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MONITORING AND EVALUATION SUPPORT FOR COLLABORATIVE LEARNING AND ADAPTING (MESCLA) ACTIVITY

U.S. BORDER APPREHENSIONS AND COMMUNITY AND PLACE ATTACHMENT IN HONDURAS

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Prepared by:

Dexis Consulting Group

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Acronyms

AIC	Akaike Information Criteria
CBP	U.S. Customs and Border Protections
GEE	Google Earth Engine
IAGS	Inter-American Geodetic Service
JOH	President Juan Orlando Hernandez
MER	Mesa Electoral Receptora
SINIT	Sistema Nacional de Información Territorial
TSE	Tribunal Supremo Electoral

EXECUTIVE SUMMARY

This report is the product of an exploration of the potential of developing a community attachment index for Honduran municipalities. The report briefly reviews some of the literature on the concept of community and place attachment. The utility of developing seeking to measure this concept is based on the hypothesis that attachment to community operates independently of other drivers of migration. The core of the report presents a quantitative, empirical analysis of six groups of municipal-level factors that the literature associates with community attachment. These groups are: 1) civic engagement; 2) social infrastructure; 3) home ownership; 4) land use patterns; 5) community roots; 6) strength of cultural ties.

Two general conclusions were reached. First, drawing upon these six sets of variables, all measured at the municipal level of aggregation, does not lend itself to developing a theoretically or empirically sound overarching measurement of community attachment that could be meaningfully summarized in a single index. Second, several of these groups of variables—together and in some cases in combination—do have meaningful and empirically identifiable relationships to each other, and most importantly, to municipal migration rates as measured by U.S. border apprehensions.

The most salient findings are as follows:

Civic Engagement.[1] We measure civic engagement using voting data from the 2013 and 2017 presidential elections. For each municipality we create two variables, the average participation rate across both elections and the percentage point change from 2013 to 2017. We find that:

- More participatory municipalities emigrated less. This relationship holds across different model specifications and over different periods of time.
  - In one model specification we find that a 1-percentage point increase in the participation rate across the 2013- 2017 period predicts a decrease of almost 180 migrants per 10,000 population over the 2013 to h1.2019 period.
- Municipalities that became more participatory from 2013 to 2017 were also less likely to send migrants.
  - Specifically, a municipality where the change in the participation rate was 1 point higher is predicted to have 89 fewer U.S. border apprehensions per 100,000 population from 2013 through h1.2019.

Social Infrastructure. We test six separate indicators of municipal endowments of social infrastructure and expect these to be negatively related to emigration. We also conduct a factor analysis and predict a latent variable "social infrastructure" index combining all six variables. These include, the number of schools as a percentage of youth population in a municipality, the health deficit per 100,000 population, the number of health centers (per 100k), the number of cemeteries (per 100k), the number of churches (per 100k), and the number of soccer fields (per 100k). We highlight two salient results here:

- Contrary to expectations, the "social infrastructure" index variable is positively related to the U.S. border apprehension rate.
  - Specifically, we find that a one standard deviation increase in social infrastructure (0.83) is associated with more than 400 additional migrants per 100,000 population from 2013 to 2017.[2]
  - This relationship is largely driven by the 2018-h1.19 period, where a one standard deviation increase in social infrastructure predicts almost 500 additional migrants per 100,000 population.

1 The results highlighted in this section come from Table 2, model 2. As review of the entire report shows, voter participation variables are included in several other models.
2 This result is from the model reported in table 6b.

- Consistent with expectations derived from the community attachment literature as applied here, the analysis finds that emigration was higher in municipalities with a greater healthcare deficit.
    - Specifically, we find that a one standard deviation increase in the health deficit per 100k (3.9) is associated with 615 more migrants apprehended at the U.S. border from 2013-2017.

Home Ownership. One indicator that is expected to increase attachment to community is the rate of home ownership, as people who own their home are more likely to be rooted to their community and less likely to emigrate, all things being equal.

