

Violence, Development, and Migration Waves: Evidence from Central American Child Migrant Apprehensions

Michael A. Clemens

Abstract

A recent surge in child migration to the United States from Honduras, El Salvador, and Guatemala has occurred in the context of high rates of regional violence. But little quantitative evidence exists on the causal relationship between violence and international emigration in this or any other region. This paper studies the relationship between violence in the Northern Triangle and child migration to the United States using novel, individual-level, anonymized data on all 178,825 US apprehensions of unaccompanied child migrants from these countries between 2011 and 2016. It finds that one additional homicide per year in the region, sustained over the whole period—that is, a cumulative total of six additional homicides—caused a cumulative total of 3.7 additional unaccompanied child apprehensions in the United States. The explanatory power of short-term increases in violence is roughly equal to the explanatory power of long-term economic characteristics like average income and poverty. Due to diffusion of migration experience and assistance through social networks, violence can cause waves of migration that snowball over time, continuing to rise even when violence levels do not.

Keywords: violence, migration, refugee, UAC, unaccompanied children, Northern Triangle, Central America, Honduras, Guatemala, El Salvador, minors, survival migration, youths, Cartagena Declaration, Global Compact, war, drug trade, smugglers, traffickers, trafficking, cocaine, cartel, gang, mara, homicide, murder, mobility, asylum, asylee

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Over the last several years the ‘Northern Triangle’ countries of El Salvador, Honduras, and Guatemala have suffered high levels of violence associated with organized criminals. Violent crime perpetrated by *maras* street gangs, Central American drug transporters, and Mexican drug cartels has been linked to a wave of forced displacement in this region (Cantor 2014). During the same period the United States has apprehended a wave of Unaccompanied Alien Children (UACs) immigrating from the same countries without authorization. This wave has been very large; for example, the number of apprehensions of 17 year-old UACs from the Northern Triangle during 2011–2016 is 8% of the total number of 17 year-olds who were initially living in those countries. Efforts to manage those children’s arrival in the United States, and to prevent future UAC migration, depend critically on understanding the links between violence in their origin countries and the decision to migrate. But little quantitative evidence exists, for these Central American children or for any other international migrants, that could empirically measure and causally identify the connection between origin-country violence and migration.

This paper uses novel, individual-level, anonymized data on all 178,825 UAC apprehensions between 2011 and 2016 to measure the causal relationship between municipal-level homicide rates and UAC migration across 893 municipalities of the Northern Triangle. It tests the robustness of the relationship to controlling for municipality and year fixed effects, flexible unobserved time trends with arbitrarily spatially-correlated effects, and higher levels of saturation including department (state)-by-year fixed effects, as well as assumptions on functional form and influential observations. It proceeds to decompose the effects of new violence and the snowballing effects of past migration by building and estimating a continuous-time discrete choice search model of innovation diffusion through social networks. This simple model explains most of the evolution of UAC apprehensions from different parts of the region over time. Finally, it decomposes the relative importance of security and economic determinants of UAC migration, both for the region as a whole and across space, municipality by municipality. The analysis focuses on the Northern Triangle because these three small countries account for approximately 80% of recent UAC apprehensions.

The analysis finds that a sustained increase of one homicide per year in the Northern Triangle over all six years 2011–2016 caused about 0.9 additional UAC apprehensions in the United

States *in any given year* between 2011 and 2016, or about 3.7 additional UAC apprehensions as a cumulative total over all years. The explanatory power of short-term increases in violence is roughly equal to the explanatory power of long-term economic characteristics like average income and poverty, and much greater than the explanatory power of short-term economic shocks like rises in overall unemployment. Across wide portions of Honduras, Guatemala, and El Salvador, rising violence does more to explain UAC rates than the local economic setting. These relationships are substantially unaffected by controlling for changes over time that affected all three countries, such as changes in U.S. immigration policy. Estimation of the diffusion model shows that inertia from past UAC movement explains about one third of the relationship between more recent violence and current UAC flows. This implies that homicides can produce waves of migration that snowball over time, continuing to rise even when violence levels do not.

The paper begins in [Section 1](#) by reviewing the literature on violence and migration with a focus on Central America. [Section 2](#) describes the Northern Triangle setting, and [Section 3](#) describes the novel database of UAC apprehensions and regional violence built for the study. [Section 4](#) presents the core empirical results and several robustness tests. [Section 5](#) derives and estimates the network diffusion model, and [Section 6](#) decomposes the security and economic determinants of UAC rates. [Section 7](#) summarizes and explores policy lessons.

1 Literature

Although the effect of violence on domestic displacement has been well studied in Latin America ([Engel and Ibáñez 2007](#); [Ibáñez and Vélez 2008](#)), there is little quantitative evidence on the effect of violent crime on international migration. An important reason for this evidence gap is that violence often varies greatly at the subnational level, but common sources of data on international migrants almost never identify their sub-national place of origin. An exception is [Shrestha \(2017\)](#), who uses a panel of towns in Nepal to find that an increase of 100 in the death rate (per 100,000 population) due to Maoist insurgency in urban areas raises by 0.8 percentage points the rate of emigration to India, Malaysia, and the Gulf. That response to

violence is conditional on relative economic opportunity abroad and access to social networks (Adhikari 2013).

Several studies therefore consider the relationship between national-level outbreaks of violence and international migration. Amuedo-Dorantes and Puttitanun (2016) find that arrivals of unaccompanied minors in the U.S. has been correlated with the national-level homicide rate in the countries of origin (the Northern Triangle and Mexico). Shellman and Stewart (2007) find a statistically significant relationship between outbreaks of civil conflict in Haiti and U.S. interdictions of unauthorized Haitian migrants. And there is some evidence that U.S. counties closer to more violent Mexican municipalities received more Mexican migrants during a large homicide wave in Mexico (Arceo-Gómez 2013), but Mexicans appear to respond to violence more through domestic migration than international migration (Martinez 2014; Atuesta and Paredes 2016). Causal attribution in this literature is complicated by the fact that confounding determinants of migration may be varying across time in correlation with national-level violence.

The economic causes and effects of migration are better understood, and complex. The real earnings gain to migration is very large—including gains between 220% and 260% for typical workers from Guatemala and Nicaragua who move to the United States (Clemens et al. 2016). Central American households use migration by younger members as a strategy to cushion themselves from negative income shocks with remittances (Molina 2015), tending to protect poor children in migrant households from negative shocks to physical growth (Carletto et al. 2011) and cognitive development (Macours and Vakis 2010). Households in the Northern Triangle that receive more remittances invest relatively more in education and housing (Cox Edwards and Ureta 2003; Adams and Cuecuecha 2010; Ambler et al. 2015) and in formal savings instruments at banks (Anzoategui et al. 2014). Emigration has been found to push wages up by reducing the labor supply in source communities in Mexico (Mishra 2007) and Honduras (Gagnon 2011).

But this does not necessarily mean that higher incomes in origin countries are associated with reduced migration. Capital constraints are binding for many low-income potential migrants, not only in the direct costs of migration but in the acquisition of tangible and intangible assets

that facilitate migration—such as education and access to international social networks. Thus migration to the United States is associated with relatively *greater* wealth among poor Salvadoran households (Halliday 2006), relative labor-market *success* in Nicaragua (Funkhouser 2009), and greater disposable income among Mexican households (Angelucci 2012, 2015). The literature finds similar patterns around the world (e.g. Bazzi 2017; surveyed in Clemens 2014).

Recent research has stressed the importance of social networks to migration decisions (Munshi 2003; Epstein and Gang 2006), particularly for first-time migrants (Massey and Aysa-Lastra 2011). The costs of informal migration are typically reduced by networks of family and friends who teach potential migrants how to access informal channels and help finance smuggling payments for Mexican migrants (Massey and Zenteno 1999; Winters et al. 2001; McKenzie and Rapoport 2010; Dolfin and Genicot 2010), as well as for Central American child migrants (e.g. Donato and Sisk 2015).

Violence, economic development, and networks are not only independent causes of migration but also deeply intertwined. Networks greatly affect the individual-level costs of migration and thus individuals' migratory responses to violence and economic conditions, and networks are in turn built by migration. Economic conditions are known to shape participation in violent crime in the United States (Ihlanfeldt 2007; Lin 2008) and Mexico (Piñeyro 2010, 159, 179; Escalante 2010), and certainly Central America as well (Seelke 2014, 5). And violence, beyond its large direct welfare cost through reduced life expectancy (Soares 2006), has been found to impede economic development (Bozzoli et al. 2010; Skaperdas 2011; Besley and Persson 2014; Jaitman et al. 2017).¹ These complex relationships imply that past violence can shape emigration not only through immediate threats to security but through enlarging migrant networks and through affecting local economic conditions.

¹Violence harms local economies through channels that include reducing entrepreneurship (Brück et al. 2013), reducing propensity to invest for future returns (Voors et al. 2012), reducing trade (Blomberg and Hess 2006), reducing children's schooling (Chamarbagwala and Morán 2011; Brown and Velásquez 2017; Monteiro and Rocha 2017), harming children's physical and cognitive development (Duque 2017), reducing earnings especially among the self-employed (Dell 2015; Velásquez 2015), disproportionately reducing the value of assets held by the poor (Ajzenman et al. 2015), and undermining democratic institutions (Trelles and Carreras 2012; Blanco 2013), as well as inducing hopelessness and pessimism for prospects of upward mobility (Moya and Carter 2014).

2 Setting

In 2012 there was a large and sudden increase in the number of child migrants arriving in the United States from the Northern Triangle of Central America—El Salvador, Guatemala, and Honduras—without any adult. These Unaccompanied Alien Children (UACs) from the Northern Triangle came to outnumber those from Mexico for the first time in 2013; they made up 75% of all UACs at the southwest border by 2014.² Detained unaccompanied children spend an average of 35 days in custody of the Department of Health and Human Services. Thereafter 95% are released to the custody of a parent, relative, or other sponsor and wait an average of a year and a half before appearing before an immigration judge (Goździak 2015; Manuel and Garcia 2016).

Violence related to drug trafficking rose sharply in the Northern Triangle after Mexico’s 2007–2009 escalation in conflict with Transnational Criminal Organizations (TCOs) there pushed trafficking routes into the Northern Triangle (UNODC 2012; Selee et al. 2013; ICG 2014). The key drivers of violence are drug trafficking, gang activity, the widespread availability of firearms, and relatively weak institutions of criminal justice (van Bronkhorst and Demombynes 2010). Outbreaks of violent crime in the Northern Triangle are highly uneven across space, tending to focus on hot spots within portions of departments (Ingram and Curtis 2014). The homicide rate in subnational areas of Central America with high drug-trafficking activity have double the homicide rates of other areas on average, controlling for factors such as relative economic disadvantage and history of civil conflict (Demombynes 2011).

Research based on qualitative survey evidence has generally concluded that violence is a leading cause of recent increases in emigration from the Northern Triangle, including unaccompanied child migration (Carlson and Gallagher 2015; MSF 2017). Interviews with convenience-samples of child migrants from the Northern Triangle find that roughly half of those in transit and large numbers of those returned to their home countries were originally forcibly displaced

²United States Government Accountability Office, *Unaccompanied Alien Children: Actions Needed to Ensure Children Receive Required Care in DHS Custody*, GAO-15-521, July 14, 2015, p. 90. UACs are defined by U.S. law as “children who lack lawful immigration status in the United States, who are under the age of 18, and who either are without a parent or legal guardian in the United States or without a parent or legal guardian in the United States who is available to provide care and physical custody” (Kandel 2017). The legal definition is set by P.L. 107–296, §462, 116 Stat. 2202–2205 (November 25, 2002) (codified, as amended, at 6 U.S.C. §279(g)(2)).

by violence ([Khashu 2010](#); [UNHCR 2014](#); [Camargo 2014](#); [IOM 2016](#); [Casa Alianza 2017](#)). Poll data across Central America find a strong individual-level association between stated future emigration intent among youths and recent experience or witness of crime victimization ([Hiskey et al. 2014](#)).

But the motives of child migrants and their families are complex and diverse. U.S. officials in Central America identify the drivers of UAC migration from the region as not just crime and violence, but also educational concerns, the desire for family reunification, and the extent of smuggling networks ([Gootnick et al. 2015](#)). Survey evidence likewise suggests that current UAC flows are determined by a complex mix of access to smuggling networks and the desire for family reunification, beyond current levels of violence ([Chishti and Hipsman 2015](#)), and by the level of generalized violence beyond direct threats to the individuals who move ([Swanson and Torres 2016](#)).³ Measuring the extent to which violence does or does not determine children's migration is inherently difficult based only on interviews with them or their families: children fleeing side-effects of violence such as school closings might state that they are moving for a better education, when in fact violence is the root cause. Conversely, children migrating for economic opportunity might state that they are fleeing violence because they believe that this motive will be seen as more legitimate.

This complexity has given rise to legal controversy in the United States over whether unaccompanied child migrants qualify for formal legal status as refugees from violent persecution, or should be treated as economic migrants (e.g. [Stinchcomb and Hershberg 2014](#); [Weiss 2015](#); [Rodríguez 2016](#); [Reynolds 2016](#); [Cantor 2016](#)). Policymakers perceive a tension between measures to protect children with humanitarian protection claims and encouraging more children to make the journey, with or without claims for asylum or other forms of humanitarian relief that are likely to be legally sanctioned ([Rosenblum 2015](#)).

