robberies raise slightly due to increases in migration in Italy, while Mastrobuoni and Pinotti (2015) find, in the same country, that among migrants recidivism is higher for those not allowed to work in the country due to the commission of economically-motivated crimes. In turn, Bell et al. (2013) estimate the impact on crime of two different migrant waves: asylum seekers in the late '90s and early 2000s and the influx of migrants due to the enlargement of the European Union. In line with the results from Italy, they find a small increase in economically-motivated crime rates due to the former wave, while migration from newly incorporated EU countries lead to a decrease in economic crimes.

Our work is also related to that of Ozden, Testaverde, and Wagner (2018) in that they concentrate on a developing country (Malaysia), but like the previous papers mentioned their focus is on international migration to that country. Similar to our results using individual-level data, they find that OLS estimates are negative, and those using instrumental variables (where the instrument is the historical share of migrants at the destination in contrast to our focus on weather shocks at the origin) are even larger in magnitude and also statistically different from zero.

This paper also fits in the literature regarding the impact that migration has on different aspects of the destination areas. In addition to the work by Boustan et al. (2010) and Kleemans and Magruder (2018) mentioned above which look at the labor market impacts of internal migration, researchers have also estimated the impact of international migration on labor market outcomes, the housing market, the use of public services and welfare, innovation and trade at the destination, among others[2].

Finally and at a broader scale, this paper adds to the literature on the determinants of crime. Since the pioneering work by Becker (1968) that studies the decision-making of a person on whether to commit a crime from an economic point of view, researchers have been interested at how crime is affected by changes in policing (Di Tella and Schargrodsky, 2004), punishments (Drago, Galbiati, and Vertova, 2009), education (Lochner and Moretti, 2004), and labor market conditions (Gould, Weinberg, and Mustard, 2002, Machin and Meghir, 2004) among others. Although our data does not allow us to determine whether it is immigrants or natives who are responsible for the increases in crime, our results suggest that migration is a driver (at least indirectly) of certain crimes.

The remainder of the paper is organized as follows: the next section will describe the different data sources we use, while the empirical strategy together with a detailed explanation of the identification assumptions can be found in Section 3. Section 4 presents the results of our analysis using data from the newspaper reports, while Section 5 shows our estimates using individual data on crime victimization. Finally, Section 6 concludes and discuss the different results.

2 Data

2.1 Crime Statistics

We use two different sources of data to construct measures of crime. On one hand we use data from the National Violence Monitoring Survey (henceforth 'NVMS'), a project carried out by the Government of Indonesia's Coordinating Ministry for People's Welfare in partnership with the World Bank and the Habibie Center (Barron, Jaffrey, and Varshney, 2014).

The Survey collected data on incidents from newspaper articles between 1998 and March 2015. To avoid biases introduced by political pressures at the national level (until 1998 the country was governed by a dictatorship and it only had its first presidential elections in 2004) the authors chose

[2]For an extensive review of this literature, see Kerr and Kerr (2011) and Nathan (2014).

to focus on subnational level newspapers. In the first years of the project, researchers focused on high-conflict provinces, which are mostly concentrated in the east of the country. However, since 2005 the data covers 15 out of the current 34 provinces where approximately half the population lives, and for the year 2014 the whole territory is part of the sample.

For each province, various local newspapers were chosen based on district coverage, violence reporting policies and their level of political affiliation (excluding those with overt political biases). After collecting and digitizing all available articles from the selected newspapers, researchers identified those containing reports about incidents and recorded the details of such incidents, including date, location, type of incident, number of individuals injured, killed and sexually assaulted, among others. The final database is composed of 241,850 episodes of violence reported in over 2 million newspapers.

Although NVMS has its own classification of incidents, we used the description of each incident to classify it into categories more in line with those typically available in crime statistics, as well as some of those used by NVMS. Looking for various keywords for each type of crime in the description, we classified each incident into several non-exclusive categories: murder, arson, mistreat, molestation, fight, destruction, shooting, robbery, plunder, theft, rape, kidnapping, human trafficking, drug trafficking and protest. We also grouped these incidents into violent (the first seven categories) and economically-motivated (the following 7) crimes.[3] We also use the information provided in the dataset regarding the number of people injured, killed, kidnapped and sexually assaulted in each incident. We aggregated the data by subdistrict (*Kecamatan*) and year to obtain a panel that could be matched to our migration data. All our outcome variables are expressed in terms of incidents per 100,000 people.

Besides avoiding the use of national-level sources, which can be affected by political pressures, the NVMS has a broader scope in terms of its geographical coverage, sources, and type of incidents than data collected by NGOs. Moreover, it is less affected by underreporting than police records, especially in the case of minor offenses. However, this dataset also has certain shortcomings. First, we can only recover certain nonviolent offenses, such as thefts, if they were related to a violent incident. Second, the type of news covered (and especially the number of incidents that make it to

[3] As a robustness check, we carried out the analysis using NVMS' classification of incidents and the results are consistent with those found using our own categorization.

the news) could be affected by the economic conditions of the location (e.g. in places where the economy is growing, more space could be devoted to the coverage of incidents), and even by the influx of migrants. Finally, the NVMS does not cover the entire territory of Indonesia (with the exception of the year 2014), and coverage is not random, but rather a function of the underlying level of conflict, with more violent territories covered in most years.

In order to overcome these issues, we complement the analysis using the NVMS with individual victimization information from the National Socio-Economic Survey (Susenas) for the years 2011 and 2012. This is an annual multi-purpose household survey carried out by Statistics Indonesia (BPS), which unlike the NVMS covers the entire country.

Each individual is asked whether they had been victims of different types of crimes (theft, robbery, fraud, rape or other) in the twelve months up to the time of the survey. Because answers to these questions do not depend on whether the individual reported the crime to the police or the severity of the incident, we expect this data to be less subject to underreporting or biases.[4] On the other hand, we only have geographic data at the district (*Kabupaten*) level, and only a few crimes are listed in the survey, so the analysis cannot be as disaggregated as with the NVMS, both in terms of crimes and location.