- The analysis shows that municipalities with higher home ownership rates sent fewer migrants.
    - Specifically, a municipality with a 1 percent higher home ownership rate is predicted to have sent 110 fewer migrants per 100,000 population from 2013-h1.2019.

Land Use. It is expected that increased investment in productive activities might similarly make populations less likely to be mobile. The indicators developed, including the share of land used for a range of different things and the change in different uses from 2014 to 2018 are limited in several ways. In a bivariate context there are several interesting bivariate correlations, however none of these are robust to the inclusion of control variables.

Community Roots. It is expected that people who have already migrated, internally or internationally, are less rooted and thus more likely to emigrate. The analysis creates two index variables: one of immobility and one of internal migration. The analysis also includes a variable for the number of individuals from families in each municipality living abroad as a percentage of the municipal population in 2013. We also test the interactions between this migration variable and the immobility and internal migration indices because we expect the relationship between immobility and U.S. border apprehensions to be different in municipalities that already have high migration and those that have low migration.[3]

- Municipalities that had higher percentages of their populations already living abroad in 2013 were considerably more likely to have their members apprehended at the U.S. border between 2013 and h1.2019. For example, a municipality with a 2% of its population living abroad as of 2013 is expected to have had almost 1,500 more of its members apprehended from 2013 to h1.2019 than a municipality with 1% of its population abroad in 2013.
- Where the 2013 migration population is 0%, a standard deviation increase (0.85) in immobility predicts more than 13,000 fewer U.S. border apprehensions from 2013 through h1.2019.

Strength of Cultural Ties

Finally, the analysis tests the extent to which places with larger shares of indigenous and Garifuna communities, controlling for other factors, sent fewer migrants to the U.S., possibly due to the presence of deeper ties to place and community. Indeed, municipalities where greater percentages identified as being members of indigenous communities were less likely to have members apprehended at the U.S. border. This relationship was robust to the inclusion of control variables for poverty and population, but the magnitude is low.

- Specifically, a one standard deviation increase in the indigenous population (30.2%) is predicted to have sent more than 700 fewer migrants per 100,000 population from 2013 through h1.2019.
- Importantly, this variable loses statistical significance in a full model.

3 We expect a similar effect with internal migration.

PURPOSE

The analysis presented below began as an attempt to identify a set of aggregate factors that indicate the level of attachment to community and place of Hondurans. We expect that people who are more attached to community and place will be less likely to emigrate. The potential utility of developing this concept, along with municipal-level empirical measurements of it, is the extent to which community attachment operates independently of other drivers of migration, such as economic opportunities, violence, access to migration networks, or climate-related drivers such as drought.

The bulk of theoretical and empirical research on "community attachment" (or the similar concept of "place attachment") focuses on the individual level. That is, individuals are conceived to vary in the degree to which they are attached to the places they live and the intensity of attachment can be related to a range of factors, some of which operate at higher levels of aggregation. The literature has identified a range of factors that are thought to explain variation in these individual level attachments to community.

The analysis developed here approaches this problem from the opposite side because of data availability. We are not conducting ethnographic or survey research to learn about the psychological attachments felt by individual Hondurans to their communities, and how these may or may not help to account for variations in individuals' migration behaviors or aspirations. Rather, the approach used here is to identify variables at the municipal level of aggregation that are expected to cause individuals living in those places to be more attached to their communities and, as a result, less likely to emigrate, all else being equal.

EXISTING RESEARCH AND CONCEPTUALIZATION OF COMMUNITY ATTACHMENT

As noted, much of the scholarship that develops and tests concepts such as "community attachment" and "place attachment," as well as other quality of life indicators, have an individual level of analysis. Furthermore, the bulk of research is focused on the rural sociology of the United States. Still, there are several useful lessons, insights, and concepts that can be drawn from this literature to inform the development of indicators of community attachment, and more broadly "rootedness" or "bondedness" in Honduras.