³Some U.S. politicians have characterized the increase in UAC arrivals as a consequence of changes to U.S. policy regarding the deportation of unauthorized immigrant children in 2013 ([Kandel 2017](#), 1), but there is no sign that UAC arrivals discontinuously rose after the policy change ([Amuedo-Dorantes and Puttitanun 2016](#)).

3 Data

This study uses novel microdata on the universe of 178,825 U.S. apprehensions of UACs from El Salvador, Guatemala, and Honduras during calendar years 2011–2016. It matches these observations to data on violence, economic conditions, and demographic conditions in their municipalities of origin.⁴ Data on UAC apprehensions come from U.S. Customs and Border Protection (CBP). They are anonymized to record only, for each individual: country and city of birth, calendar year of apprehension, age at apprehension, and in which of CBP's 20 geographic sectors the apprehension occurred. The city of birth provided by the child and recorded by CBP allowed matching 161,735 children (90.4%) to a municipality of birth.⁵ Most of the children in the universe (53.7%) are age 16–17, but all ages are represented ([Figure 1](#)). About a third (31.9%) are female. These UACs represent a substantial fraction of all children in the region in some age ranges. For example, the number of 17 year-old UACs from the Northern Triangle apprehended during 2011–2016 is approximately 8.1% of the total number of 17 year-olds living in the Northern Triangle when the wave began.⁶

The nature of the data circumscribe the interpretation of the results to follow. The data on UACs contain only children who are unaccompanied and try to reach the United States, succeed in reaching the United States, and are apprehended there. They do not include any adult migrants, any child migrants who travel accompanied by any family member age 18 or over, any UACs who enter without being apprehended, or any UACs who depart their country of origin but either do not attempt to reach the U.S. or never succeed in reaching U.S. territory. A minority of unaccompanied child migrants try to reach other countries, primarily Mexico. Among overall unauthorized Northern Triangle migrants apprehended by and returned by Mexico, roughly three quarters of those from Honduras and El Salvador have the United States as their final destination, and roughly half of those from Guatemala ([EMIF 2016](#), 15). About 40 percent of Central American child migrants headed to the United States or Mexico are apprehended by Mexico ([Rodrigo and Rietig 2015](#); [Rosenblum and Ball 2016](#)).

⁴The three countries' collective territory is divided into administrative regions as 53 departments, and within those, 893 municipalities.

⁵The most common reason for a failure to match was a missing value for city of birth (2.5% of records). Thereafter the most common reason was because the child provided the name of a department (and that name was not also the name of a municipality in any department).

⁶Calculation in the Appendix.

Beyond this, the data on UACs' localities of origin report the city of birth, not city of last residence. This has the advantage that it captures effects of violence on children who are displaced within the country before they leave it, as is often the case. It has the disadvantage that it introduces measurement error in the case of children who first moved away from their city of birth for reasons other than violence, and were subsequently displaced by violence from their new home city.

The database on violence comprises municipality-by-year homicide counts 2009–2016 for all three countries. Because the panel for homicides extends two years further back in time than the panel for UAC apprehensions, this implies that one or two lags of homicides can be included in panel regressions without affecting the number of observations, whereas including three or more lags reduces the number of observations. Unemployment data are available in comparable form for all three countries for only two years in this period—2011 and 2014—and at the department level rather than the municipality level, as they are based on surveys only representative by department. Municipality-level data on income per capita, poverty fraction, adult illiteracy, school enrollment, overall population, and youth population change sufficiently slowly that, for a six-year study like this one, it is sufficient to use data from a single year: usually a year in the range 2009–2013, the same for all three countries for any given variable. Details of these data are in the Appendix.

The data on violence contain only data on homicides. Homicide statistics have two major advantages as an indicator of violent crime. First, homicides are much more likely to be recorded in official statistics than other types of crime. While crimes such as extortion or even kidnapping are often never reported to police, homicides are often recorded even if the crime itself is never reported by those affected—because data usually include information from coroners processing unidentified bodies. Second, homicide statistics are available at high levels of geographic disaggregation, whereas surveys on other types of crime victimization are only representative across broad regions. The important disadvantages of homicide data include their omission of other types of violent crime that could affect migration decisions, and their omission of people who disappear without any clear evidence of homicide.⁷

⁷In 2016 there were 5,280 homicides in El Salvador, and the National Civil Police of El Salvador reports 2,090 disappearances (Cidón 2017). Some disappearances are not homicides, and some disappearances that are homi-

For these reasons, in all results discussed here, the homicide rate should be considered as a proxy for overall levels of violent crime. There is evidence that it is an informative proxy for this purpose. Killings by violent gangs in Central America are closely associated with other crimes, particularly extortion (ICG 2017). Table 1 shows, using data from crime victimization surveys in the Northern Triangle, that reports of murders in respondents' neighborhoods are highly correlated with reports of other types of crime. For example, 47% of people reporting murders in their neighborhood also report extortion in the same neighborhood.

While recent increases in UAC apprehensions have occurred alongside intense violent crime in the countries of origin, there is no obvious relationship between the rate of increase of UAC apprehensions from a country and changes in the nationwide level of homicides in that country in the same year. Figure 2 shows recent trends in homicides and in UAC apprehensions for the countries of the Northern Triangle. Figure 2a shows that they have exhibited very high homicide rates, making the Northern Triangle one of the most violent regions on earth. While national homicide rates in the region range between roughly 40 and 100 (per 100,000 population per year), the corresponding rate for the United States is 4.9. But UAC rates have clearly not varied directly with contemporaneous homicide rates at the national level. UAC rates at the national level have steadily risen while homicide rates for the same years have fluctuated around high levels. Figure 2b shows the number of UAC apprehensions in the United States each calendar year. Figure 2c shows UAC apprehensions in the U.S. per 100,000 population in the origin country. To show the scale of UAC movement relative to the youth population, Figure 2d shows the UAC rate per 100,000 youths in the origin country (defined as age 8–17, measured in 2013).

Likewise, simple geographic correlation of UAC apprehensions and violence offers mixed indications about the drivers of UAC rates (Figure 3). Figure 3a shows the average homicide rate in 893 municipalities across the Northern Triangle during 2011–2016. Figure 3b shows the total number of UACs 2011–2016 (cumulative) originating in each municipality. There is evident overlap between some of the most violent municipalities of Honduras and the greatest numbers of UACs, but UACs also depart some of the least-violent areas of western Guatemala in large numbers. Figure 3c shows the average annual rate of UACs per 100,000 youths (age

cides are counted when unidentified bodies are discovered. Some disappearances that are homicides are either never reported at all, or are reported but never counted as homicides because no body is ever found.

8–17) in each municipality during 2011–2016, showing that some of the regions where any given youth is most likely to become a UAC (especially in the Sierra Madre de Chiapas mountains of northern El Salvador) do not exhibit the highest levels of violence.

4 The effect of violence on UAC apprehension rates

This study seeks better identification of the causal relationship between homicides and UAC apprehensions than is possible with national-level data by exploring the subnational relationship in a six-year panel. [Figure 4](#) shows the simple, bivariate relationships in the pooled data between key variables and the rate of UAC apprehensions. UAC apprehensions rise with the homicide rate. UAC apprehensions first rise, and then fall, with average income per capita. UAC apprehensions markedly fall with increasing poverty. These last two patterns, corroborated by the survey literature discussed above, suggest that access to credit and smuggling networks are binding constraints on the poorest residents of the region. But all of these bivariate relationships could be misleading; UAC rates could be higher in places with less poverty because those places are more violent. This section and the next will seek to sort out these causal pathways and competing explanations.

4.1 The homicide-migration relationship

A first approach to the data is simply to ask whether municipalities with higher rates of violence (homicides per 100,000 population, per year) exhibit higher rates of UACs (also expressed per 100,000 population per year). [Table 2](#), column 1 shows the simple regression of the UAC rate on the homicide rate, with all municipalities and years pooled. The correlation between UACs and homicides is positive and statistically significant, but could arise for a number of reasons other than an effect of violence on emigration.

The most obvious potential confounder is any time-invariant traits of different municipalities that could determine UAC rates, such as the initial extent of migrant networks, urbanization, poverty, ethnic mix, and country (or even population itself, which can generate spurious correlation as a common divisor of both the homicide rate and the UAC rate). The rest of the

table introduces fixed effects, using the specification

$$\dot{c}_{i,t} = \alpha + \beta' \mathbf{h}_{i,t} + \phi_i + \chi_t + \varepsilon_{i,t}. \quad (1)$$

where c is the stock of child migrants apprehended in the U.S. as a fraction of the home-area population and a dot denotes the time derivative; thus $\dot{c}_{i,t}$ is the rate of apprehensions in the United States in year t of unaccompanied children from municipality i per 100,000 population of that municipality; $\mathbf{h}_{i,t}$ is a vector of the K current and lagged homicide rates in municipality i per 100,000 population; ϕ_i are municipality fixed effects; χ_t are year fixed effects; β' is a vector of K coefficients and α a coefficient to be estimated, and $\varepsilon_{i,t}$ is an error term.⁸

Column 2 of the table introduces municipality fixed effects ϕ_i only. With this change, the coefficient rises from 0.45 to 0.61. This indicates that cross-municipality differences in observed or unobserved time-invariant traits are not driving the correlation in column 1. The rise of the coefficient when between-group effects are eliminated implies that UACs do not, on average, tend to depart in relatively greater numbers from places that are persistently violent, but rather from places that have experienced recent increases in violence. Columns 3, 4, and 5 progressively add lags of the homicide rate, and the last row of the table presents the sum of the coefficient estimates on current and all included lags of homicides, $\sum_{k=0}^K \hat{\beta}_k$ (and its standard error).

Another important potential confounder could be conditions that varied over time for all countries equally, such as policy changes in the United States, the expansion of smuggling routes in Mexico and from there into the United States, or the world price of cocaine. Columns 6 through 9 thus repeat the regressions with year fixed effects χ_t added alongside the municipality fixed effects. The coefficients shrink by roughly one tenth of their magnitude, indicating that changes over time common to the whole Northern Triangle are not driving the homicide-UAC relationship.

With three lags of the homicide rate included (Table 2, column 9), the sum of the coefficients on the homicide rates rises to 0.928 and is statistically significant at the 1% level. This repre-

⁸Here and below, tables show [Liang-Zeger \(1986\)](#) standard errors clustered by municipality, to allow for arbitrary structure and degree of serial correlation.

sents the number of UACs from the average municipality in a given year caused by a sustained increase of one in the number of homicides per year in that municipality—that is, an increase that is sustained over the previous three years as well as during the current year. Put differently, the result implies that it takes an increase of 1.08 homicides per year on average ($1/0.928$), sustained across four years in child migrants' municipalities of origin, to cause one additional UAC apprehension in the United States. If that increase is sustained thereafter it continues to cause one additional UAC apprehension every year on average.

Figure 5 shows graphically the result in Table 2, column 9. It is a plot of predictive marginal effects from a sustained change in the homicide rate (that is, a change for all years from $t - 3$ through t) on the contemporaneous UAC rate (at t). The horizontal and vertical dotted lines show the sample mean homicide rate and UAC rate, respectively.

4.2 Nonlinearities and influential observations

The estimates in Table 2 could be sensitive to influential observations—municipality-years with extraordinary numbers of UACs, homicides, or both—or to the imposition of a linear functional form. Figure 6 presents semiparametric fixed-effects regressions of the contemporaneous UAC rate on each current or lagged homicide rate in isolation (unconditional on other lags), using the Robinson (1988) double-residual method controlling for municipality fixed effects. The bandwidth is 50 homicide rate-points, but comparison of this figure to Figure 5 suggests that the overall slope of the semiparametric relationship does not greatly differ from the slope with a linear relationship imposed. This suggests that the estimates in Table 2 are not driven by outlying influential observations.

That said, there is notable nonlinearity in the relationship: the slope markedly rises at higher (conditional) homicide rates. The figures suggest that above a homicide rate of 100, the marginal relationship between homicide and UAC rates is roughly 3–4 times what it is below a homicide rate of 100. In other words, where the linear relationship suggests that a three-year sustained increase in the homicide rate of 1 causes ~ 0.9 additional UAC arrivals, the local coefficient may be closer to ~ 0.5 for municipalities below a homicide rate of 100 and closer to ~ 1.5 – 2.0 for municipalities above a homicide rate of 100.

4.3 Unobserved common trends

An important robustness check on the results above is to investigate whether the homicide-migration relationship arises spuriously from unobserved common shocks. It is possible in principle that some unobserved trend, affecting different localities to different degrees, drives both homicides and UAC apprehensions independently. For example, areas experiencing economic decline could both experience increases in gang recruitment and thus violence, and experience rising child emigration—but due the economic decline rather than the violence.