For the two years of data, we have information from over 2 million individuals. In addition to victimization, the survey collects demographic and socioeconomic information about each respondent, such as gender, level of education, type of residence location (urban or rural) and whether the person is a native or a migrant in the location where the survey takes place. We take advantage of this additional data to examine heterogenous effects of migration on crime for different subpopulations, something that is not possible with the NVMS data.

Table 2 presents summary statistics for this sample. It comprises 2,045,225 individuals in 318 districts. The sample is split evenly between men and women, and the average age is 29 years. On average, 16% of individuals in each district were born in a different location, a lower proportion than observed in the IFLS data since the level of geographic aggregation is higher. About 1% of all individuals in the sample were victims of a crime in the 12 months prior to being surveyed. Theft constitutes the most common crime, with 0.6% of respondents reporting they experienced a theft in

[4] It is still possible (although less likely) that individuals fail to remember minor crimes that took place several months before the interview.

the previous year. Robbery and other types of crimes have a prevalence in 0.1% of the population each, while fraud and rape are even less common.

2.2 Migration

Because the NVMS does not include data on migration at the subdistrict level, we obtain migrant shares per subdistrict and year using the Indonesia Family Life Survey (IFLS), a longitudinal study that has been carried out in five waves since 1993 and is known for its relatively low rates of attrition. It's first round covered 13 out of the then 27 Indonesian provinces in such a way that is representative of 83% of the country's population.

The team behind the IFLS made significant efforts to recontact each surveyed individual, even if they had split from their origin household and/or moved to a different area. As a result, recontact rates are above 90 percent between any two rounds, and 87 percent of the original households were contacted in all five rounds (Strauss et al., 2016). This renders the data appropriate to study migration-related topics. In addition to migration data, the dataset contains extensive information on the respondents' labor market outcomes, education, and other characteristics.

Using the migration modules of the IFLS, we created a panel dataset of 32,701 individuals aged 12 and above with their location in every year between 2005 and 2014, resulting in 157,525 individual-year observations. In addition to location data that is based on recall between waves, the dataset contains information on where respondents were born and where they lived at age 12.

Indonesia is divided in 34 provinces, each of them containing districts (*Kabupaten*), further subdivided into subsdistricts (*Kecamatan*). Our geographical unit of analysis is the subdistrict, and we define a migrant as a person who does not live at his/her subdistrict of birth, as opposed to natives who still live where they were born. Although other definitions have been explored, this is the most commonly used definition in the literature (UNDP, 2009).

For each destination we count the number of migrants in each year and call this the migrant stock. This number is divided by the total population in that destination to get the migrant share of the population, which is used as the main migration variable in this study. The final dataset contains 1,013 subdistricts hosting 32,701 individuals.

Using the IFLS, we also compute for each subdistrict the share of migrants who arrived from each destination in the 20 years prior to our analysis period in order to construct rainfall weights.

Hence, for a given destination, we give more importance to rainfall shocks that occur in an origin that has historically "sent" more migrants to that subdistrict. Our results are robust to the use of different time windows (such as 10 or 15 years) to create these rainfall weights.

Because Susenas does not have information at the subdistrict level, when we carry out our analysis using victimization data we define a migrant as a person who does not reside in his/her *district* of birth. For the years 2011 and 2012 Susenas includes information about place of birth at the district level. We can use this information in combination with the current location of the individual to determine if s/he is a native or migrant. We use this information in combination with the number of individuals surveyed in each district to create migrant shares at the district level.

We prefer to construct a measure of migrant shares from Susenas itself instead of using data from the IFLS at the district level. This is because, if no IFLS respondents were present at a given location in the years 2011 or 2012, we would not be able to include that district in the analysis. Instead, using the same source of data for our dependent and independent variable ensures there is no loss of information.

Since we do not have nationwide migration data before 2011 to construct the rainfall weights, we use the 2005 Intercensal Population Sample (SUPAS), a nationally representative survey carried out every 10 years to provide demographic data complementary to the census. Like Susenas, it collects information about each respondent's province and district of birth, as well as current province and district of residence, which we can use to calculate the share of migrants from each origin who are present in every destination.

2.3 Weather

We use weather data obtained from the Center for Climatic Research of the University of Delaware (Matsuura and Willmott, 2015). Monthly estimates of precipitation and temperature are available for grids of 0.5 by 0.5 degree, which is approximately 50 by 50 kilometers on the equator. These data are based on interpolated weather station data and are matched to IFLS household locations using GIS data. Figure 1 shows the survey locations of the IFLS on a map of Indonesia as red dots and the blue grids represent the weather data that the locations are mapped to.

We construct different measures of rainfall shocks (using either levels or z-scores obtained by substracting the mean and dividing by the standard deviation of precipitation in each location over time), both per season (July-June) and calendar year (January-December). Since rainfall shocks at the origin are used to predict migration to each destination, we use in each case the type of shock that better achieves this.

3 Empirical Strategy

The main goal of this paper is to estimate how migration to a given destination d affects crime rates in that location. In principle, our goal is to estimate an equation as the following:

$$Crime_{dt} = \beta_0 + \beta_1 migrants_{dt} + \mu_d + \psi_t + \varepsilon_{dt} \tag{1}$$

Where the dependent variable is a measure of crime rates at destination d in year t and the independent variables include the share of migrants living in that location, while μ_d and ψ_t are destination and year fixed-effects, respectively.

Since the parameter of interest is β_1, its identification relies on the assumption that $Cov(migrants_{dt}, \varepsilon_{dt}) = 0$. However, the decision to migrate is likely to be correlated with unobservable characteristics of the destination which at the same time have an effect on crime rates, such as labor market conditions at the destination, differences in levels of corruption across regions, etc. Moreover, crime itself may be a factor considered by migrants when choosing where to move, producing a reverse causality problem.