Scholarship by Eacott and Sonn (2006) and Sundblad and Sapp (2011) cited by Jaquet and colleagues (2016) focuses on the importance of 1) "social and emotional ties to family and friends," 2) "involvement in community groups and organizations," and 3) characteristics of the "local natural environment" (p. 7). The underlying concept of both place and community attachment relates to the extent to which people are "bonded" to the places where they live. In some conceptualizations this has to do with community members' perceptions that where they live is unique and irreplaceable (also see Hidalgo and Hernandez 2001).

According to Belanche and colleagues (2017), who focus on urban identity formation, community attachment has cognitive, affective, and evaluative dimensions of place identity. Urban identity is both related to the fact that different cities have their own identities based on their "own features and constructed by collective attribution" while also being related to each person's self-identification. Based on the literature, the authors hypothesize first that urban identities are influenced by social representations of a "city's culture, history, politics, social factors and environmental issues." For the purposes on our research on Honduras, we may extend this hypothesis to include social representations relevant in rural communities, recognizing that they may be manifested in different ways. Second, the authors hypothesize that "Socio-demographic characteristics" also shape place identities. These factors include age, gender, education level, place of birth, place where grown up, length of residence and home ownership (Belanche et al. 2017: 140).

McKnight and colleagues (2017) argue that the rootedness to place is in some ways stronger in rural communities (in Montana), but that this is mediated by proximity to urban centers. Specifically, they argue that while urban centers offer a wider array of organizations and institutions that facilitate social interactions, traditional norms of reciprocity, as well as denser kinship networks and social capital can have attachment-enhancing effects in rural places (McKnight, et al. 2017: 292). As such, these effects might be expected to cancel each other out and analysts should model their complex interactive effects to understand how dynamics of community attachment are different in rural as compared to urban locales. To do this, they model both population size and proximity to urban places and find that the strongest community attachments happen in rural locales that are closer to urban centers. The ways in which this might play out in Honduras could be significantly different, particularly as these relate either to internal or international migration.

In research on the determinants of immobility in rural Peru, Adams (2016) identifies three reasons people do not migrate: "high levels of satisfaction, resource barriers and low mobility potential" (429). Related to the case of Honduras, among those who are dissatisfied with local conditions, the typical reasons for immobility was attachment to place, rather than resource constraints, as found in the UK Foresight report (2011).

Community attachment research tends to be based on survey analysis of individuals, and the construction of index variables by combining Likert-scale type responses of questions, sometimes direct questions, about feelings of community attachment. In one study, Jennings and Krannich (2013) develop a multidimensional conceptualization and measurement of community attachment, using structural equation and latent variable methods. The dimensions identified are: "…social bonds, participation, and sentiments…"

As we collect enough data at the municipal level of aggregation to measure different components hypothesized to increase levels of community attachment and thus make mobility less likely, we will explore similar latent-variable methods to estimate this higher-order concept. However, we begin by developing each set of variables separately, and exploring the relationship with migration flow data at the municipal level.

COMPONENT PARTS OF COMMUNITY ATTACHMENT AT THE MUNICIPAL LEVEL

The primary and original motivation of this report is to identify and explore municipal-level indicators of community attachment in Honduras. As the literature defines and measures attachment to community as operating at the individual level—and we have no data at the individual level—there may be significant challenges to the validity of this exercise. Many (all?) of the indicators that we explore in this section might be measuring discrete municipal-level phenomena. Some of these might lead individuals in those places to be more (or less) attached to their communities; however, this does not mean that the indicators themselves measure community attachment. Nevertheless, there are reasons to expect that these variables do affect migration flow from these municipalities, which we estimate in the following section. Before this, we outline the key groups of variables measured and the source of the data.

<u>Variables explored</u>

We identify 6 sets of variables that we expect may relate or shape community attachment, and thus explain variations in migration intensity. These include: 1) civic engagement; 2) social infrastructure; 3) home ownership; 4) land use patterns; 5) community roots; 6) strength of cultural ties. Detailed discussion of the sources and methods of calculating these variables in presented in the Annex A and descriptive statistics are reported in Annex B.