[Table 3](#) employs two stringent robustness tests for unobserved common shocks. The first four columns transform the fixed-effects model (1) into a multilevel model with random municipality-specific time trends,

$$\hat{c}_{i,t} = \alpha + \beta \mathbf{h}_{i,t} + \phi_i + \omega_i t + \varepsilon_{i,t}, \quad (2)$$

where the coefficient on year t is the municipality-specific $(\omega^0 + \omega_i^1)$, with ω_i^1 assumed random and normally distributed. As before, the bottom row of the table sums the coefficients on lagged homicides, and shows the standard error of the sum. We should expect the homicide-migration relationship to fall in magnitude, since in this specification we are controlling away part of the relationship of interest: for example, a municipality-specific time trend in gang penetration that results in more UAC migration is controlled away. But it should be concerning if municipality-specific linear time trends absorb most or all of the homicide-migration relationship. They do not: in [Table 3](#) the relationship diminishes by about a third of the coefficient magnitude relative to [Table 2](#).

Municipality-specific linear time trends are a special case of the more flexible Interactive Fixed Effects (IFE) estimator ([Totty 2015](#)), developed by [Bai \(2009\)](#) and implemented by [Gomez \(2015\)](#). This specification allows any form of time-varying omitted factor with municipality-specific consequences:

$$\hat{c}_{i,t} = \alpha + \beta \mathbf{h}_{i,t} + \phi_i + \lambda_i' \mathbf{F}_t + \varepsilon_{i,t}, \quad (3)$$

where λ'_i are municipality-specific factor loadings and F_t are unobserved time-specific common factors in each period. Unlike (2), this specification allows the data to determine the form of the common shock F_t and the spatial correlation in λ_i .

The remaining columns of Table 3 apply the IFE estimator for a single factor to the same regressions as above. The summed homicide effect at the bottom of the table loses about 40% of its magnitude relative to Table 2 (0.928 to 0.575), but remains statistically significant. Here again the robustness test is demanding: the time-varying unobserved factors that are being controlled away could well include much of the relationship of interest, such as the growing penetration of drug trade routes and gang presence into the country and its heterogeneous effects on violence in different municipalities. The fact that the homicide-migration relationship retains statistical significance and much of its magnitude in the presence of these controls implies that the relationship does not spuriously arise from common trends in both violence and migration arising from unobserved changes independently driving both over time.

4.4 Flexible nationwide or department-wide unobserved shocks

An even more stringent test is to control for all possible countrywide or department-wide time-variant confounding shocks, by adding country-by-year fixed effects or department-by-year fixed effects. Country-by-year fixed effects would account for a country-specific shock in any year, such as Guatemala's 2015 political crisis. Department-by-year fixed effects would account for any form of department-level economic shock by year, such as poor employment conditions in any department-year.

Here again we should expect the magnitude of the relationship between violence and migration to decline, because much of the relationship of interest is being controlled away. For example, some of the arbitrary department-specific shocks could include the violence produced by a sudden conflict between violent gangs and cartels in particular departments; violence in one municipality can have spilled over from violence in other municipalities of the same department; and the migration of children in one municipality could be affected by violence in the rest of that municipality's department. Because violence comes in both spatial and temporal clumps, we should not interpret the coefficients in these highly saturated models as estimat-

ing the true relationship between violence and migration, but as representing the relationship between violence that is exclusively local—occurring in that municipality but nowhere else in the department.

[Table 4](#) accounts for any country-specific shocks that affect UAC migration in all municipalities equally (cols. 1–4) and any department-specific shocks that affect UAC migration in all municipalities equally (cols. 5–8). In these final columns the entire effect of homicides on UAC migration is being identified by intra-departmental, intra-year variance in homicide rates across municipalities. If these highly saturated models were to fully absorb the homicide-migration relationship this would be concerning. It would suggest that the violence-UAC relationship arises only due to correlations over broad geographic areas, possibly driven by unobserved confounders, since many outbreaks of violence are highly localized.

But the statistical significance and roughly one third of the magnitude of the homicide effect from [Table 2](#) survives in the most saturated model of [Table 4](#) (last column, bottom row), again suggesting the robustness of the core result. It suggests that the core result does not arise spuriously from changing economic conditions at the department level that are caused by or happen to coincide with violence, but from violence itself. It accords with the observation that outbreaks of violence are often much greater in some municipalities of a given department than others, whereas intradepartmental variance in employment conditions is rarely as large, given the ability of workers facing poor employment conditions in one municipality to work in a nearby municipality.

5 Migration waves

While the evidence above suggests a strong causal relationship between violence at the origin and UAC apprehension rates, it leaves unanswered a question of research and policy interest. If violence is an important cause of UAC apprehensions, why did UAC apprehensions rise greatly and steadily in the years after 2011 ([Figure 2b](#)), when national-level homicide rates did not ([Figure 2a](#))? This section models and tests the role of network diffusion in producing ‘snowballing’ or waves of migrants.

5.1 A model of migration and network diffusion

The qualitative survey literature discussed above makes it clear that potential UACs rely heavily on the migration experience of those in their family and social networks in considering the decision to move. [Holland and Peters \(2017\)](#) build a political theory in which migrant waves can arise through diffusion of information through social networks, even without a large change in the contemporaneous fundamental drivers of migration, and offer evidence of such waves in the Middle East. This suggests that some portion of current UAC migration could arise because past homicides drove both the creation of migrant networks that facilitate current migration *and* current homicides through persistence of homicides, but not strictly because current homicides cause current UAC migration.

This section explores the role of networks by modeling the relationship between migration, overseas networks, and mortality risk with a continuous-time discrete choice model. The canonical search model of this type is due to [McCall \(1970\)](#) and [Mortensen \(1970\)](#) (surveyed by [Rogerson et al. 2005](#); [Abbring 2010](#)). It has been applied to describe migration first by [David \(1974\)](#) and subsequently in a long literature surveyed early by [Molho \(1986\)](#) and recently by [Faggian \(2014\)](#).

Consider families deciding about the welfare of younger children, or older children deciding about their own welfare. Suppose that children, when they become workers, can earn wage $w > 0$ in the home country or earn $w^* > w$ abroad. In each period they have probability $0 \leq \theta < 1$ of receiving migration assistance from a relative abroad, as capital or information. Workers who receive assistance always migrate. If they do not receive assistance, they decide whether to remain in the home country and face mortality risk $0 \leq \mu < 1$, or emigrate and pay migration cost $\kappa > 0$. Migration is irreversible and the interest rate is r . In the stationary state, the discounted expected utility of a migrant (V^*) is related to that of a non-migrant (V) by the Bellman equation

$$V^* = \frac{1}{1+r} (w^* + V^* - r(\kappa - \mu V)). \quad (4)$$

The first two terms in the right-hand sum indicate that the following period, a migrant will retain the future flow of foreign benefits and will have earned one period of the foreign wage.

The last term reflects the per-period opportunity cost from paying the migration cost and the per-period benefit of saving oneself from the (capitalized) expected loss due to home-country mortality (μV).

Suppose that a non-migrant without family assistance chooses to migrate if the mortality risk μ exceeds some critical value $\tilde{\mu}$. The non-migrant's Bellman equation is

$$V = \frac{1}{1+r} \left(w + \theta V^* + (1-\theta) \left[\int_0^{\tilde{\mu}} V d\Psi(\mu) + \int_{\tilde{\mu}}^1 V^* d\Psi(\mu) \right] \right), \quad (5)$$

where $\mu \sim \psi(\mu)$ with cumulative distribution $\Psi(\mu)$. Define the expected mortality risk above the critical mortality level as $\bar{\mu} \equiv E[\mu \mid \mu > \tilde{\mu}]$ and below the critical level as $\underline{\mu} \equiv E[\mu \mid \mu \leq \tilde{\mu}]$. Finally, use $W^* \equiv \frac{w^*}{r} - \kappa$ as shorthand for the capitalized net economic gain from migration. Equations (4) and (5) give⁹

$$\tilde{\mu} = \frac{w}{w + W^*(1+\theta)} + \frac{W^*(\theta \underline{\mu} + \bar{\mu} - r)}{w + W^*(1+\theta)}, \quad (6)$$

which defines $\tilde{\mu}$ only implicitly, since $\bar{\mu} = \bar{\mu}(\tilde{\mu})$ and $\underline{\mu} = \underline{\mu}(\tilde{\mu})$. The first term on the right side of equation (6) reflects the basic intuition that as the home wage w rises relative to the benefits of migration (W^*), workers tolerate greater risk in the home country and the critical risk rises. The second term captures feedback effects: as the migration cutoff changes, so does the risk faced by the average non-migrant ($\underline{\mu}$) and the risk that would have been faced by the average unassisted migrant had they not migrated ($\bar{\mu}$)—both of which shape the net benefits of migration.

The net instantaneous static effects in equation (6) can be determined with the implicit function theorem, yielding $\frac{\partial \tilde{\mu}}{\partial w} > 0$, $\frac{\partial \tilde{\mu}}{\partial w^*} < 0$, and $\frac{\partial \tilde{\mu}}{\partial \kappa} > 0$. As the home wage rises and migration gets more costly, workers tolerate more risk in the home country, while as the foreign wage rises they tolerate less risk. The sign of $\frac{\partial \tilde{\mu}}{\partial \theta}$ is indeterminate.

The dynamics of migration behavior emerge from the two-part stopping rule specified above: workers migrate when assistance is offered by family abroad *or* when their mortality risk

⁹What follows is derived in the Appendix.

exceeds the critical value. The migration hazard rate is thus

$$\frac{f(t)}{\phi - F(t)} = \theta + (1 - \Psi(\mu)) - \theta(1 - \Psi(\mu)), \quad (7)$$

where $f(t)$ is the probability that a person migrates in period t conditional on not having yet migrated, $F(t)$ is the corresponding cumulative distribution function, and $0 \leq \phi < 1$ is the maximum fraction of the population willing to migrate at any time.¹⁰

The problem becomes empirically tractable with three assumptions imposed on (7). First, the probability of migration assistance from a relative abroad is proportional to the fraction of possible migrants who have migrated: $\theta \equiv \alpha \frac{F(t)}{\phi}$, where $\alpha > 0$. Second, the probability that a representative migrant's expected risk of death exceeds the critical risk is proportional to the average homicide rate h : $(1 - \Psi(\mu)) \equiv \beta h$, where $\beta > 0$. Third, neither θ nor $(1 - \Psi(\mu))$ is large, thus $\theta(1 - \Psi(\mu)) \approx 0$. Equation (7) then reduces to

$$\frac{\dot{c}_t}{\phi - c_{t-1}} = \frac{\alpha}{\phi} c_{t-1} + \beta h_t, \quad (8)$$

where c is the stock of child migrants as a fraction of the home-area population and a dot denotes the time derivative. This is the well-characterized model of innovation diffusion called the “mixed-influence” model by [Mahajan and Peterson \(1985\)](#).¹¹ As in the earlier logistic (Verhulst) and Gompertz models, the rate of diffusion is proportional to the number of potential adopters remaining; but unlike those other models, the “mixed-influence” model accounts separately for two different influences on diffusion.

The first term of equation (8) captures “internal influence”, when previous adopters of an innovation cause new adoption—in the present case, prior migrants inspire, inform, and assist new migrants in a snowball effect. The second term captures “external influence” on diffusion—in the present case, an exogenous shock to mortality risk encourages migration independently of the snowball effect. Equation (8) implies that if network diffusion is a major determinant

¹⁰In general, the probability of event A or event B occurring is $\Pr(A \cup B) \equiv \Pr(A) + \Pr(B) - \Pr(A \cap B)$.

¹¹Often called the [Bass \(1969\)](#) model in management science, but closely related to prior models in economics ([Mansfield 1961](#)), sociology ([Coleman 1964](#)), and communications ([Taga and Isii 1959](#)). The economic innovation of Bass was to give a theoretical account of the “external influence” parameter ([Rossman et al. 2008](#)). [Moretto and Vergalli \(2008\)](#) calibrate a mixed-influence diffusion model with migration data.

of UAC migration, the analysis can improve on the empirical model in (1) by controlling for *past* UAC migration at the local level, and its interaction with *current* violence.

5.2 Estimates of the network diffusion channel

Table 5 explores the role of network diffusion predicted by equation (8). Column 1 simply repeats Table 2, column 9 for comparison. The next column adds a control for the pre-existing stock of UAC apprehensions $c_{i,t-1}$.¹² Column 3 proceeds to include an interaction term between homicides and the prior UAC stock. Both the prior stock and the interaction term are statistically significant at the 1% level. The coefficient on the prior stock, 0.198, implies that an increase in the stock of prior UACs from a municipality of five children raises the per-year flow of new UACs by one. This, and the coefficient on the interaction term, imply that in an average municipality with a homicide rate of 100 (a little over double the average), the coefficient on the prior stock would be $0.198 + (100 \times 0.000642) = 0.262$. In other words, in a typical municipality with double the average homicide rate, it only takes an increase of four in the stock of previous UACs to raise the per-year flow of new UACs by one.

The results are similar when prior UAC migration is measured by the lagged flow rate (\dot{c}_{t-1}) rather than by the lagged stock (c_{t-1}), in columns 4 and 5. This suggests the important role of cumulative previous flows in shaping current flows. Because all of these regressions include municipality fixed effects, there is the potential for Nickell’s (1981) dynamic panel bias. The last column of the table therefore uses the Arellano-Bond (1991) panel estimator to instrument for the lagged change in UAC flow with higher-order lagged levels of UAC flow. The results change little, suggesting that dynamic panel bias is not substantial in the rest of the table.

