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

Brian Feld and Marieke Kleemans

Department of Economics - University of Illinois at Urbana-Champaign

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Abstract

We estimate the causal effect of internal migration on crime in Indonesia, combining detailed longitudinal location data from over 30,000 individuals with crime information from two million subnational newspapers over the course of 10 years. To address endogeneity in the choice to migrate, we instrument the share of migrants in a destination with rainfall shocks at the origin locations from where the migrants arrive. While OLS estimates suggest a positive and quantitatively small association between migration and both violent and economically motivated crime rates, estimation using instrumental variables indicates that migration causes an increase only on certain economic crimes. This is consistent with the existing literature on the effect of international migration to developed countries, but the effect is larger: a 1% increase in the proportion of migrants in the population, leads to a 4 percentage increase in economically motivated crimes.

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 could have 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 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, 2017). 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 data from over 200 thousand incidents retrieved from 2 million newspapers in a ten-year period. The fact that we focus our attention on a developing country with relatively weak institutions compared to those studied in the existing literature[1] 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. 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 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

[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.

this problem by instrumenting migration with pre-existing migrant enclaves at the destination, we follow Kleemans and Magruder (2017) 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 point to 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 statistical significance, the magnitude of the effect is much higher, with a 1-point increase in the percentage of migrants leading to a rise in nonviolent crime rates of 10%. This translates into an elasticity of 4 at the mean.

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. Surprisingly, 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. However, the low F-statistics shown in the first stage may be behind these results.

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 (2017) 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, and Section 5 will conclude.

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

2 Data

2.1 Crime Statistics

Crime data by subdistrict (*Kecamatan*) was obtained 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. It documented 241,850 episodes of violence reported in over 2 million subnational newspapers between 1998 and 2015 and coded them into different type of incidents[3]. Unlike other sources of crime and violence data that only cover major episodes of collective violence or rely on police reports, the NVMS is broader in scope (and thus it has a much larger number of records) and does not depend on individuals reporting a crime, so it is less likely to be affected by underreporting although minor offenses (such as thefts) are less likely to appear in newspapers than violent crimes. Hence, we expect our results for economically-motivated crime to be a lower bound for the true effect of internal migration on this outcome.

While earlier efforts to register episodes of violence were concentrated in the eastern provinces of the country, 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.

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[4]. We also use the information provided in the dataset regarding the number of people injured, killed, kidnapped and sexually assaulted in each incident. We collapsed the data of incidents by subdistrict 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.

[3] For additional details, see Barron, Jaffrey, and Varshney (2014).

[4] 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.

2.2 Migration

To obtain estimates on migrant shares per year at the subdistrict level we use 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 subdistricts (*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 1,479 subdistricts hosting 32,701 individuals. Table 1 presents summary statistics for the data used throughout this study. Because individuals are included in our location panel only after being 12 years old, our sample is almost entirely composed of working-age adults. The average share of individuals who live in a subdistrict other than their subdistrict of birth is over 35%. This is consistent with previous reports that one out of 4 Indonesians live at least part of their lives in a district different from their birth district (Deb and Seck, 2009), so we would expect this number to be higher when looking at data at a lower administrative level.

Crime rates appear to be quite low. Although it should be noted that the majority of our analysis takes place in regions considered non-violent by the NVMS, Indonesia has low crime rates compared to other developing countries, especially of the violent type (Cameron and Shah, 2014). Another potential reason for the low crime rates observed is that, as explained above, our data relies on newspaper coverage of the crime, so it is likely that certain economically-motivated crimes are more likely to go unnoticed by the media.

2.3 Weather

Weather data are 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 use rainfall levels (measured as average millimeters per month) during the calendar year as our main weather variable. However, results are robust remain largely similar if we instead use seasonal (July-June) rainfall levels, or precipitation z-scores (obtained by subtracting the mean and dividing by the standard deviation of each location across time).

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. A naïve approach would then be 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 (2017) 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.

We run our analyses using an individual-year panel to increase the power of our estimators, although all 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.

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

4.1 OLS

Columns 1 to 3 of Table 2 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. The only independent variables included are the percentage 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, 0.94% higher economically-motivated crime rates and 0.52%

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 0.82% 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.

4.2 Instrumental Variables

Despite these results, we cannot give a causal interpretation to the estimates obtained for the reasons described in the previous section. Instead, we do this here by instrumenting migration percentages with rainfall shocks at the origin. We present the results in Table 3, 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 16.13, 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 2, 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 4% 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 4 and 5 shows the results for each type of economic and violent crime, respectively. Consistent with the results from Table 3, only robbery and plunder increase because of migration, and these surges are nontrivial at 3.85 and 8.72% 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.