To overcome the endogeneity problems, most of the existing literature that aims to estimate the causal effect of migration on crime use an instrument based solely on the existing immigrant community from each origin on every destination. This can control for the migrant's decision on where to locate but assumes the decision on whether to migrate is as good as random. However, as noted by Munshi (2003), if unobserved local conditions at the destination are correlated in time, they will affect both the size and composition of the migrant community and the decision of a person to migrate. Thus, besides the use of historical migration patterns we include a push factor in our instrument, namely weather in the migrant's origin area as an instrument to get exogenous variation in the number of migrants entering a destination area. We follow the procedure of Kleemans and Magruder (2018) to find the labor market impact of internal migration in Indonesia, to name a few.

The reasoning behind using this instrument is as follows: to the extent that economic outcomes at the origin locations depend on rainfall, we expect more people to migrate following a negative economic shock due to rainfall. Defining a catchment area for each destination as the origin areas from which it receives migrants, we estimate how the migrant share of the population in the destination changes as a function of rainfall shocks at its catchment area. Formally, the equation we estimate in the first stage is:

$$migrants_{dt} = \pi_0 + \pi_1 \sum_{o \in C(d)} \omega_o rainfall_{ot-1} + \pi_2 rainfall_{dt-1} + \nu_d + \rho_t + \zeta_{dt} \tag{2}$$

It should be noted that in order to capture possible correlation between origin and destination rainfall, we include past rainfall at the destination both in the first and second stage equations.

For the analysis using incident data from newspapers, we run our analyses using a location-year panel, weighting each observation by the number of individuals who live in the subdistrict each year according to the panel we created using the IFLS. This is done in order to adjust for differences in the location size, and all our regressions are clustered at the location level. As a robustness check, we also run our analysis including controls for each individual's age, gender, years of education and household size to control for average sociodemographic characteristics at the destination. The results including these controls are nearly identical to our preferred specification.

In turn, the analysis using individual-level victimization data from Susenas is carried out at the individual level. Migrant shares are constructed for each year by dividing the number of individuals surveyed in each district who were not born in that district by the total number of individuals surveyed in the district. We also rely on the 2005 inter-censal population survey (SUPAS) to create the rainfall weights. Regressions are run with location and year fixed-effects and no demographic controls, but the results are robust to their inclusion in the model.

The main assumption underlying this approach is the exclusion restriction, which states that the only channel through which rainfall in the origin area affects crime in the destination area is through changes in the share of immigrants. Given that we have controlled for destination area rainfall and that deviations from historical rainfall patterns are hard to predict, this restriction amounts to assuming that local rainfall is a sufficient statistic for the direct effects of global rainfall patterns on crime. This would be violated if, for example, rainfall at origin locations disrupted trade to destination areas. A negative rainfall shock could create scarcity of certain goods at the destination and a greater incentive to steal such goods. Alternatively, if individuals living in destination areas depend on monetary transfers from origin locations, a negative shock could reduce income at the destination and thus the opportunity cost of committing crime. These alternative channels are more likely to become a concern after extreme weather events, which is one of the reasons why we prefer our continuous measure of precipitation levels at the origin.

4 Results - Newspaper reports

We begin by presenting ordinary least squares estimates of the association between internal migration and the number of crimes as reported in local newspapers in Table 3. Columns 1 to 3 presents the result of estimating equation 1 when the dependent variable is the number of crimes, violent crimes and economically motivated crimes per year in each location per 100,000 inhabitants, respectively over the period 2005-2014. Besides location and year fixed-effects, the only independent variables included are the share of migrants in that subdistrict, and the amount of rainfall in the subdistrict during the previous calendar year (in meters). Because we include location and time fixed-effects, changes in migrant shares should be interpreted as flows of migrants from one year to the next, while rainfall is interpreted as a deviation from the location's average rainfall during the period. In turn, columns 4 through 7 show the association between migration and the yearly rate of individuals assassinated, injured, kidnapped and sexually assaulted during crime events, respectively. In all cases, the standard errors are clustered at the subdistrict level.

As it can be seen, the results point to a positive correlation between migration flows and crime. Taken at their means, a one-point increase in the share of migrants in the subdistrict is associated with 0.36% higher violent crime rates, 0.92% higher economically-motivated crime rates and 0.51% more overall crimes per 100,000 individuals. Considering the average migration rates, these results translate into elasticities of 0.13, 0.33 and 0.18, respectively. In addition to this, the yearly rate of individuals injured during criminal incidents is 0.81% higher for each percentage point increase in the percentage of migrants, which corresponds to an elasticity of 0.29 at their respective means. Considering the low baseline values, it seems the relationship between migration and crime is weak but nevertheless positive.

Despite these results, we cannot give a causal interpretation to the estimates shown above. This is not only because the decision to migrate are endogenous, but also because where individuals migrate is not random, and could in fact be driven by reasons that also affect crime at the destination. In order to overcome these problems, we instrument migration shares with rainfall shocks at the origin. We present the results in Table 4, where the first column shows the first stage and the remaining columns provide the second-stage results.

According to the estimates in column 1, rainfall at the origin is negatively correlated with in-migration at destination locations, while rainfall at the destination itself is associated with an influx of migrants. We would expect these results if a sizable portion of the economy depends on rain-fed agriculture, and the second result warns against not considering local conditions at the destination that may incentivize migrants to arrive. An increase in the in the amount of rain during the previous year of one meter with respect to the historical mean is associated with approximately half a percentage point decrease in the flow of migrants. The F-statistic of the null hypothesis that the instrument is not significant is 17.66, above the traditional threshold of 10 suggested in the literature (Angrist and Pischke, 2009).

Columns 2 through 7 show that, compared to the OLS estimates presented in Table 3, when migration is instrumented with weather shocks at the origin only economically-motivated crimes increases as a consequence of an inflow of migrants. However, the size of this effect is quite large: taken at their mean values, a 1% increase in the percentage of migrants induces a 3.9% increase in economically-motivated crimes per 100,000 individuals. The larger magnitude with respect to previous studies on the matter may reflect the different institutional settings (particularly the weak enforcement of the law) of Indonesia compared to developed countries.