Table 5 also tests the relative importance of violence and network diffusion in shaping current UAC flows. In the last row of the table, which sums the coefficients on homicides, the effect of violence falls by one third (from 0.928 to 0.624) between columns 1 and 2. Thus implies that about one third of the apparent effect of current violence acts through the facilitation of current UAC flows by past UAC flows—that were in turn created by past violence. This offers

¹²Here, the prior stock $c_{i,t-1}$ is estimated as the sum of all UAC apprehensions from municipality i in all years from the beginning of the panel up to and including year $t - 1$.

a partial answer to the question of why UAC flows responding to violence could increase over time disproportionately to increases in current violence. It implies that UAC migration is a self-reinforcing ‘snowball’ phenomenon: It is affected by current violence, but once begun it can continue in part from the inertia created by network effects. This simple model of violence and network diffusion explains most of the variance in UAC flows across municipality-years: overall R^2 ranges from 0.53 to 0.59. Within-municipality R^2 ranges from 0.44 to 0.46.

6 Security versus economic motives

A further question of both research and policy interest is the relative importance of violence and economic conditions in determining movement by UACs. This section constructs various tests of this type. The interpretation of these tests should be delimited by the inability of any summary statistic to fully capture either the relevant forms of violence or the relevant economic conditions.

[Table 6](#) tests how the relationship between violence and UAC migration at the municipality level is altered by controlling for unemployment at the departmental level.¹³ Unemployment is measured in all three countries by national sample surveys that are representative at the departmental level only; and only in two years of the period of interest are such surveys available for all three countries: 2011 and 2014. Column 1 shows pooled Ordinary Least Squares for the 893 municipalities in two years, and column 2 adds a control for the departmental unemployment rate.¹⁴ The coefficient on unemployment is positive, indicating that UACs have a greater tendency to leave municipalities in departments with high unemployment. But the coefficient estimate on homicides barely changes, suggesting that the link between UAC migration and violence does not arise spuriously from a spatial correlation between violence and poor labor market conditions. This accords with previous evidence in [Table 4](#).

¹³Specifications in [Table 2](#) with year fixed-effects control for changing economic conditions at the national level, such as increases in the nationwide unemployment rate. However nationwide economic shocks can affect different regions differently. The Appendix compares the nationwide unemployment rate to the departmental unemployment rates in Honduras, 2007–2014. There is high variance of the departmental rates around the nationwide rate, both in levels and changes. In 2014 the nationwide rate was 5.0% but departmental rates ranged from 1.2% to 7.0%. From 2013 to 2014 the nationwide change in the unemployment rate was +1.1% but the departmental changes ranged from –0.6% to +4.1%.

¹⁴In Honduras the official unemployment rate covers workers age 10+, whereas in Guatemala and El Salvador it covers age 12+.

Columns 3 and 4 of [Table 6](#) repeat the same pair of regressions adding municipality fixed effects. The coefficient on homicides does not substantially change, but the coefficient on departmental unemployment becomes statistically insignificant. This suggests that the positive relationship between unemployment and UAC migration in column 2 arises because other time-invariant traits of municipalities cause them to have persistently high unemployment, not due to short-term (three-year) shocks to unemployment.

The preceding analysis suggests that the principal variance in important economic determinants of UAC migration may occur across space rather than over time. That is, UACs may primarily leave places where their concerns about the future are long-term rather than short-term. [Table 7](#) tests the relative importance, in cross-section, of recent changes in homicide rates and other municipality traits related to economic development: average income per capita (2009 US\$ at Purchasing Power Parity); poverty rate (fraction, by national poverty line, 2007); adult illiteracy (% , 2009); and the child school enrollment rate.¹⁵ It reports cross-sectional regressions of the form $\tilde{c}_i = \alpha + \beta \Delta h_i + \gamma' \mathbf{X}_i + \varepsilon_{i,t}$, where \tilde{c}_i is cumulative total UAC apprehensions 2011–2016 from municipality i per 100,000 population, Δh_i is the mean across years of the change in the homicide rate of municipality i during the preceding three years, and \mathbf{X}_i is a vector of development traits x_i .

[Table 7](#), column 1 reports a coefficient on the homicide rate similar to the magnitude implied by the coefficient estimates in [Table 2](#) (recall that here the outcome is *cumulative* UAC apprehensions per 100,000 population 2011–2016, not apprehensions in a single year). A sustained increase of one homicide per year causes 3.8 cumulative total UAC apprehensions from that municipality over the whole period under study. The partial correlation of the UAC rate and income per capita is negative but statistically insignificant. The partial correlation of UAC rates with the poverty rate is negative, as in the bivariate plot in [Figure 4](#). The regressions control for the size of the overall population and the youth population (age 8–17) specifically.

¹⁵The school enrollment rate used here proxies for gross enrollment but is not identical to it. It is simply the ratio of the total number of people enrolled in grades 1–9 collectively in each municipality, to the total number of people in the municipality age 8–17. This is for reasons of census data availability; strictly speaking, gross enrollment for these grades should be calculated with the number of children age 6–15. That said, the measure calculated here is a close proxy for true gross enrollment. The regressions in [Table 7](#) must be run in cross-section because all development indicators are available at municipal-level disaggregation for only a single year during the period of interest—innocuous in this setting because they change little over a six-year period. The reference year for development indicators is deliberately chosen to be in a year early in or prior to the period 2011–2016 so they are mostly or entirely predetermined, not affected by high UAC rates.

The table reports, in square brackets below each coefficient estimate, the Shapley value of each estimate (Huettner and Sunder 2012). This is the percentage of the total explanatory power of all included regressors that arises from each regressor. Thus for example the explanatory power of the change in the homicide rate (21.4%) is similar to the explanatory power of the relative size of the youth population (21.1%).

Column 2 of Table 7 adds interaction terms between the homicide rate and income per capita, and between the homicide rate and the poverty rate. The negative coefficient on the interaction with income implies that the effect of homicides on UAC apprehensions is relatively lower in areas with higher *average* incomes, all else equal. The negative coefficient on the interaction with poverty implies that the effect of homicides on UAC apprehensions is relatively lower in areas where poverty is greater—such as where large marginalized communities lack access to smuggling networks—all else equal. Column 3 shows that all of these findings are robust to controlling for further indicators of the overall level of development: the adult illiteracy rate and the child school enrollment rate.

The Shapley values of Table 7 are informative about the overall relative importance of homicides and economic conditions as drivers of UAC migration. In column 3, 12.2% of the explanatory power of the regressors comes from homicides alone, an additional 25.3% (11.1 + 14.2) comes from the interaction of homicides with basic economic conditions, and 35.3% (3.1 + 15.5 + 15.1 + 1.6) comes from conditions of economic development in isolation. This allows the broad conclusion that violence and the interaction of violence with economic conditions together explain roughly as much of UAC rates at the municipal level as do economic conditions by themselves.

We can decompose this relative importance not just for the dataset overall, but for each municipality. One of many ways to spatially decompose the relative contributions of security and economic determinants of UAC rates is to use the coefficient estimates in Table 7, column 1 to calculate for each municipality the difference

$$\delta_i \equiv \left| \hat{\beta} (\Delta h_i - \overline{\Delta h}) \right| - \left| \hat{\gamma}_{\text{inc}} (x_{\text{inc},i} - \bar{x}_{\text{inc}}) + \hat{\gamma}_{\text{pov}} (x_{\text{pov},i} - \bar{x}_{\text{pov}}) \right|, \quad (9)$$

where an overbar indicates the cross-section mean of the regressor. For a given municipality, the difference $\bar{\delta}_i$ is greater than zero if recent changes in that municipality's homicide rate are predicted to have a larger effect on its UAC rate than its income per capita and poverty rate, given the coefficient estimates for the entire Northern Triangle. [Figure 7](#) maps the values of $\bar{\delta}_i$ across the region for the period 2011–2016. Bright red areas show $\bar{\delta}_i \gg 0$, where recent changes in the homicide rate are predicted to determine much more of the UAC rate than economic factors. Light red areas show $\bar{\delta}_i \approx 0$, where homicide shocks and economic traits are predicted to weigh roughly equally. Green areas show $\bar{\delta}_i \ll 0$, where recent changes in the homicide rate are predicted to determine much less of the UAC rate than economic factors. In Honduras, homicides are predicted to be the dominant explanation in San Pedro Sula and large swathes of the coast and border regions with Guatemala and Nicaragua. In Guatemala, homicides are predicted to be the dominant explanation in many coastal and border municipalities as well as much of the north. In El Salvador, homicides are predicted to outweigh economic determinants in some of the most violent southern coastal areas.

An alternative spatial decomposition of interest is shown in [Figure 8](#). This displays schematically the relative predicted change in UAC apprehension rate per unit change in the homicide rate, for each municipality. That is, this map shows

$$\frac{\partial \bar{c}_i}{\partial h_i} = \hat{\beta} + (\hat{\gamma}_{x_{\text{inc}} \times h})x_{\text{inc},i} + (\hat{\gamma}_{x_{\text{pov}} \times h})x_{\text{pov},i}, \quad (10)$$

where $\hat{\beta}$ is the coefficient on Δh and $\hat{\gamma}_{x_{\text{inc}} \times h}$ and $\hat{\gamma}_{x_{\text{pov}} \times h}$ are the coefficient estimates on the interaction terms in [Table 7](#), column 2. The decomposition model predicts that a given decline in the homicide rate will cause a relatively greater decline in the UAC rate in, for example, areas in and around Guatemala City and San Salvador, but relatively less in Tegucigalpa and many rural areas. This prediction arises because relatively high incomes and low poverty in and around Guatemala City and San Salvador give potential UACs better access to migration as a response to violence.

7 Discussion

This evidence implies that violence can be a major determinant of international migration from poor regions, interacting in complex ways with economic determinants of migration as well as prior migration flows. The analysis finds that an increase of one homicide per year in the Northern Triangle sustained over four years caused about 0.9 additional Unaccompanied Child migrant apprehensions in the United States in any given year between 2011 and 2016. Extensive robustness checks indicate that the relationship increases at higher levels of violence, and that the core finding is not driven by confounding with department-level economic shocks, influential outliers, or unobserved regionwide shocks. The relationship is substantially unchanged when time trends of arbitrary form are included; this implies that the violence-migration relationship was driven by events in the region and was unaffected by changes in U.S. immigration policy during the period.

The analysis finds that changes in homicide rates have persistent effects on UAC rates. Homicides in a given year have detectable effects on UAC apprehensions several years later. This occurs through three channels: a direct effect; an indirect effect because homicides in a given year also beget future homicides which then separately affect UAC rates; and a second indirect effect because homicides in a given year raise UAC rates in that year, and UAC rates snowball over time. About one third of the relationship between violence and UAC migration in a given year is driven by these snowball effects, in which past migration due to past violence facilitates current migration. This implies that sustained reduction in the pressure for child migration will require sustained reductions in homicide rates.

A further finding is that short-term economic shocks, such as a three-year rise in overall unemployment, did not affect UAC rates between 2011 and 2014. UAC rates are higher for places that have persistently higher unemployment rates, but not higher for places that—holding constant their long-term characteristics—experience short-term negative economic shocks. UAC rates are also not relatively higher on average in places with persistently high homicide rates, but in places that have experienced recent increases in the homicide rate. The principal drivers of UAC decisions therefore appear to be short-term shocks to violence

(not long-term geographic patterns of violence) together with long-term economic forces (not short-term economic shocks).

The findings on the economic determinants of UAC apprehensions suggest the complexity of development and migration. UAC migration is much higher in municipalities with *lower* poverty rates, all else equal, as well as modestly higher in municipalities with higher average incomes. These results might seem counterintuitive without the context of prior research findings that access to smuggling networks, family connections abroad, and the ability to finance the journey are major determinants of unauthorized migration by both children and adults. The patterns observed here are compatible with a model in which violence creates a strong impetus for child migration, an impetus to which relatively better-off families are able to be more responsive: those who have higher aspirations, more access to financial and practical assistance from abroad, and more domestic access to finance and smugglers. This suggests that further economic development without lasting reductions in violence is unlikely to reduce pressure for UAC migration.

These findings suggest that overseas policies by migrant-destination countries can shape migration, including economic migration, through their effect on violence (Keefer et al. 2010). The United States targets foreign assistance activities at parts of Central America that are the most violent and are the origins of intense emigration (GAO 2013). Aid policy interventions designed to reduce violence are a subject of active experimentation and research (Muggah and Aguirre 2013; Moestue et al. 2013; Berg and Carranza 2015; USAID 2016; Chioda 2017). There is rigorous evidence that aid interventions to improve local service provision reduced violent insurgency in Iraq (Berman et al. 2011)—though related measures in the Philippines may have sparked short-run violent countermeasures by organized criminals (Crost et al. 2014), and Nunn and Qian (2014) find that food aid can increase violence in some conflict settings. A randomized evaluation of one community-based crime and violence prevention project in the Northern Triangle supported by U.S. foreign assistance found that it reduced neighborhood-level reports of homicides by 50% (Berk-Seligson et al. 2014).¹⁶ The causal links between such interventions and violence, together with the causal link between violence and child mi-

¹⁶The policy intervention by the Central America Regional Security Initiative, which was also carried out in Panama, is a complex mix that includes environmental redesign (such as street lighting), youth programs (such as workforce development and mentorships), and community policing.

gration, suggest that policies favoring the prevention of violence can have important effects on child migration in this region.