1) *Civic Engagement.* Social and political commitment to community and country can have an independent effect on the likelihood of staying. Migration scholarship inspired by the work of Albert O. Hirschman (1973, 1978) considers the choice people have when faced with unfavorable

conditions where they live: they can 1) exit (i.e., emigrate), 2) exercise voice (i.e., seek to change those unfavorable conditions); or 3) remain loyal (i.e., neither exit or seek change using voice).

We hypothesize thus, that where people are more civically engaged—where they exercise voice at higher rates—populations are less likely to choose "exit" and migrate. We assume that voting participation is a proxy for broader civic engagement and thus, that those municipalities with higher voter participation rates are likely to send fewer migrants. To test this hypothesis for Honduras, we estimate voter participation in each municipality using electoral data reported by the Tribunal Supremo Electoral of Honduras from the presidential elections of 2017 and 2013.

2) *Social Infrastructure.* We hypothesize that people from communities that have better social infrastructure of different varieties will be more tied to their communities and less likely to emigrate. Specific categories of social infrastructure that we have collected data for include schools, health centers, an indicator of the deficit in health care, churches, soccer fields, and cemeteries. For each of these social infrastructure variables, we calculate the per capita rate. For schools, we calculate the rate per youth population.

3) *Home ownership.* One factor of community rootedness is the ownership of illiquid assets that are place-bound. One such asset that might increase attachment to place or community is home ownership rate.

4) *Land use and land use change.* We expect populations that are more rooted to the places they live to be less likely to migrate, and the type and direction of change of productive investment could have such a rooting effect. This might operate in direct and indirect ways, with families that invest in businesses or productive activities becoming more rooted and potentially less likely to emigrate. Indirectly, more productive or commercial investments might be expected to increase the community attachment feelings of individuals and families. We do not have data on new businesses created or business expansions. However, we have collected comprehensive data on the percentage of each municipality where the land is used for different activities including different agricultural uses, forests, grasslands, waterways, and urban use. We have these percentages for 2014 and 2018 and are thus able to consider the effect of different land uses shares as well as the effect of changes in these shares over this period. At the same time, there is a counterhypothesis that may be relevant for some land uses. For example, increasing industrialization—or capitalization—of agriculture can have the economic impact of reducing demand for labor, as production becomes less labor intensive. At the same time, as cases of land conflict surrounding the expansion of African Palm plantations suggest, most notably in the Bajo Aguan region, certain land uses could be expected to have the opposite effect of displacing populations, potentially internationally.

5) *Community roots.* There is an expectation that those who have moved once are more likely to move again and those who still live in the same place where they were born are more likely to remain there. Similarly, we expect that people who have been in a place longer become less likely to leave. To assess the effect of these factors on emigration, we include variables measuring the percentage of municipal population born locally, elsewhere in Honduras, or abroad. Similarly, we construct variables measuring the percentage of municipal population that lived in the same place 5 years before (when asked in 2013); elsewhere in Honduras, or in another country.

6) *Strength of cultural ties.* Finally, we include variables measuring the percentage of municipal populations that identify with an indigenous or Afro-Honduran communities, with the expectation that individuals from these communities may have higher levels of community attachment rooted in the strength of ethno-cultural ties. Additionally, however, mobilization in defense of collective land rights and against the development of large-scale dam projects or the expansion of African palm plantations could generate both attachment as well as displacement. That is, the civic

engagement of movement membership and mobilization might be a factor explaining rootedness despite the presence of other mobility drivers, while land conflicts and violence might also generate internal or international displacement.

RESULTS

This section reports estimates of the bi-variate correlation between the variables described above and migration flow as well as multivariate regression analyses. The section is organized into thematic subsections that report the bi-variate and simple multivariate analyses first for each of the six groups of factors. The final subsection presents the results of a comprehensive model including variables from all categories of factors.