Tables 5 and 6 shows the results for each type of economic and violent crime, respectively. Consistent with the results from Table 4, only robbery and plunder increase because of migration, and these surges are nontrivial at 3.9 and 9.3% respectively for a 1% increase in the percentage of migrants in the population. However, applying a correction for multiple hypothesis tests would lead us to accept the null hypothesis of no effect. Moreover, baseline rates are very low for this to be economically meaningful.

4.1 Heterogeneity by type of destination

In Table 7, we show estimates of crime rate, violent crime rate and economically-motivated crime rates separately for urban and rural destinations, using both OLS and 2SLS. As it is possible to see from this Table, all the estimates presented before using OLS are driven by urban destinations. While the results of the top panel in columns 1-3 for the association between the percentage of migrants and crime are very similar (although larger in magnitude) to those of Table 2 and statistically significant, those of the lower panel are small in magnitude and not statistically different from zero.

Instrumental variable estimates, on the other hand, remain indistinguishable from zero both for urban and rural destinations with the exception of economically-motivated crimes in urban destinations. However, the estimates become very imprecise due to lack of statistical power and, in the case of rural locations, origin rainfall being a bad predictor of migrations to rural areas, as evidenced by the small first stage F-statistic. If out-migrations due to weather shocks affect particularly rural areas, it would be expected that migrants would leave for an urban area where economic opportunities will be less affected by the shock. Moreover, in general we observe fewer migrations to and across rural areas than there are to and across urban areas, a fact already documented by Hamory Hicks, Kleemans, Li, and Miguel (2017).

5 Individual victimization data

In this section we turn to the analysis of victimization data from the National Socio-Economic Survey. Table 8 presents the association between the migrant share in the district and the probability that a person living in that district was a victim of a crime. As it can be seen, estimates are very small in magnitude and statistically indistinguishable from zero. Moreover, signs are not consistent, with estimates for crimes such as theft and fraud being positively signed, while others like robbery and other types of crime have a negative sign.

As with the OLS estimates for incident articles, these estimates cannot be given a causal interpretation. In Table 9 we aim to do this by instrumenting migrant shares with the second lag of the z-score of seasonal rainfall at the origin. We find that an increase of 1 percentage point in the share of migrants at the destination reduces the probability that a person is victim of any crime by

0.187 percentage points. Given that in our sample the probability of being a crime victim is 1%, this represents a 18.7% decrease in the likelihood of being victim of a crime. Because the average district has a share of migrants of 16%, this represents and an elasticity of -2.99.

When we disaggregate between the different types of crime, we find that the likelihood of being a victim of theft decreases by 15% when the share of migrants at the destination districts increases due to rainfall socks at the origin by 1pp., which corresponds to an elasticity of -4.62. We also observe evidence suggesting that robbery and other types o crime decrease as well as small increases in fraud and rape as a consequence of migration, but we cannot reject the null hypothesis of no impact.

It should be noted that in all cases, the F-statistic of the excluded instrument is low at 6.67. This means that our estimates are biased towards those obtained through OLS. This means that the effects shown are likely lower bounds to the true impact of migration on crime.

5.1 Heterogeneity

The availability of individual victimization data together with demographic characteristics of the respondents allow us to explore whether migration has differential impact on crime for certain sub-populations.

We start by studying heterogeneous impacts of migration on crime by the type of destination. The results are shown in Table 10, where we split the sample between individuals living in urban and rural destinations. Although we lose statistical power by splitting the sample, it can be seen that the results shown before for the pooled sample are driven by crime reductions in urban areas, where as expected baseline crime levels tend to be higher.

A 1 percentage point increase in the share of migrants in an urban location reduces the likelihood of being a crime victim in that location by 0.244 percentage points, or a decrease of more than 20% from its average. The corresponding change for rural destinations is 0.116 pp. or a 12.9% reduction from the mean probability, although this change is not statistically different from zero. Although we cannot detect an effect for any particular type of crime, point estimates for urban areas are more almost twice as large than those for rural areas for theft, and more than three times as large for robbery and other types of crimes. On the other hand, point estimates for fraud are almost five times larger for rural areas compared to urban locations.

In turn, Table 11 shows the results when we split the sample by gender. Although differences are not substantial, we do observe that women become less likely be victims of crimes than men when the share of migrant increases. While a 1pp. increase in the share of migrants at the destination reduces the likelihood that men be victims of a crime by 0.173 percentage points (which corresponds to a 13.3% reduction from its average probability), the corresponding reduction for women is 0.201pp., which translates to a 28.7% decline from the mean.

When looking at particular crimes, we find that the decreases in theft are marginally significant for women, but not for men, although the point estimates are very similar (suggesting a reduction in the likelihood of becoming a victim of 0.107 and 0.101, respectively). Women are also 0.036 percentage points (3.6%) less likely to be victims of fraud, while we find a much smaller (0.006 percentage points) and not statistically significant reduction for men. Interestingly, although OLS estimates suggest a marginally significant and positive association between migration and rape among women, 2SLS estimates show now causal relationship between these variables. However, we should note that in none of these cases we can reject the null hypothesis that instrumental variable estimates are equal across gender.

Finally, Table 12 presents results for natives and migrants, separately. The reductions in crime we observed for the pooled sample appears to be driven by migrants, who experience a 0.277 percentage point reduction in the likelihood of being victim of a crime (18.47%) as a consequence of a 1pp. increase in the share of migrants at the destination. When victimization is broken down by type of crime, we find a marginally significant reduction of 0.135 percentage points in the likelihood of being victim of theft, while for other crimes we cannot rule out a null impact.

If migrants are more likely to be the targets of criminals (as suggested by the difference in mean values between migrants and natives), this result might suggest that when the share of migrants in a location increases, it creates a safer environment for themselves.

6 Conclusions and discussion

Although there is a growing literature estimating the impact of migration on crime, it has almost exclusively focused on international migrants to developed countries, and it is usually challenging to fully account for unobserved conditions at the destination that persist over time and establish causality. The impact that internal migration has on crime at the destination, has received considerably less attention. This is despite the fact that the latter is much larger in magnitude than international migration, and that internal migrants face different opportunity costs than international migrants for engaging in criminal activities.