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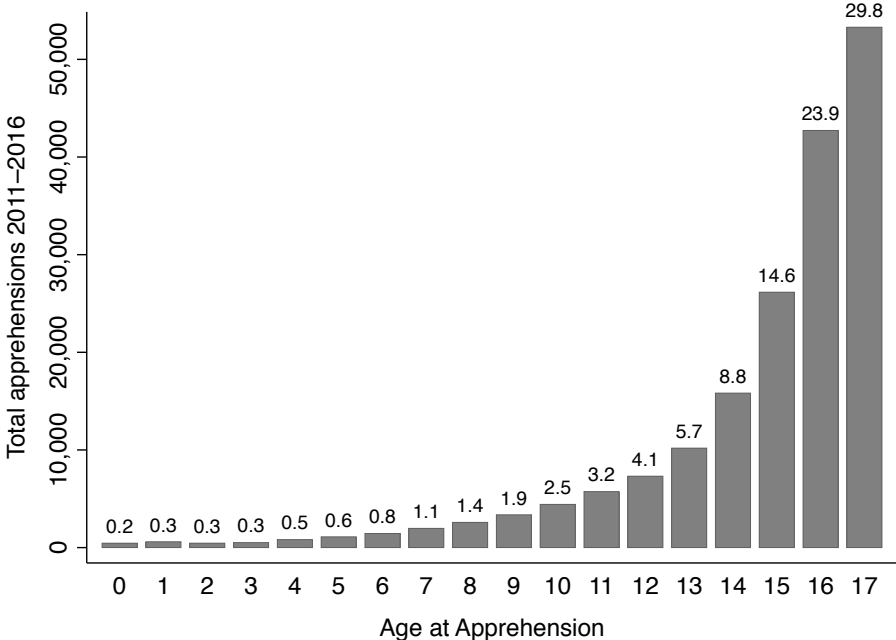
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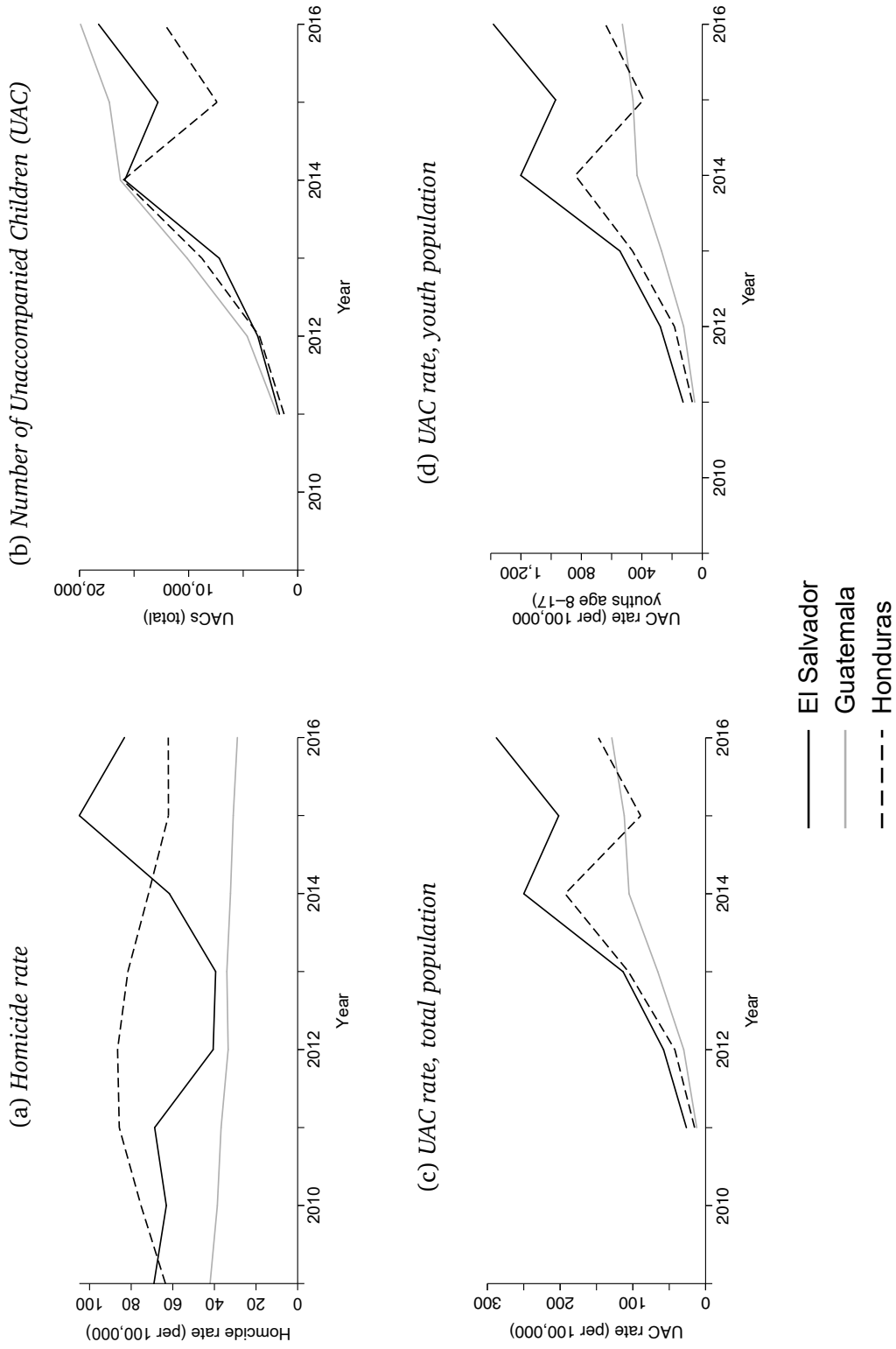
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Figure 1: AGE DISTRIBUTION OF UNACCOMPANIED CHILDREN FROM THE NORTHERN TRIANGLE



Bars labeled with percent of total. Numbers of UACs are cumulative total for the universe of United States apprehensions of UACs from Guatemala, Honduras, and El Salvador in calendar years 2011–2016.

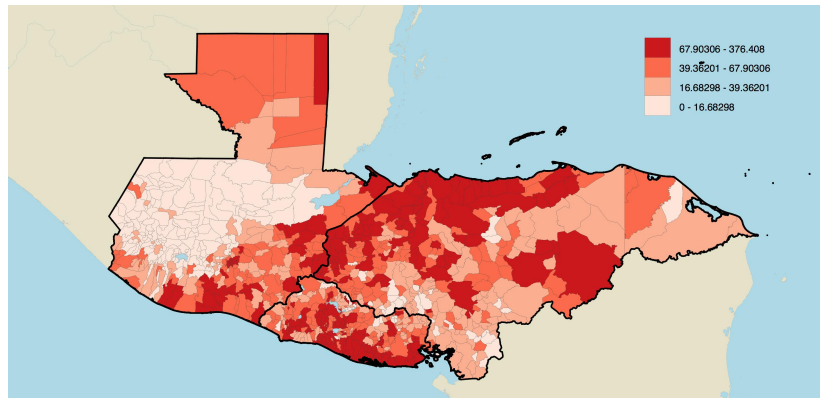
Figure 2: HOMICIDES AND UNACCOMPANIED CHILD MIGRANTS IN THE NORTHERN TRIANGLE



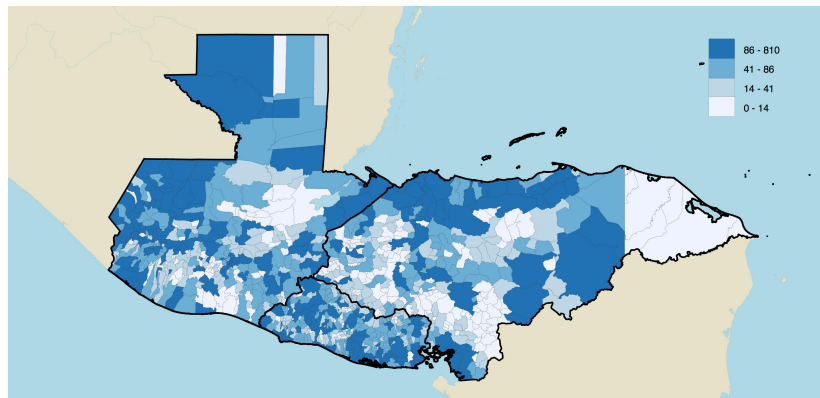
UAC data show the full universe, not only the children who could be matched to a municipality of origin. National population size in denominator of each rate is measured at 2013.

Figure 3: SPATIAL DISTRIBUTION OF HOMICIDES AND UNACCOMPANIED CHILD ORIGINS

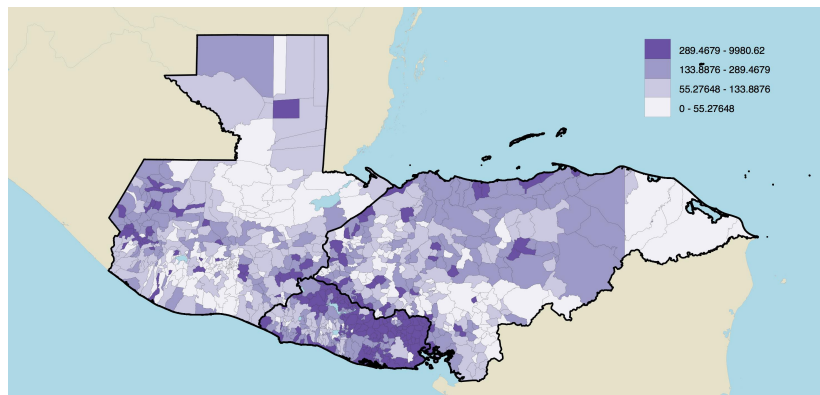
(a) *Homicide rate, per 100,000 population, average 2011–2016*



(b) *UAC total, cumulative 2011–2016*

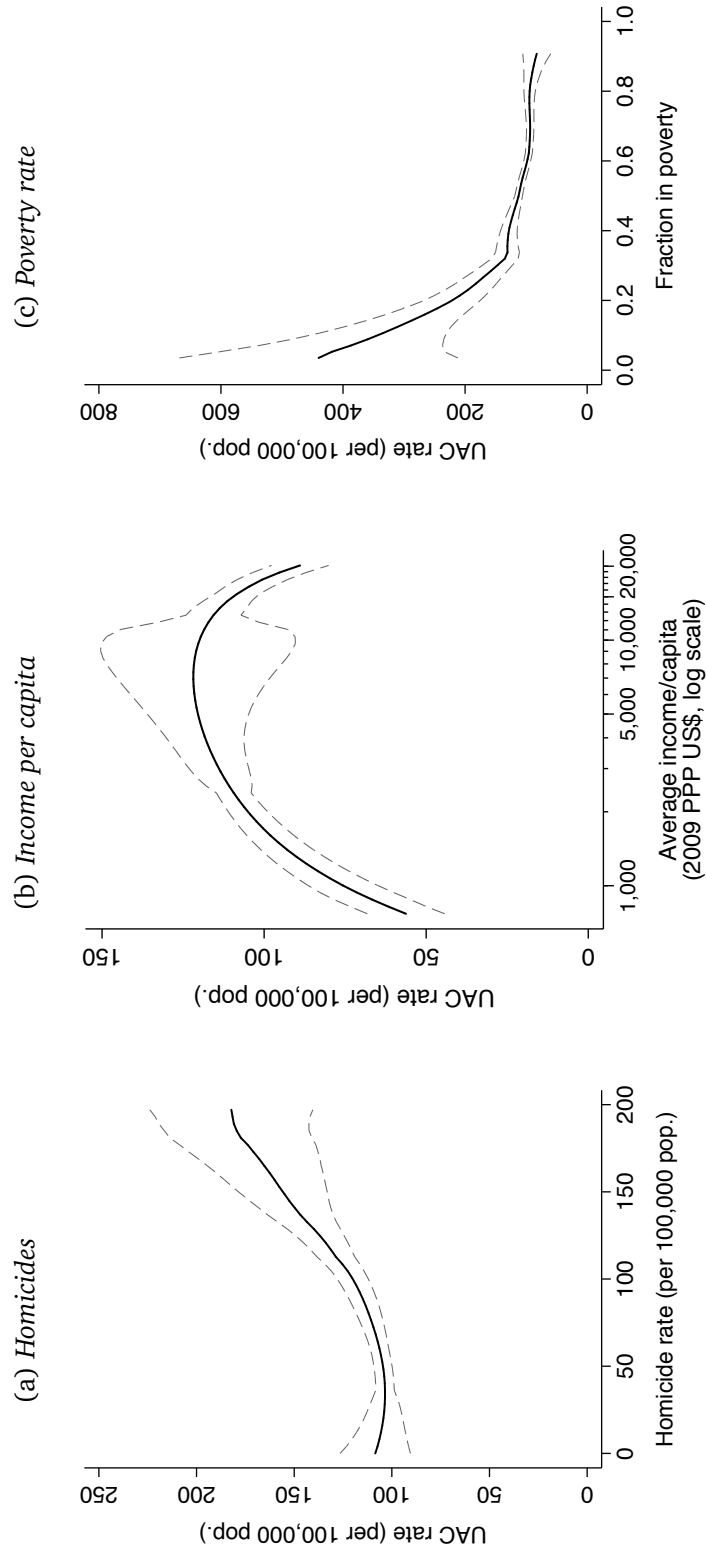


(c) *UAC rate, annual per 100,000 youths, average 2011–2016*



*Youths' defined as population age 8–17.