4.3 Heterogeneity by type of destination

In Table 6, 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 Conclusion

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 (although much larger in magnitude than international migration) has on crime at the destination, has received considerably less attention.

We make the first attempt at filling this gap by estimating the causal effect of internal migration in Indonesia. We combine extensive data on migration, crime and weather to construct an instrument for the share of migrants at the destination that deals both with the decision to migrate and the choice of destination.

While OLS estimates point to a positive association between the share of migrants in the population and both economically-motivated and violent crime, as well as the number of people injured in these incidents, our 2SLS estimate point to a positive and sizable causal impact of migration exclusively on economic crime. According to our results, a 1 percent increase in the share of migrants at the destination from its average produces a surge in property crimes rates of 4%. Nevertheless we should be careful in trying to generalize these results to other contexts, even within developing economies. More data and studies in different countries are still needed in order to have a better idea about the range of these impacts.

The direction of our results are consistent with the findings of Kleemans and Magruder (2017) regarding the worsening of labor market conditions that natives face as a consequence of migration, as well as studies that link these negative economic shocks to crime, even though it is not possible for us to determine whether it is immigrants or natives who cause the crimes. This is quite relevant not only from an academic but also from a policy perspective, since it would have different implications for what policymakers could do in order to soften these impacts. Our next step would be thus to identify whether areas more severely impacted by internal migration in terms of natives' labor prospects are also the hardest hit by increases in crime.

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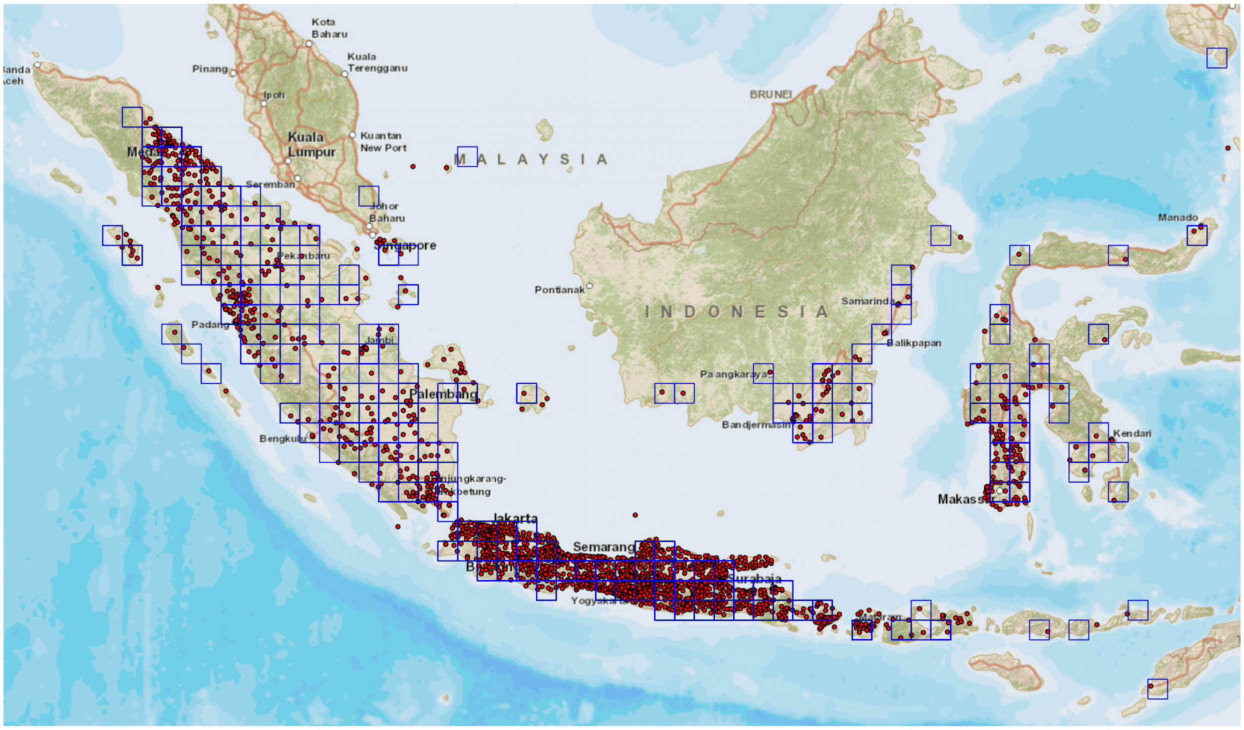