We make the first attempt at filling this gap by estimating the causal effect of internal migration in Indonesia. To do this, we use different sources of crime data: news reports of incidents from local newspapers and individual victimization records from a nationally representative survey. We also instrument the share of migrants at the destination using precipitation data with the intention to overcome endogeneity concerns regarding both the decision to migrate as well as the destination chosen.

We find opposite results depending on the type of crime data used. When we focus on news reports we observe a positive and large impact of migration on economically-motivated crimes: incidents reports per 100,000 individuals in the subdistrict go up by almost 4% for a 1% increase in the share of migrants arriving at that subdistrict. We find no relationship between internal migration and violent crimes, even though OLS estimates suggested a positive association between these two variables. These results are in line with existing studies in terms of significance and sign, but the magnitudes we find are larger, potentially due to the weaker institutions of Indonesia compared to the developed countries, which have been the focus of most of the literature.

On the other hand, when we use individual victimization reports we find a negative causal relationship between migration and crime: A 1 percent increase in the share of migrants at in a district reduces the likelihood that a person becomes a crime victim in that district by 3%. In particular, we find that the probability of being victim of a theft decreases by 4.6%, and we find negatively signed but statistically insignificant effects for other crimes. Because in this case our instrument is weak, these estimates are likely lower bounds for the true impact of migration on crime, as OLS estimates are small and not statistically different from zero.

We take advantage of demographic information available in the survey to estimate heterogenous effects for different groups of our sample. When we do so, we find that the results described above are driven mostly by women, individuals living in urban areas, and migrants. Although previous studies have shown that migrants'labor market outcomes are negatively affected by new migration (Card, 2001; Lewis, 2011), if migrants are more likely to be the target of criminals the influx of individuals may create a safer environment for all migrants.

Even though the sources of our data and their geographic coverage are not the same, it is still intriguing to find such differing impacts of migration on crime. Here, we put forward some potential explanations, with the caveat that we do not have the means to test these hypothesis.

First, it is possible that the increase observed in news reports is associated with reporting bias from the newspapers. The reason for this bias may be intentional, i.e. to increase negative views about migrants among the native population. On the other hand, if migrants move to areas with good economic prospects (i.e. with higher economic growth rates and lower unemployment) newspapers might devote a larger amount of space to cover other type of news that could be of interest for the population, including incidents.

On the other hand, the data and estimates obtained from the household survey suggests that migrants are more likely to be the target of crimes and those more likely to experience a reduction in crime as a consequence of internal migration. It is possible that the increase in the migrant community has a double effect: on one hand it makes it reduces the vulnerability among individuals of the same community while it empowers those who are victims of a crime to report it, hence increasing the probability that a crime will be covered in the news even if there are fewer crimes.

Additional sources of data (e.g. from police reports) are required to have a better understanding of these results. Moreover, studies in other countries, especially those with similar characteristics to those of Indonesia, would help increase our understanding of the impact that internal migrants have on crime.

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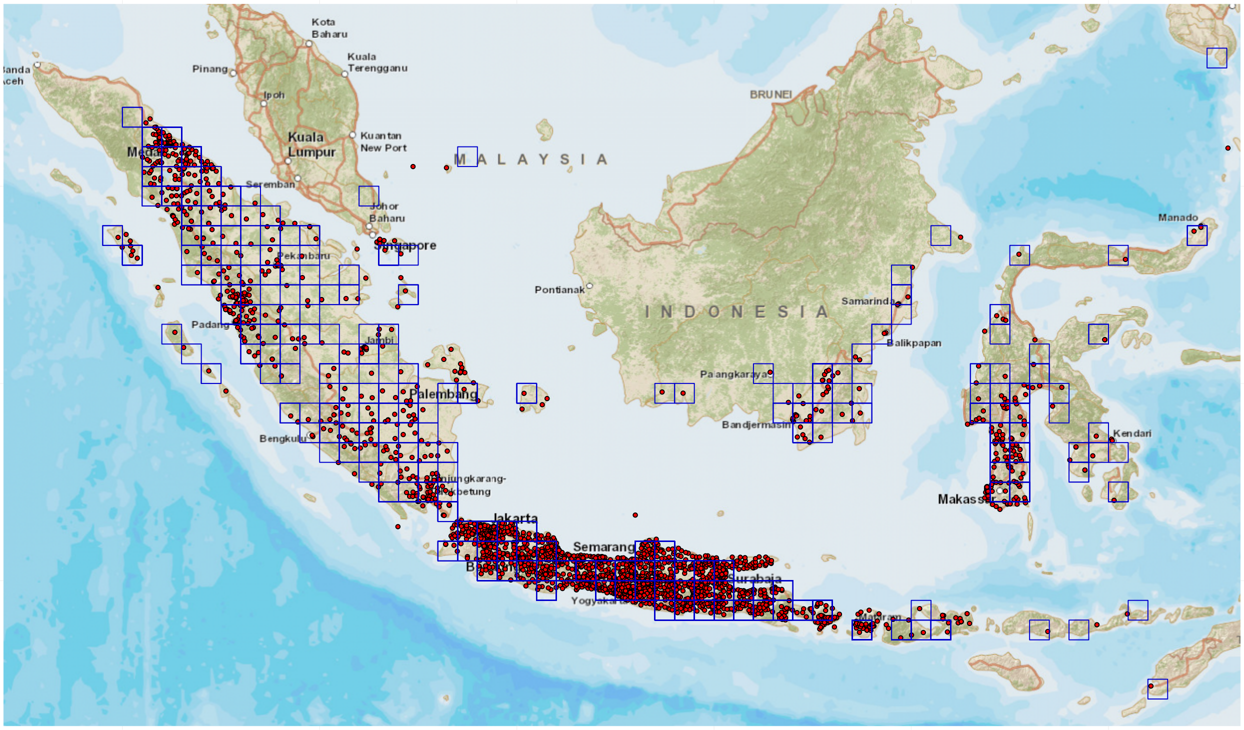

Figure 1: Location of IFLS households and gridded weather data

Table 1: Summary Statistics for the sample using NVMS data

Variable	Mean	Std. Dev.
Share male	0.47	0.09
Age	35.28	4.05
Household size	4.48	0.95
Years of education	8.64	2.09
Individuals of migrant origin at destination (share)	0.37	0.26
Precipitation (mm per month)	161.76	57.58
Yearly crime rate per 100,000 people		
Total crime	14.63	15.37
Economic crime	4.21	5.36
Violent crime	10.41	11.18
People injured in incidents	9.94	12.95
People assassinated in incidents	1.48	1.78
People sexually assaulted	1.72	2.88
People kidnapped	0.08	0.34
Number of observations	7,171	
Number of locations	1,013	

Note: Sources: Indonesia Family Life Survey, National Violence Monitoring System and University of Delaware.