Figure 4: BIVARIATE RELATIONSHIPS WITH UAC RATE IN POOLED DATA



Local linear regressions with 95% confidence interval, Epanechnikov kernel. Bandwidths: homicides 50; inc./cap. 1.2 natural log points; poverty fraction 0.1. Data pooled across municipality-years. Average income per capita is estimated in 2009 (in 2009 PPP US\$). Poverty fraction estimated in 2007, at national poverty line.

Table 1: CORRELATION OF CRIME VICTIMIZATION WITHIN FAMILIES AND NEIGHBORHOODS(a) *Family-level crime experience*

	Murder	Extortion	Burglary	Kidnapping
Murder	1.000			
Extortion	0.077	1.000		
Burglary	0.074	0.084	1.000	
Kidnapping	0.174	0.064	0.102	1.000

(b) *Neighborhood-level crime experience*

	Murder	Extortion	Burglary	Drug sales
Murder	1.000			
Extortion	0.471	1.000		
Burglary	0.512	0.468	1.000	
Drug sales	0.477	0.482	0.486	1.000

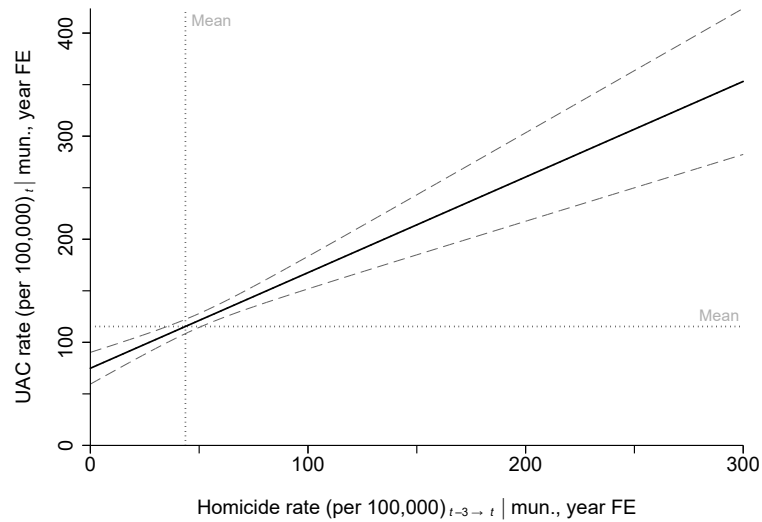
All correlations shown are significant at the 1% level. Pooled data from Latinobarómetro surveys 2008, 2010, 2012, and 2014 in Guatemala, Honduras, and El Salvador. 18,562 observations, correlations weighted by sampling weight. Variables are 0 if the respondent reports no incidence of each crime in their family or neighborhood, 1 otherwise. Family-level questions: Murder: “¿Algún pariente o persona que vivía en la casa con usted fue asesinada en los últimos doce meses? in the past 12 months?” Extortion: “¿En los últimos doce meses, ha sido usted víctima de un chantaje, extorsión o renta?” Burglary: “¿Se metieron a robar en su casa en los últimos doce meses?” Kidnapping: “¿Fue usted o algún pariente que vive en su hogar víctima de un secuestro en los últimos doce meses?” Neighborhood-level questions: Murder: “¿Han ocurrido asesinatos en los últimos 12 meses en su barrio/colonia?” Extortion: “¿Han ocurrido extorsiones o cobro de impuesto de guerra en los últimos 12 meses en su barrio/colonia?” Burglary: “¿Han ocurrido robos en los últimos 12 meses en su barrio/colonia?” Drug sales: “¿Han ocurrido ventas de drogas ilegales en los últimos 12 meses en su barrio/colonia?”

Table 2: CORE RESULTS: HOMICIDE RATES AND UAC APPREHENSION RATES

<i>Dep. var.:</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
UAC rate \hat{c}	OLS	Municipality fixed effects			Municipality and year fixed effects				
Homicide rate h_t	0.451** (0.178)	0.609** (0.289)	0.375*** (0.113)	0.386*** (0.113)	0.600*** (0.0828)	0.543** (0.261)	0.317*** (0.0865)	0.352*** (0.0906)	0.523*** (0.0702)
h_{t-1}			0.348** (0.145)	0.198*** (0.0510)	0.146*** (0.0531)		0.244** (0.119)	0.115* (0.0609)	0.133*** (0.0395)
h_{t-2}				0.471 (0.341)	0.115*** (0.0417)			0.440 (0.331)	0.113*** (0.0358)
h_{t-3}					0.187*** (0.0492)				0.158*** (0.0447)
Constant	91.07*** (7.630)	84.07*** (12.81)	74.86*** (9.877)	56.66*** (17.38)	70.10*** (7.425)	-9.988 (18.87)	-11.84 (12.25)	-26.58 (19.99)	-0.890 (7.861)
<i>N</i>	5276	5276	5212	5147	4222	5276	5212	5147	4222
adj. R^2	0.004	0.012	0.011	0.016	0.035	0.130	0.156	0.162	0.290
Clusters	893	893	893	893	893	893	893	893	893
$\sum \hat{\beta}$	0.451*** (0.178)	0.609*** (0.289)	0.723*** (0.225)	1.055** (0.412)	1.048*** (0.172)	0.543*** (0.261)	0.561*** (0.165)	0.907*** (0.361)	0.928*** (0.143)

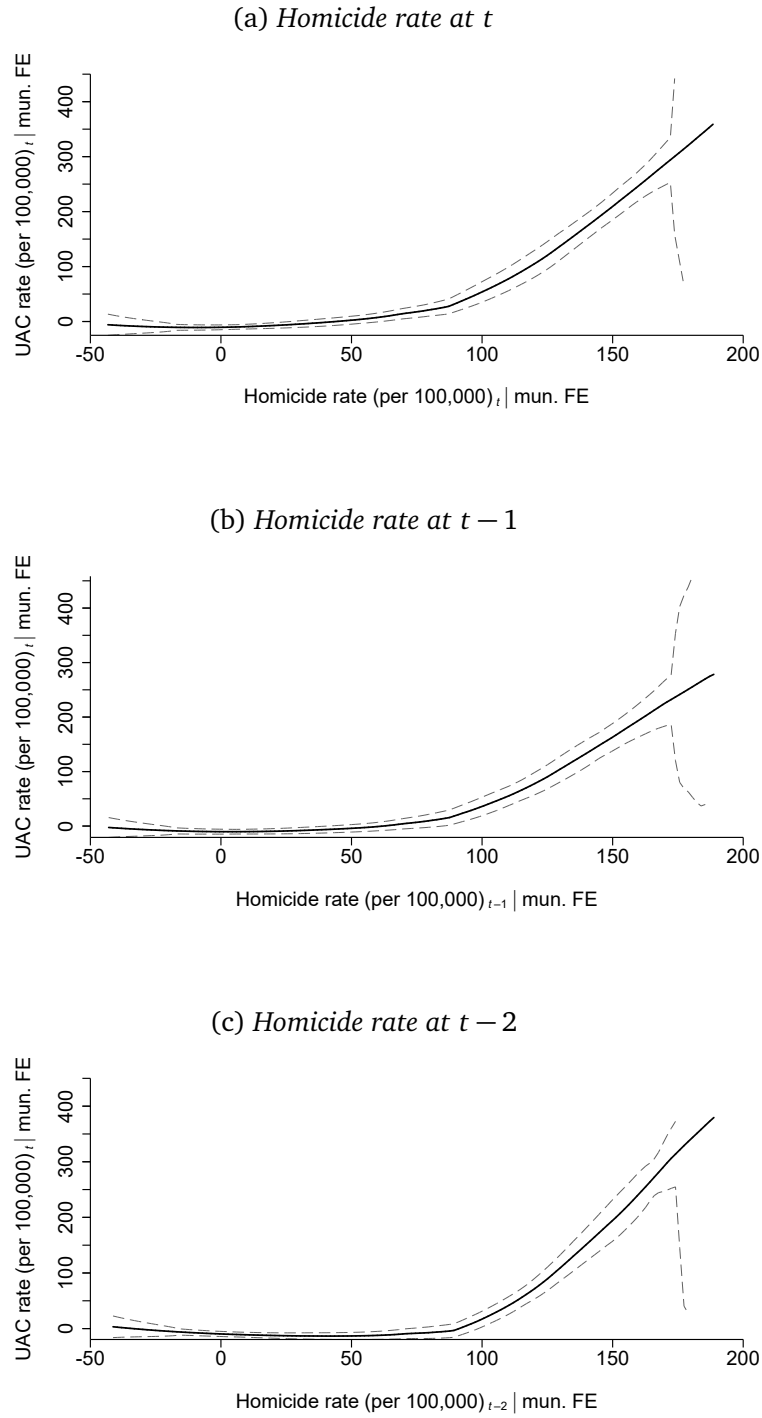
Liang-Zeger (1986) standard errors in parentheses clustered by municipality. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unit of observation is municipality-year. $\sum \hat{\beta}$ is the sum of the coefficients on the homicide rate and its lags in each regression.

Figure 5: PREDICTIVE MARGINS FOR UAC RATE BY HOMICIDE RATE (4-YEAR SUSTAINED CHANGE)



Uses the coefficient estimates from [Table 2](#), col. 9, which are conditional on municipality and year fixed effects. Dashed lines show 95% confidence interval. Shows the predicted UAC rate per 100,000 population in year t given a constant homicide rate from year $t-3$ to t inclusive. Vertical dotted line shows sample mean homicide rate; horizontal dotted line shows sample mean UAC rate.

Figure 6: SEMIPARAMETRIC FIXED-EFFECTS REGRESSIONS



Robinson (1988) double-residual method for each lag in isolation, controlling for municipal fixed effects. Local linear with 95% confidence interval, Bandwidth 50, Epanechnikov kernel, standard errors clustered by municipality.

Table 3: UNOBSERVED COMMON SHOCKS

<i>Dep. var.:</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UAC rate \dot{c}	Multilevel (municipality-specific time trend)				Interactive Fixed Effects			
Homicide rate h_t	0.487** (0.238)	0.248*** (0.0833)	0.262*** (0.0748)	0.436*** (0.0716)	0.233*** (0.0869)	0.183*** (0.0646)	0.227*** (0.0553)	0.301*** (0.0689)
h_{t-1}		0.203* (0.120)	0.0247 (0.0873)	0.0607 (0.0371)		0.0939*** (0.0350)	0.112*** (0.0323)	0.111** (0.0467)
h_{t-2}			0.404 (0.328)	0.0772** (0.0344)			0.111*** (0.0294)	0.0941** (0.0386)
h_{t-3}				0.115*** (0.0351)				0.0688** (0.0289)
Year	36.61*** (2.846)	36.33*** (2.788)	34.60*** (2.559)	30.21*** (1.498)				
N	5276	5212	5147	4222	5276	5212	5147	4172
Clusters	893	893	893	893	893	893	893	893
$\sum \hat{\beta}$	0.487*** (0.238)	0.450*** (0.138)	0.690*** (0.279)	0.688*** (0.128)	0.233*** (0.087)	0.277*** (0.094)	0.450*** (0.092)	0.575*** (0.128)

Standard errors clustered by municipality in parentheses. Multilevel model includes municipality fixed-effects and municipality-specific time-trends. Interactive Fixed Effects estimator (Ba1 2009) assumes one factor and includes municipality fixed effects. All regressions include constant term (not reported). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\sum \hat{\beta}$ is the sum of the coefficients on the homicide rate and its lags in each regression. Constant term included but not reported.

Table 4: COUNTRY-BY-YEAR AND DEPARTMENT-BY-YEAR FE

<i>Dep. var.:</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UAC rate \hat{c}	Country-by-year FE			Department-by-year FE				
Homicide rate h_t	0.294 (0.208)	0.0528 (0.0865)	0.114* (0.0600)	0.272*** (0.0761)	0.288 (0.221)	0.0669 (0.0664)	0.108* (0.0650)	0.262*** (0.0721)
h_{t-1}		0.0195 (0.0824)	-0.0839 (0.110)	0.00124 (0.0531)		0.0357 (0.103)	-0.0679 (0.0722)	-0.0245 (0.0440)
h_{t-2}			0.396 (0.329)	0.0564 (0.0389)			0.316 (0.312)	-0.00604 (0.0424)
h_{t-3}				0.162*** (0.0614)				0.103*** (0.0450)
<i>N</i>	5276	5212	5147	4222	5276	5212	5147	4222
adj. R^2	0.163	0.199	0.203	0.353	0.201	0.245	0.260	0.457
Clusters	893	893	893	893	893	893	893	893
$\sum \hat{\beta}$	0.294 (0.208)	0.072 (0.094)	0.426* (0.258)	0.492*** (0.153)	0.288 (0.221)	0.103 (0.116)	0.357 (0.322)	0.334** (0.142)

Standard errors clustered by municipality in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\sum \hat{\beta}$ is the sum of the coefficients on the homicide rate and its lags in each regression. Constant term included but not reported.