Figure 1: Location of IFLS households and gridded weather data

Table 1: Summary Statistics

Variable	Mean	Std. Dev.
Share male	0.47	0.5
Age	35.52	15.18
Household size	4.45	2.16
Years of education	8.65	4.11
Individuals of migrant origin at destination (%)	35.5	25.8
Precipitation (mm per month)	162.28	56.66
Yearly crime rate per 100,000 people		
Total crime	14.04	15.19
Economic crime	9.98	11.03
Violent crime	4.05	5.31
People injured in incidents	9.58	12.71
People assassinated in incidents	1.44	1.77
People sexually assaulted	1.65	2.83
People kidnapped	0.07	0.33
Number of individual-year pairs	157,525	
Number of individuals	32,701	
Number of locations	1,479	

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

Table 2: 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
Percentage of migrants	0.073***	0.038***	0.036*	0.079***	0.003	0.001	0.000
	(0.026)	(0.010)	(0.019)	(0.026)	(0.003)	(0.007)	(0.001)
Destination rainfall in previous calendar year	-0.001	-0.002	0.002	0.002	-0.003	0.005*	-0.000
	(0.010)	(0.004)	(0.008)	(0.009)	(0.002)	(0.003)	(0.000)
Mean dependent variable	14.04	4.05	9.98	9.58	1.44	1.65	0.07
Location FEs	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y
Observations	157,525	157,525	157,525	157,525	157,525	157,525	157,525
Number of locations	1,479	1,479	1,479	1,479	1,479	1,479	1,479

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. Percentage 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, times 100. 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 3: Two-stages least squares estimates of the relationship between migration and crime

	(1) Percentage 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 in previous calendar year	-0.065***							
	(0.016)							
Percentage of migrants		0.32	0.46**	-0.10	0.42	0.08	-0.00	0.00
		(0.499)	(0.185)	(0.371)	(0.450)	(0.071)	(0.115)	(0.016)
Destination rainfall in previous calendar year	0.043***	-0.00	-0.00	0.00	0.00	-0.00	0.01*	-0.00
	(0.015)	(0.011)	(0.005)	(0.008)	(0.010)	(0.002)	(0.003)	(0.000)
Mean dependent variable	35.5	14.04	4.05	9.98	9.58	1.44	1.65	0.07
F-statistic of excluded instrument	16.13							
Location FEs	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Observations	157,525	157,525	157,525	157,525	157,525	157,525	157,525	157,525
Number of locations	1,479	1,479	1,479	1,479	1,479	1,479	1,479	1,479

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. 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 4: 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
Percentage of migrants	0.23**	0.14***	0.08	0.02	-0.00	-0.00
	(0.115)	(0.047)	(0.057)	(0.014)	(0.008)	(0.001)
Mean dependent variable	2.12	0.57	1.20	0.07	0.04	0.00
Location FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Observations	157,525	157,525	157,525	157,525	157,525	157,525
Number of locations	1,479	1,479	1,479	1,479	1,479	1,479

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. Percentage 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, times 100. Regressions include rainfall levels at the destination in the previous calendar year. 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 5: Two-stages least squares 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
Percentage of migrants	0.03	-0.04	-0.06	0.01	0.05	0.00	-0.08*	0.02
	(0.042)	(0.032)	(0.156)	(0.036)	(0.098)	(0.112)	(0.043)	(0.051)
Mean dependent variable	0.72	0.15	3.40	0.44	1.98	1.88	0.70	0.62
Location FEs	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Observations	157,525	157,525	157,525	157,525	157,525	157,525	157,525	157,525
Number of locations	1,479	1,479	1,479	1,479	1,479	1,479	1,479	1,479

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. Percentage 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, times 100. Regressions include rainfall levels at the destination in the previous calendar year. 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 6: 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						
Percentage of migrants	0.088**	0.054***	0.036	0.08	0.33**	-0.21
	[0.036]	[0.015]	[0.026]	[0.421]	[0.155]	[0.314]
Observations	83,392	83,392	83,392	83,392	83,392	83,392
First stage F-stat				14.31	14.31	14.31
Panel B: Rural locations						
Percentage of migrants	-0.009	-0.009	-0.001	1.41	2.51	-1.07
	[0.024]	[0.008]	[0.019]	[4.551]	[3.572]	[3.945]
Observations	73,916	73,916	73,916	73,916	73,916	73,916
First stage F-stat				0.509	0.509	0.509
Destination rainfall in previous calendar year	Y	Y	Y	Y	Y	Y
Location FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Demographic controls	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. Percentage 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, times 100. All regressions use individual-level data and standard errors are clustered at the destination level.
** $p<0.01$, ** $p<0.05$, * $p<0.1$