To measure migration flow, we focus on the cumulative apprehension rate per 100,000 municipal population 1) from 2013-h1.2019;[4] 2) 2013-2017; and 3) 2018-h1.2019. There are two reasons to focus on these different periods. First, for variables that we measure at points in time between 2013 and 2019, for example voting in the 2017 election, it is important to identify the extent to which migration flow might be the cause, rather than the effect. With civic engagement, and possibly other variables, there are theoretical reasons (and some empirical evidence) to believe that higher migration could lead to *decreased* civic engagement, as the absence of family and community members and the economic support coming from abroad could make those who stay behind become disengaged from Honduran politics ("exit without leaving" as Goodman and Hiskey called it in a 2008 article). The second reason it is important to analyze the correlates of apprehension rates during different time periods is that there is reason to believe that the profile and possibly the drivers of migration have shifted over time.

CIVIC ENGAGEMENT

Table 1 shows the Pearson's correlation statistics for the three apprehension variables discussed above (2013-h1.2019; 2013-2017; and 2018-h1.2019) and the specified participation rate variables. Additionally, we include variables indicating the average competitiveness of the municipality (based on the gap between first and second place vote shares), whether a municipality "swung" between support for the opposition or the National Party candidate in both elections, President Juan Orlando Hernandez (-1=swung JOH to opposition, 0=stable; 1=swung opposition to JOH) and the political alignment of the municipality (0=opposition both elections, 1=swing; 2=JOH both elections).

4 Where h1.2019 refers to the first half-year of 2019, January through June.

Table 1. Civic Engagement and US Border Apprehensions Pearson's Correlations			
	Apprehensions/100k		
Variables	2013-19	2013-17	2018-19
2013 Participation Rate	-0.3460*	-0.4335*	-0.2253*
2013 Participation Rate (adj.1)	-0.2847*	-0.3654*	-0.1772*
2013 Participation Rate (adj.1a)	-0.2816*	-0.3644*	-0.1722*
2013 Participation Rate (adj.1b)	-0.3124*	-0.3980*	-0.1970*
2017 Participation Rate	-0.3951*	-0.4656*	-0.2850*
2017 Participation Rate (adj.1)	-0.3471*	-0.4119*	-0.2477*
2017 Participation Rate (adj.1a)	-0.3477*	-0.4139*	-0.2465*
2017 Participation Rate (adj.1b)	-0.3699*	-0.4385*	-0.2642*
2017 Participation Rate (adj.2)	-0.1318*	-0.1884*	-0.0642
2017 Participation Rate (adj.3)	-0.1171*	-0.1757*	-0.0501
2017 Participation Rate (adj.4)	-0.072	-0.1341*	-0.0069
2017 Participation Rate (adj.5)	-0.05	-0.1165*	0.0167
Average Participation Rate, 2013&17	-0.3829*	-0.4638*	-0.2642*
Average Participation Rate, 2013&17 (adj. 1)	-0.3274*	-0.4021*	-0.2209*
Average Participation Rate, 2013&17 (adj. 1a)	-0.3266*	-0.4032*	-0.2180*
Average Participation Rate, 2013&17 (adj. 1b)	-0.3533*	-0.4325*	-0.2395*
Change in Participation Rate, 2013-2017	-0.1706*	-0.1506*	-0.1706*
Change in Participation Rate, 2013-2017 (adj. 1)	-0.1831*	-0.1648*	-0.1801*
Change in Participation Rate, 2013-2017 (adj. 1a)	-0.1844*	-0.1652*	-0.1822*
Change in Participation Rate, 2013-2017 (adj. 1b)	-0.1780*	-0.1585*	-0.1769*
Average competitiveness (2013&17)	-0.0962	-0.0895	-0.0915
Swing Direction (+=toward JOH)	-0.1728*	-0.1712*	-0.1516*
Political Alignment (High=JOH; Middle=swing; Low=Opp.)	-0.1506*	-0.1851*	-0.1011

* Statistically significant at the 0.05 level

As can be seen in Table 1, the bivariate results are consistent with the hypothesis that cumulative migration rates should be lower in places with higher levels of civic engagement—as proxied by voter participation. The strength of the correlations and the robustness of the finding across multiple operationalizations of the participation rate are stronger focusing on the 2013-2017 period. However, the expected negative correlation is present for the unadjusted participation rate and the participation rates adjusted using the 2013 census data (1, 1a, and 1b). These results are matched, with slightly different magnitudes when calculated for the Chamber of Deputies election in 2017 (slightly higher) and while focusing on valid votes rather than total votes (slightly lower).[5] These relationships hold across 2013 and 2017 elections and are present when the participation rates are averaged.