Table 5: EXTERNAL VIOLENCE VERSUS INTERNAL NETWORK DIFFUSION

<i>Dep. var.:</i>	(1)	(2)	(3)	(4)	(5)	(6)
UAC rate \dot{c}	Municipality and year fixed effects					
	Arellano Bond					
Stock c_{t-1}		0.192*** (0.0146)	0.198** (0.0205)			
$c_{t-1} \cdot h_t$			0.000642*** (0.000151)			
Flow \dot{c}_{t-1}				0.452*** (0.0366)	0.476*** (0.0426)	0.492*** (0.0544)
$\dot{c}_{t-1} \cdot h_t$					0.000724** (0.000357)	
h_t	0.523*** (0.0702)	0.408*** (0.0546)	0.205** (0.0513)	0.385*** (0.0568)	0.287*** (0.0597)	0.340*** (0.0782)
h_{t-1}	0.133*** (0.0395)	0.0542* (0.0296)	0.0717*** (0.0264)	0.0412 (0.0312)	0.0715** (0.0304)	0.0742** (0.0376)
h_{t-2}	0.113*** (0.0358)	0.0586* (0.0310)	0.0996*** (0.0287)	0.0561* (0.0311)	0.118*** (0.0421)	0.0596 (0.0370)
h_{t-3}	0.158*** (0.0447)	0.103*** (0.0359)	0.128*** (0.0411)	0.0963*** (0.0365)	0.127* (0.0656)	0.110** (0.0487)
N	4222	4222	4222	4222	4222	3329
Clusters	893	893	893	893	893	893
R^2 within groups	0.291	0.456	0.464	0.440	0.444	—
R^2 overall	0.0642	0.528	0.546	0.585	0.590	—
$\sum \hat{\beta}$	0.928*** (0.143)	0.624*** (0.086)	0.504** (0.084)	0.579*** (0.086)	0.603*** (0.092)	0.584*** (0.117)

Standard errors clustered by municipality in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\sum \hat{\beta}$ is the sum of the coefficients on the homicide rate and its lags in each regression. Arellano-Bond (1991) regression in column 6 uses all lags from $t-2$ backward, and robust standard errors. All columns include a constant term (not reported). Columns 3 and 5 also include interactions with the three lagged homicide rates (not reported), that is, in column 3: $(c_{t-1} \cdot h_{t-1})$, $(c_{t-1} \cdot h_{t-2})$, and $(c_{t-1} \cdot h_{t-3})$, and in column 5: $(\dot{c}_{t-1} \cdot h_{t-1})$, $(\dot{c}_{t-1} \cdot h_{t-2})$, and $(\dot{c}_{t-1} \cdot h_{t-3})$.

Table 6: UNEMPLOYMENT, 2011 AND 2014 ONLY

<i>Dep. var.:</i> UAC rate \hat{c}	(1)	(2)	(3)	(4)
	Pooled OLS		Municipality fixed effects	
Homicide rate, h_t	0.679*** (0.164)	0.628*** (0.167)	0.754*** (0.252)	0.743*** (0.254)
Unemployment rate, u_t		8.004** (4.021)		-9.336 (10.28)
ln Population	21.47 (51.03)	0.408 (52.29)		
ln Youth pop.	-50.60 (51.08)	-28.08 (52.54)		
Constant	278.0*** (107.2)	266.6** (108.5)	62.49*** (14.06)	101.9** (44.99)
<i>N</i>	1754	1734	1754	1734
Clusters	893	893	893	893

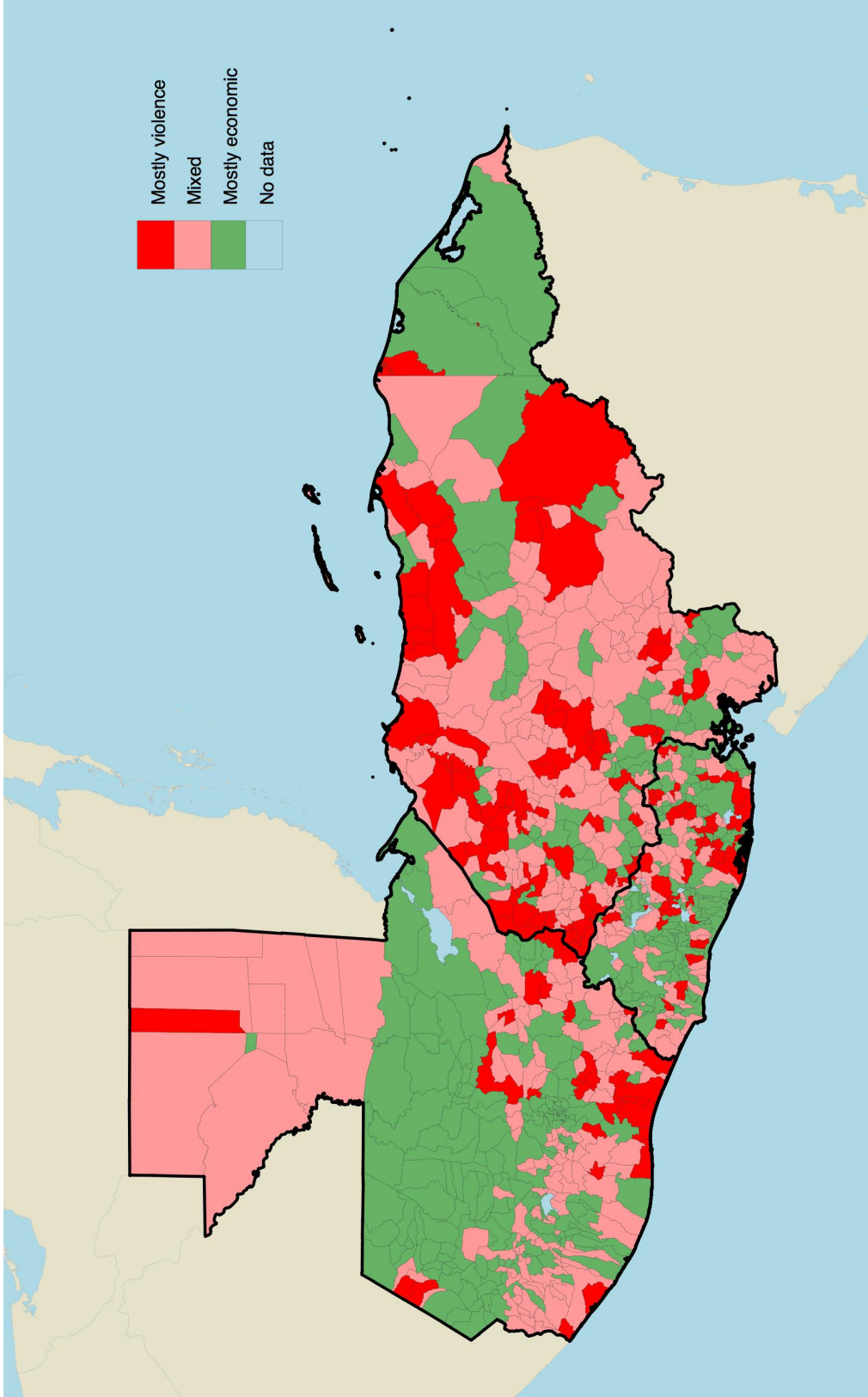
Standard errors clustered by municipality in parentheses. Department-level unemployment estimates only available for all three countries in 2011 and 2014. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Youth population defined as number of people age 8–17.

Table 7: DECOMPOSITION IN CROSS-SECTION

<i>Dep. var.:</i> UAC rate \dot{c}	(1)	(2)	(3)
	Cross-section OLS		
3-year chg. in homicides: Δh	3.748** (1.606) [21.4]	117.2** (50.75) [16.1]	122.9** (50.74) [12.2]
Income per capita: $\ln y$	-147.9 (177.2) [5.0]	-12.62 (178.5) [2.7]	57.01 (183.6) [3.1]
$\Delta h \times \ln y$		-10.32* (5.384) [14.7]	-10.91** (5.396) [11.1]
Poverty rate (frac.): p	-1514.7*** (519.3) [27.4]	-966.8* (538.6) [14.1]	-1567.2*** (554.3) [15.5]
$\Delta h \times p$		-61.99*** (16.49) [17.5]	-66.76*** (16.37) [14.2]
\ln Population	-806.8** (362.8) [25.2]	-1098.6*** (394.1) [19.3]	-1537.3*** (493.4) [14.9]
\ln Youth pop.	609.6* (363.6) [21.1]	886.7** (393.5) [15.7]	1336.1*** (494.3) [12.4]
Adult illiteracy (%)			26.84*** (7.275) [15.1]
Child school enrollment (%)			330.4* (177.0) [1.6]
Constant	5510.5*** (1666.7)	4580.1*** (1694.8)	4013.5** (1846.4)
N	886	886	886

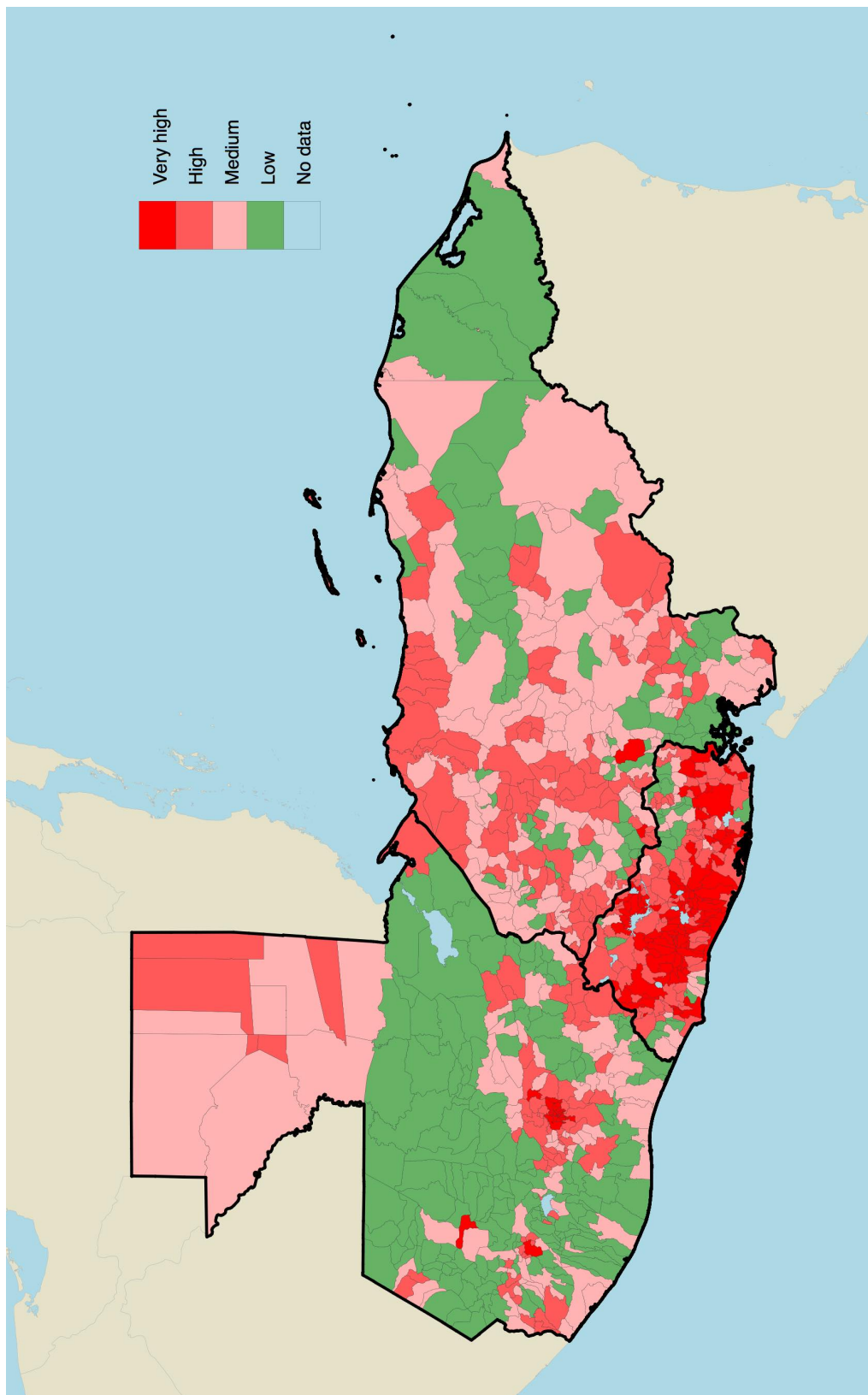
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Owen value in square brackets shows percent of regression's explanatory power arising from each variable (Huettner and Sunder 2012). Δh_i is the average over all years, for each municipality, of $h_t - h_{t-3}$.

Figure 7: SPATIAL DECOMPOSITION OF UAC DETERMINANTS



Shows δ_i for each municipality calculated from equation (10) using the coefficient estimates from Table 7, col. 1. Bright red areas show $\delta_i \gg 0$, where recent changes in the homicide rate are predicted to determine much more of the UAC rate than economic factors. Light red areas show $\delta_i \approx 0$, where homicide shocks and economic traits are predicted to weigh roughly equally. Green areas show $\delta_i \ll 0$, where recent changes in the homicide rate are predicted to determine much less of the UAC rate than economic factors.