Table 2: Summary Statistics from Susenas respondents

Variable	Mean	Std. Dev.
Share male	0.50	0.50
Age	29.11	19.96
Share living in urban area	0.40	0.49
Migrant origin (share)	0.16	0.13
Precipitation (mm per month)	187.45	53.90
Crim victim in the past year (share)		
Any crime	0.010	0.099
Theft	0.006	0.081
Robbery	0.001	0.039
Fraud	0.000	0.032
Rape	0.000	0.004
Other crime	0.001	0.025
Number of observations	2,045,225	
Number of locations	318	

Note: Sources: National Socio-Economic Survey 2011 and 2012 and University of Delaware.

Table 3: Ordinary least squares estimates of the relationship between migration and crime

	(1) Total crime	(2) Economic crime	(3) Violent crime	(4) Individuals injured	(5) Individuals killed	(6) Individuals sexually sexually assaulted	(7) Individuals kidnapped
Share of migrants	7.476***	3.852***	3.721*	8.087***	0.297	0.056	0.051
	(2.785)	(1.097)	(2.057)	(2.856)	(0.282)	(0.724)	(0.074)
Destination rainfall	12.058	6.802	6.380	14.362	-1.622	5.565*	0.004
	(12.567)	(4.912)	(9.179)	(11.558)	(2.273)	(3.006)	(0.527)
Mean dependent variable	14.63	4.21	10.41	9.94	1.48	1.72	0.08
R-squared	0.644	0.611	0.616	0.600	0.329	0.288	0.188
Observations	7,171	7,171	7,171	7,171	7,171	7,171	7,171
No. of locations	1,013	1,013	1,013	1,013	1,013	1,013	1,013
Location FEs	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y

Note: Dependent variables are yearly rates per 100,000 inhabitants and were created by dividing the total number of crimes, economically-motivated crimes, violent crimes and number of individuals inured, killed, sexually assaulted and kidnapped in the subdistrict each year (according to the data collected by the National Violence Monitoring System) by the population in that subdistrict according to the 2010 population census. Share of migrants is constructed as the ratio of individuals not born in the subdistrict to the total number of individuals living in that subdistrict in each year. Destination rainfall refers to the amount of precipitation at the destination in the previous calendar year. Regressions are weighted by the number of individuals in each location in each year, and standard errors are clustered at the destination level.
** p<0.01, ** p<0.05, * p<0.1

Table 4: Two-stages least squares estimates of the relationship between migration and crime

	(1) Share of migrants	(2) Total crime	(3) Economic crime	(4) Violent crime	(5) Individuals injured	(6) Individuals killed	(7) Individuals sexually assaulted	(8) Individuals kidnapped
Origin rainfall	-0.750***							
	(0.179)							
Share of migrants		44.21	43.71***	3.05	56.07	2.04	4.22	0.59
		(45.049)	(16.497)	(33.637)	(43.465)	(5.923)	(10.526)	(1.436)
Destination rainfall	0.656***	6.66	0.95	6.48	7.31	-1.88	4.95	-0.08
	(0.172)	(11.497)	(5.093)	(8.540)	(10.138)	(2.303)	(3.365)	(0.457)
Mean dependent variable	0.372	14.63	4.21	10.41	9.94	1.48	1.72	0.08
F-statistic of excluded instrument	17.66							
Observations	7,171	7,171	7,171	7,171	7,171	7,171	7,171	7,171
No. of locations	1,013	1,013	1,013	1,013	1,013	1,013	1,013	1,013
Location FEs	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: Column 1 shows the results of regressing the percentage of the population in the subdistrict from migrant origin on rainfall levels in the subdistrict's catchment area from the previous calendar year according to Equation 2 and the subdistrict's own rainfall level in the previous calendar year. For columns 2 through 8, the dependent variables are identical to those reported in Table 2. Origin rainfall refers to the weighted amount of precipitation at origin locations in the previous calendar year. Destination rainfall refers to the amount of precipitation at the destination in the previous calendar year. Regressions are weighted by the number of individuals in each location in each year, and standard errors are clustered at the destination level.
** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Two-stages least squares estimates of the relationship between migration and each type of economically motivated crime

	(1) Robbery	(2) Plunder	(3) Theft	(4) Kidnap	(5) Drug Traffic	(6) Human Traffic
Share of migrants	22.53**	14.73***	6.05	2.00*	-0.50	-0.08
	(10.176)	(4.373)	(5.375)	(1.200)	(0.686)	(0.097)
Destination rainfall	2.77	-1.20	-0.58	-0.18	-0.04	0.09*
	(3.235)	(1.397)	(1.968)	(0.454)	(0.182)	(0.046)
Mean dependent variable	2.19	0.60	1.25	0.07	0.04	0.00
Observations	7,171	7,171	7,171	7,171	7,171	7,171
No. of locations	1,013	1,013	1,013	1,013	1,013	1,013
Location FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y