The percentage point change in the municipal participation rate from 2013 to 2017 was similarly negatively related to emigration, with municipalities that became more participatory being less likely to send migrants during both periods.

5 The latter is not surprising given the positive correlation between the Null/Blank Vote share and cumulative migration.

Finally, there was no statistically significant relationship between competitiveness and apprehension rate, however municipalities that swung from the opposition to JOH were less likely to migrate, as were those that supported JOH in both elections. The fact that the relationship is weaker and does not meet the standard for statistical significance of $p<0.05$ for the 2018-19 period might suggest that emigration shaped municipal political alignment, rather than the other way around. Though much more analysis is required to confirm the robustness of this relationship.

Table 2 presents a multivariate linear regression (OLS) model on the cumulative apprehension rate from 2013 through 2019. The participation rate variables used are the 2013 to 2017 average of unadjusted participation and adjustment 1b, which subtracts from the denominator of eligible voters the number of migrants that departed Honduras in 2009 or after. In addition, the models include the percentage point change in participation from 2013 to 2017, the "swing" and political alignment variables, as well as control variables for the municipal poverty rate and population. The models also control for departmental fixed effects.[6] The models only differ in the participation rate and participation rate change variables. Tables 3 and 4 show equivalent models for the 2018-h1.2019 and 2013-2017 periods, respectively. The principal variable of interest in this analysis in the participation rate, which is being used as a proxy for civic engagement.

Table 2. Municipal Participation Rate Associated with Less Migration

Linear Regression Absorbing Department Effects, 2013-h1.2019

VARIABLES	(1) Part.	(2) Part1b
Participation Rate, 2013&17	-19,562***	-17,956***
	(2,691)	(2,773)
Change in Participation Rate, 2013-17	-7,732**	-8,917**
	(3,910)	(3,883)
Swing Direction (+=toward JOH)	-733.6*	-758.2*
	(443.3)	(450.4)
Municipal Party Alignment[7]		
Swing	-34.92	-1.738
	(582.8)	(592.1)
Solid JOH	-1,277**	-1,210**
	(513.2)	(520.9)
Probability Poor, 2013	-3,643	-4,584
	(3,040)	(3,077)
Population	-0.00148	-0.00150
	(0.00214)	(0.00218)
Constant	20,523***	19,813***
	(1,763)	(1,838)
Observations	298	298
R-squared	0.565	0.551
Adjusted R-squared	0.527	0.511

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6 Utilized the *areg* command in Stata to estimate these models, and 'absorb' the fixed effects at the level of the department.
7 Base category is opposition aligned in 2013 and 2017.

Table 3. Municipal Participation Rate Associated with Less Migration

Linear Regression Absorbing Department Effects, 2018-h1.2019

VARIABLES	(1) Part.	(2) Part1b
Participation Rate, 2013&17	-7,660***	-7,005***
	(1,484)	(1,517)
Change in Participation Rate, 2013-17	-4,146*	-4,600**
	(2,156)	(2,124)
Swing Direction (+=toward JOH)	-297.8	-307.7
	(244.4)	(246.4)
Municipal Party Alignment[8]		
Swing	75.36	88.20
	(321.3)	(323.9)
Solid JOH	-445.3	-419.1
	(282.9)	(285.0)
Probability Poor, 2013	-299.3	-675.1
	(1,676)	(1,683)
Population	-0.000364	-0.000365
	(0.00118)	(0.00119)
Constant	8,276***	7,981***
	(972.0)	(1,006)
Observations	298	298
R-squared	0.531	0.523
Adjusted R-squared	0.490	0.481