Figure 8: SPATIAL DECOMPOSITION OF CHANGE IN UACs PER CHANGE IN HOMICIDES



Shows predicted $\partial \tilde{c} / \partial \Delta h$ for each municipality using the coefficient estimates from Table 7, col. 2. Green areas show low values of predicted $\partial \tilde{c} / \partial \Delta h$ conditional on income per capita and poverty fraction; progressively intense red areas show higher values of predicted $\partial \tilde{c} / \partial \Delta h$ conditional on income per capita and poverty fraction.

Online Appendix

“Violence, Development, and Migration Waves: Evidence from Central American child migrant apprehensions ”

A1 Model derivation

Equation (4) gives the difference in discounted expected utility between migrating and not migrating,

$$V^* - V = \frac{W^*}{r} - (1 - \mu)V - C. \quad (\text{A.1})$$

Workers migrate if $V^* - V > 0$, that is if

$$\mu > 1 - \frac{W^*}{r}V \equiv \tilde{\mu} \implies V = \frac{W^*}{1 - \tilde{\mu}} \xrightarrow{\text{into (A.1)}} V^* - V = W^* \left(\frac{\mu - \tilde{\mu}}{1 - \tilde{\mu}} \right), \quad (\text{A.2})$$

a result used below. Equation (5) gives

$$\begin{aligned} (1+r)V &= w + \underbrace{\theta \int_0^{\tilde{\mu}} V^* d\Psi(\mu) + \theta \int_{\tilde{\mu}}^1 V^* d\Psi(\mu)}_{\equiv \theta V^*} + (1-\theta) \int_0^{\tilde{\mu}} V d\Psi(\mu) + (1-\theta) \int_{\tilde{\mu}}^1 V^* d\Psi(\mu) \\ &= w + \theta \int_0^{\tilde{\mu}} (V^* - V) d\Psi(\mu) + \int_0^1 V d\Psi(\mu) + \theta \int_{\tilde{\mu}}^1 (V^* - V) d\Psi(\mu) \end{aligned}$$

Plugging in equation (A.2) and dividing both sides by $V = \frac{W^*}{1 - \tilde{\mu}}$,

$$\begin{aligned} -\frac{w}{W^*}(1 - \tilde{\mu}) &= -r + \theta \left(\int_0^{\tilde{\mu}} \mu d\Psi(\mu) - \tilde{\mu} \int_0^{\tilde{\mu}} d\Psi(\mu) \right) + \int_{\tilde{\mu}}^1 \mu d\Psi(\mu) - \tilde{\mu} \int_{\tilde{\mu}}^1 d\Psi(\mu) \\ &= -r + \theta \underline{\mu} - \theta \tilde{\mu} + \bar{\mu} - \tilde{\mu} \end{aligned} \quad (\text{A.3})$$

Solving equation (A.3) for $\tilde{\mu}$ gives equation (6).

A2 Estimation of UAC flows relative to child population at origin

Honduras: Honduras’s Instituto Nacional de Estadística estimates that the number of 17 year-olds in 2013 was 180,681 in Honduras. [Data downloaded from www.ine.gob.hn on March 10, 2017]

El Salvador: El Salvador’s Dirección General de Estadística y Censos has not published estimates by age of the 2013 population at the time of this writing. In El Salvador the number of 17 year-olds in 2007 was 122,879 (2.139% of the total 2007 population of 5,744,113) and the number of 11 year-olds in 2007 was 141,243, while the total population in 2013 was

6,344,069. This allows two different rough estimates of the 2013 population of 17 year-olds in El Salvador: 1) simply ‘aging forward’ the 11 year-olds of 2007, assuming minimal mortality gives 141,243, and 2) applying the 17 year-old fraction of the population in 2007 (2.139%) to the total population in 2013 (6,344,069) gives an estimate of 135,700. Here an estimate of 136,000 is used. [Data downloaded from www.digestyc.gob.sv on March 12, 2017]

Guatemala: Guatemalas’ Instituto Nacional de Estadística has produced demographic estimates of population by age for 2015, and only for five-year age ranges. But it is possible to estimate the number of 17 year-olds as a fraction of all children age 13–17 by noting this fraction for the two other countries: In El Salvador 2007, of children aged 13–17, 18.965% were age 17; and in Honduras 2013, of children aged 13–17, 19.443% were age 17. The Guatemalan government estimates that in 2015, there were 1,779,267 children age 15–19, implying that there were roughly 1,780,000 children age 13–17 in 2013. Using the above estimates from El Salvador and Honduras, approximately 19% of these or 338,200 would be age 17 in 2013. [Data downloaded from epidemiologia.mspas.gob.gt on March 10, 2017]

Adding up these estimates for the three countries gives $180,681 + 136,000 + 338,200 = 654,881$ people age 17 in all three countries combined in 2013. The cumulative total number of apprehensions of 17 year-old UACs from these three countries during 2011–2016 was 53,287, or 8.1% of all 17 year-olds in the Northern Triangle.

A check on these figures is provided by United Nations estimates from the [World Population Prospects, 2015 revision](#). It estimates the total population of 15–19 year-olds in all three countries combined as 3.14 million in 2010, and 3.34 million in 2015. Since 17 year-olds sit in the middle of this age range, their population is well-approximated by simply dividing by 5: 628,000 in the year 2010, and 667,600 in the year 2015. Interpolating these for 2013 gives an estimate of 647,800, slightly lower than the estimates of the national governments. Using this figure would imply that the number of 17 year-old UAC apprehensions 2011–2016 was 8.2% of the number of all 17 year-olds in the Northern Triangle.

A3 Data sources

A3.1 UACs from the Northern Triangle

Anonymized microdata provided by U.S. Customs and Border Protection. The city of birth reported to CBP by each child was matched using a Jaro-Winkler distance (JWD) algorithm against a list of all municipality names in the Northern Triangle. This successfully matched about two thirds of the children to a municipality of origin. Unsuccessful matches were then matched by JWD against concordances of geographic areas published by the Encuesta sobre Migración en la Frontera Sur de México (‘Emif Sur’), a research consortium based at El Colegio de la Frontera Norte. These files, built from data originally provided by the census bureaus of the countries of the Northern Triangle, contain lists of every cantón in El Salvador matched to a municipality; every pueblo, colonia, condominio, caserío, aldea, finca, granja, and hacienda in Guatemala matched to a municipality; and every aldea, caserío, barrio, and colonia in Honduras matched to a municipality. This brought the overall rate of matching a

child to a municipality of birth to 90.4% (161,735 matched out of the universe of 178,825). The rate of successful matches was similar across the three countries.

A3.2 Homicides

El Salvador: Municipal level homicide data 2009–2016. 2009–2012 from Fundacion Dr. Guillermo Manual Ungo (FUNDAUNGO) [Atlas de la violencia en El Salvador \(2009-2012\)](#). 2013–2016 from Organo Judicial de la Republica de El Salvador, [Portal de Transparencia](#). Individual year PDFs follow: [2013](#); [2014](#); [2015](#); [2016](#).

Guatemala: Municipal level homicide data 2009–2016. All years kindly provided by Carlos Mendoza.

Honduras: Municipal level homicide data 2009–2016. 2009–2012 from Fundación Dr. Guillermo Manual Ungo (FUNDAUNGO) [Atlas de la violencia en Honduras \(2009-2012\)](#). 2013–2015 from Instituto Universitario en Democracia, Paz, y Seguridad (IUDPAS) yearly homicide maps available [online](#). The data were accessed by viewing the page sources for the maps and searching for the underlying Google ‘fusion’ table. Individual tables for each year are linked as follows: [2013](#); [2014](#); [2015](#). 2016 data manually retrieved from Secretaria de Seguridad Policia Nacional (SEPOL), [Incidencia por Municipio](#), on April 26, 2017.

A3.3 Other variables

Income per capita:

El Salvador: Municipal level income per capita for 2009 from United Nations Development Programme (UNDP) and Fundacion Dr. Guillermo Manual Ungo (FUNDAUNGO), [Almanaque 262: Estado del desarrollo humano en los municipios de El Salvador 2009](#), p. 13.

Guatemala: Municipal level income per capita for 2009 was calculated as follows. Municipal level consumption figures in Romero and Zapil (2009) “[Dinámica Territorial del consumo, la pobreza y la desigualdad en Guatemala](#)”, Annex IV.2 p. 83 were averaged by department, weighted by municipal population, to yield the corresponding department-level consumption per capita. The ratio of municipal consumption per capita to department consumption per capita for each municipality was then applied to department level income per capita listed on p. 22 [here](#) to yield the 2009 municipal level income per capita. These figures were then [inflated](#) according to Guatemala’s CPI and [converted](#) from quetzales to 2009 PPP dollars.

Honduras: Municipal level income per capita for 2009 from United Nations Development Programme, [Informe Nacional de Desarrollo Humano 2011](#), Statistical Annex. Indicator 1, p. 307.

Poverty

El Salvador: Municipal level poverty rates for 2007 from Melgar and Amaya (2013), [Informe de Pobreza Rural en El Salvador](#) Annex 3. The poverty line is recalculated with each year’s

household survey factoring in both the cost of a basic food basket and the household's income level. The Melgar and Amaya study is based on the 1998 and 2009 surveys; more details [here](#).

Guatemala: Municipal level poverty rates for 2006 from Romero and Zapil (2009), “[Dinámica Territorial del consumo, la pobreza y la desigualdad en Guatemala](#)”, Annex IV.2 p. 83. The source does not include a firm definition of poverty, but likely follows the household survey methodology linked [here](#), based on the ability to afford a minimum consumption basket and other basic goods and services.

Honduras: Municipal level poverty rates for 2006 imputed through averaging [2013](#) and [2001](#) values.

Unemployment

El Salvador: Department level unemployment figures for 2011 and 2014 from Dirección General de Estadística y Censos (DIGESTYC) El Salvador, [Encuesta de Hogares de Propósitos Múltiples \(EHPM\)](#). Data for 2011 are on p. 13 and data for 2014 on p. 27 of the corresponding year PDFs. These data refer to the economically active population 16 years and older.

Guatemala: Department level unemployment figures for 2011 and 2014 from Instituto Nacional de Estadística (INE) Guatemala, [Encuesta Nacional de Condiciones de Vida \(ENCOVI\)](#), kindly shared with the author via email. These data refer to the economically active population 15 years and older.

Honduras: Department level unemployment figures for 2014 downloaded [here](#); 2011 data calculated from Encuesta Permanente de Hogares de Propósitos Múltiples (EHPM) microdata according to published methodology. These data refer to the economically active population 10 years and older.

Adult illiteracy

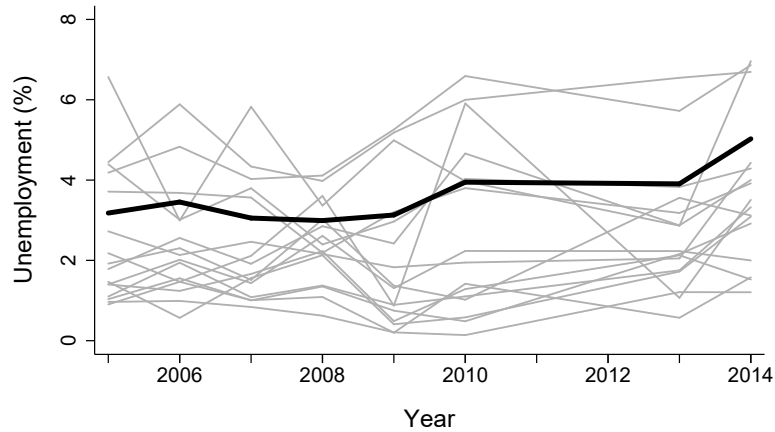
El Salvador: Municipal level adult literacy rates for 2009, ages 15 and over from United Nations Development Programme (UNDP) and Fundación Dr. Guillermo Manuel Ungo (FUNDAUNGO), [Almanaque 262: Estado del desarrollo humano en los municipios de El Salvador 2009](#), p. 13.

Guatemala: Municipal level adult literacy rates for 2010, ages 15 and over from the United Nations Development Programme, [Informe Nacional de Desarrollo Humano](#) - department level publications including full municipality breakdowns.

Honduras: Municipal level adult literacy rates for 2009, ages 15 and over from the United Nations Development Programme, [Informe Nacional de Desarrollo Humano 2011](#), Statistical Annex. Indicator 1, p. 307

School Enrollment

Figure A1: HONDURAS UNEMPLOYMENT: DEPARTMENTAL VS. NATIONAL



Black line shows nationwide unemployment rate, gray lines show rate in each department implied by EHPHM survey data. No data for Islas de la Bahía and Gracias a Dios departments.

El Salvador: Municipal counts of students enrolled in grades 1–9 for 2013, downloaded from the [Ministry of Education](#).

Guatemala: Municipal counts of students enrolled in grades 1–9 for 2013, downloaded from the [National Education Statistics System](#).

Honduras: Municipal counts of students enrolled in grades 1–9, downloaded from an [archived Honduran government website](#).

A4 Departmental vs. national unemployment

[Figure A1](#) compares departmental unemployment rates to the national-level unemployment rate in the data of the Encuesta Permanente de Hogares de Propósitos Múltiples (EHPHM), various years.