Note: Dependent variables are yearly rates per 100,000 inhabitants and were created by dividing the total number of each type of crime that occured in the subdistrict in every year (according to the data collected by the National Violence Monitoring System) by the population in that subdistrict according to the 2010 population census. Share of migrants is constructed as the ratio of individuals not born in the subdistrict to the total number of individuals living in that subdistrict in each year. Regressions include rainfall levels at the destination in the previous calendar year. Destination rainfall refers to the amount of precipitation at the destination in the previous calendar year. Regressions are weighted by the number of individuals in each location in each year, and standard errors are clustered at the destination level.
** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Instrumental variables estimates of the relationship between migration and each type of violent crime

	(1) Murder	(2) Arson	(3) Mistreat	(4) Molestation	(5) Fight	(6) Rape	(7) Destruction	(8) Shooting
Share of migrants	2.21	-3.39	-0.02	3.30	9.88	-1.09	-6.19*	1.80
	(3.604)	(2.230)	(14.305)	(3.164)	(9.500)	(8.687)	(3.687)	(4.532)
Destination rainfall	-1.19	0.95	3.67	-1.54	-4.15	5.05	1.82	0.80
	(1.323)	(0.634)	(3.564)	(1.333)	(2.531)	(3.419)	(1.376)	(1.502)
Mean dependent variable	0.75	0.15	3.54	0.44	2.08	1.99	0.73	0.64
Observations	7,171	7,171	7,171	7,171	7,171	7,171	7,171	7,171
No. of locations	1,013	1,013	1,013	1,013	1,013	1,013	1,013	1,013
Location FEs	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: Dependent variables are yearly rates per 100,000 inhabitants and were created by dividing the total number of each type of crime that occured in the subdistrict in every year (according to the data collected by the National Violence Monitoring System) by the population in that subdistrict according to the 2010 population census. Share of migrants is constructed as the ratio of individuals not born in the subdistrict to the total number of individuals living in that subdistrict in each year. Destination rainfall refers to the amount of precipitation at the destination in the previous calendar year. Regressions are weighted by the number of individuals in each location in each year, and standard errors are clustered at the destination level.
** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: OLS and 2SLS estimates for rural and urban locations

	OLS			2SLS		
	(1) Total crime	(2) Economic crime	(3) Violent crime	(4) Total crime	(5) Economic crime	(6) Violent crime
Panel A: Urban locations						
Share of migrants	8.304*	5.570***	2.921	17.74	34.96**	-15.53
	(4.300)	(1.643)	(3.224)	(42.546)	(16.008)	(31.188)
Observations	3,527	3,527	3,527	3,527	3,527	3,527
First stage F-stat				13.823	13.823	13.823
Panel B: Rural locations						
Share of migrants	0.014	-1.291	1.200	155.54	183.30	-25.16
	(2.726)	(0.951)	(2.009)	(368.326)	(232.930)	(313.258)
Observations	3,644	3,644	3,644	3,644	3,644	3,644
First stage F-stat				0.581	0.581	0.581
Destination rainfall	Y	Y	Y	Y	Y	Y
Location FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y

Note: Dependent variables are yearly rates per 100,000 inhabitants and were created by dividing the total number of crimes, economically-motivated crimes and violent crimes in the subdistrict each year (according to the data collected by the National Violence Monitoring System) by the population in that subdistrict according to the 2010 population census. The sample of destinations is devided into urban and rural according to each individual's response regarding the type of location they live in. Migrant share is constructed as the ratio of individuals not born in the subdistrict to the total number of individuals living in that subdistrict in each year. Destination rainfall refers to the amount of precipitation at the destination in the previous calendar year. Regressions are weighted by the number of individuals in each location in each year, and standard errors are clustered at the destination level.
** p<0.01, ** p<0.05, * p<0.1

Table 8: OLS estimates of the relationship between share of migrants and being a victim of crime with individual data

	(1) Crime victim	(2) Theft victim	(3) Robbery victim	(4) Fraud victim	(5) Rape victim	(6) Victim of other crime
Share of migrants	-0.002	0.008	-0.006	0.003	0.000	-0.007
	(0.011)	(0.007)	(0.006)	(0.002)	(0.000)	(0.007)
Destination rainfall ago	-0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean dependent variable	0.010	0.007	0.001	0.001	0	0.001
R-squared	0.003	0.003	0.002	0.001	0	0.002
Observations	2,045,225	2,045,225	2,045,225	2,045,225	2,045,225	2,045,225
No. of locations	318	318	318	318	318	318
Location FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y

Note: Dependent variables are indicators that take value one if the individual was a victim of each type of crime during the previous year. Share of migrants is constructed as the ratio of individuals not born in the district to the total number of individuals living in that district in each year. Destination rainfall refers two the second lag of the z-score of rainfall in the destination. All regressions use individual-level data and standard errors are clustered at the destination level.
** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9: 2SLS estimates of the relationship between share of migrants and being a victim of crime with individual data

	(1) Crime victim	(2) Theft victim	(3) Robbery victim	(4) Fraud victim	(5) Rape victim	(6) Victim of other crime
Migrant share	-0.187**	-0.105*	-0.028	0.003	0.001	-0.031
	(0.093)	(0.060)	(0.031)	(0.002)	(0.002)	(0.022)
Destination rainfall	-0.001*	-0.001**	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean dependent variable	0.010	0.007	0.001	0.001	0	0.001
F-statistic of excluded instrument	6.674	6.674	6.674	6.674	6.674	6.674
Observations	2,045,225	2,045,225	2,045,225	2,045,225	2,045,225	2,045,225
No. of locations	318	318	318	318	318	318
Location FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y

Note: Dependent variables are indicators that take value one if the individual was a victim of each type of crime during the previous year. Share of migrants is constructed as the ratio of individuals not born in the district to the total number of individuals living in that district in each year. Destination rainfall refers two the second lag of the z-score of rainfall in the destination. All regressions use individual-level data and standard errors are clustered at the destination level.
** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10: Estimates of the relationship between share of migrants and being a victim of crime by type of destination

	Crime victim		Theft victim		Robbery victim		Fraud victim		Rape victim		Victim of other crime	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Panel A: Urban locations												
Share of migrants	-0.010	-0.244*	0.012	-0.128	-0.011	-0.047	0.002	-0.007	0.000	0.001	-0.012	-0.058
	(0.017)	(0.143)	(0.009)	(0.081)	(0.007)	(0.043)	(0.003)	(0.015)	(0.000)	(0.002)	(0.011)	(0.045)
Mean dependent variable	0.012	0.012	0.008	0.008	0.002	0.002	0.001	0.001	0.000	0.000	0.001	0.001
Observations	812,938	812,938	812,938	812,938	812,938	812,938	812,938	812,938	812,938	812,938	812,938	812,938
First stage F-stat		4.797		4.797		4.797		4.797		4.797		4.797
Panel B: Rural locations												
Share of migrants	0.010	-0.116	-0.001	-0.068	0.005	0.002	0.005	-0.034	0.001*	0.001	0.001	-0.016
	(0.014)	(0.098)	(0.011)	(0.083)	(0.008)	(0.042)	(0.004)	(0.029)	(0.000)	(0.004)	(0.003)	(0.020)
Mean dependent variable	0.009	0.009	0.006	0.006	0.001	0.001	0.001	0.001	0.000	0.000	0.001	0.001
Observations	1,232,287	1,232,287	1,232,287	1,232,287	1,232,287	1,232,287	1,232,287	1,232,287	1,232,287	1,232,287	1,232,287	1,232,287
First stage F-stat		6.382		6.382		6.382		6.382		6.382		6.382
Destination rainfall	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Location FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Dependent variables are indicators that take value one if the individual was a victim of each type of crime during the previous year. Share of migrants is constructed as the ratio of individuals not born in the district to the total number of individuals living in that district in each year. Destination rainfall refers two the second lag of the z-score of rainfall in the destination. All regressions use individual-level data and standard errors are clustered at the destination level.
** p<0.01, ** p<0.05, * p<0.1

Table 11: Estimates of the relationship between share of migrants and being a victim of crime by gender of victim

	Crime victim		Theft victim		Robbery victim		Fraud victim		Rape victim		Victim of other crime	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Panel A: Women												
Share of migrants	-0.017*	-0.201**	-0.004	-0.107*	-0.007	-0.032	-0.001	-0.036*	0.001*	0.000	-0.005	-0.024
	(0.010)	(0.096)	(0.007)	(0.057)	(0.006)	(0.033)	(0.002)	(0.021)	(0.000)	(0.003)	(0.007)	(0.019)
Mean dependent variable	0.007	0.007	0.004	0.004	0.002	0.002	0.001	0.001	0.000	0.000	0.001	0.024
Observations	1,026,249	1,026,249	1,026,249	1,026,249	1,026,249	1,026,249	1,026,249	1,026,249	1,026,249	1,026,249	1,026,249	1,026,249
First stage F-stat		6.638		6.638		6.638		6.638		6.638		6.638
Panel B: Men												
Share of migrants	0.013	-0.173*	0.021**	-0.101	-0.006	-0.026	0.007*	-0.006	-0.000	0.001	-0.009	-0.038
	(0.014)	(0.100)	(0.010)	(0.073)	(0.006)	(0.031)	(0.004)	(0.014)	(0.000)	(0.002)	(0.008)	(0.026)
Mean dependent variable	0.013	0.013	0.009	0.009	0.001	0.001	0.001	0.001	0.000	0.000	0.001	0.001
Observations	1,523,941	1,523,941	1,523,941	1,523,941	1,523,941	1,523,941	1,523,941	1,523,941	1,523,941	1,523,941	1,523,941	1,523,941
First stage F-stat		6.704		6.704		6.704		6.704		6.704		6.704
Destination rainfall	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Location FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Dependent variables are indicators that take value one if the individual was a victim of each type of crime during the previous year. Share of migrants is constructed as the ratio of individuals not born in the district to the total number of individuals living in that district in each year. Destination rainfall refers two the second lag of the z-score of rainfall in the destination. All regressions use individual-level data and standard errors are clustered at the destination level.
** p<0.01, ** p<0.05, * p<0.1

Table 12: Estimates of the relationship between share of migrants and being a victim of crime by migrant status of victim

	Crime victim		Theft victim		Robbery victim		Fraud victim		Rape victim		Victim of other crime	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Panel A: Natives												
Share of migrants	0.004	-0.167	0.011	-0.103	-0.003	-0.023	0.002	-0.015	0.000	0.001	-0.005	-0.022
	(0.010)	(0.101)	(0.007)	(0.068)	(0.006)	(0.037)	(0.002)	(0.018)	(0.000)	(0.003)	(0.006)	(0.021)
Mean dependent variable	0.009	0.009	0.006	0.006	0.001	0.001	0.001	0.001	0.000	0.000	0.001	0.001
Observations	1,687,832	1,687,832	1,687,832	1,687,832	1,687,832	1,687,832	1,687,832	1,687,832	1,687,832	1,687,832	1,687,832	1,687,832
First stage F-stat		6.328		6.328		6.328		6.328		6.328		6.328
Panel B: Migrants												
Share of migrants	-0.040*	-0.277**	-0.011	-0.135*	-0.015*	-0.048	0.001	-0.040	0.000	0.000	-0.014	-0.057
	(0.022)	(0.114)	(0.014)	(0.071)	(0.008)	(0.029)	(0.005)	(0.026)	(0.000)	(0.002)	(0.012)	(0.036)
Mean dependent variable	0.015	0.015	0.011	0.011	0.002	0.002	0.002	0.002	0.000	0.000	0.001	0.001
Observations	357,393	357,393	357,393	357,393	357,393	357,393	357,393	357,393	357,393	357,393	357,393	357,393
First stage F-stat		7.047		7.047		7.047		7.047		7.047		7.047
Destination rainfall	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Location FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Dependent variables are indicators that take value one if the individual was a victim of each type of crime during the previous year. Share of migrants is constructed as the ratio of individuals not born in the district to the total number of individuals living in that district in each year. Destination rainfall refers two the second lag of the z-score of rainfall in the destination. All regressions use individual-level data and standard errors are clustered at the destination level.
** p<0.01, ** p<0.05, * p<0.1