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

8 Base category is opposition aligned in 2013 and 2017.

Table 4. Municipal Participation Rate Associated with Less Migration		
Linear Regression Absorbing Department Effects, 2013- 2017		
	(1)	(2)
VARIABLES	Part.	Part1b
Participation Rate, 2013&17	-11,861***	-10,905***
	(1,439)	(1,489)
Change in Participation Rate, 2013-17	-3,498*	-4,234**
	(2,090)	(2,085)
Swing Direction (+=toward JOH)	-421.5*	-436.3*
	(237.0)	(241.8)
Municipal Party Alignment[9]		
Swing	-108.6	-88.23
	(311.6)	(317.9)
Solid JOH	-828.3***	-787.1***
	(274.3)	(279.7)
Probability Poor, 2013	-3,350**	-3,917**
	(1,625)	(1,652)
Population	-0.00116	-0.00118
	(0.00114)	(0.00117)
Constant	12,157***	11,738***
	(942.5)	(986.9)
Observations	298	298
R-squared	0.543	0.524
Adjusted R-squared	0.503	0.482

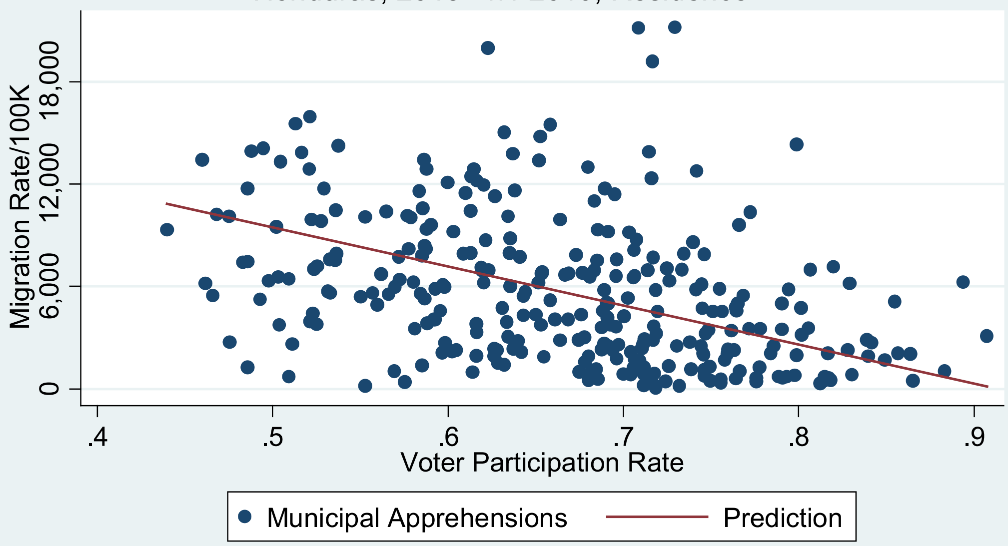
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

These multivariate regression analises demonstrate that the particpation rate retains a robust and statistically significant negative relationship with the cumulative migration rate when adding in control variables for municipal poverty and absorbing the effects of unmeasured department-level factors. Additionally, across the models and the years, those municipalities that became more (less) participatory sent fewer (more) migrants; those that swung from the opposition to supporting the incumbent and those that solidly supported JOH in both elections were also less likely to sent migrants. However, the latter results are driven by migration during the 2013 to 2017 period and are not statistically significant determinants of the migration rate in 2018-19. Participation is a better predictor of cumulative migration from 2013-2017 and the relationship, while still present, is somewhat weaker for 2018-h1.2019. Figures 1a – 3a present scatter plots showing the relationships between migrant apprehension rates and voter participation for each of the three time periods and each of the three operationalizations of voter participation, and show the fitted line showing the apprehension rate at each level of voter participation as predicted by the model.

9 Base category is opposition aligned in 2013 and 2017.

Figure 1a. Civic Engagement and Migrant Apprehension Rate

Honduras, 2013 - h1.2019, Residence

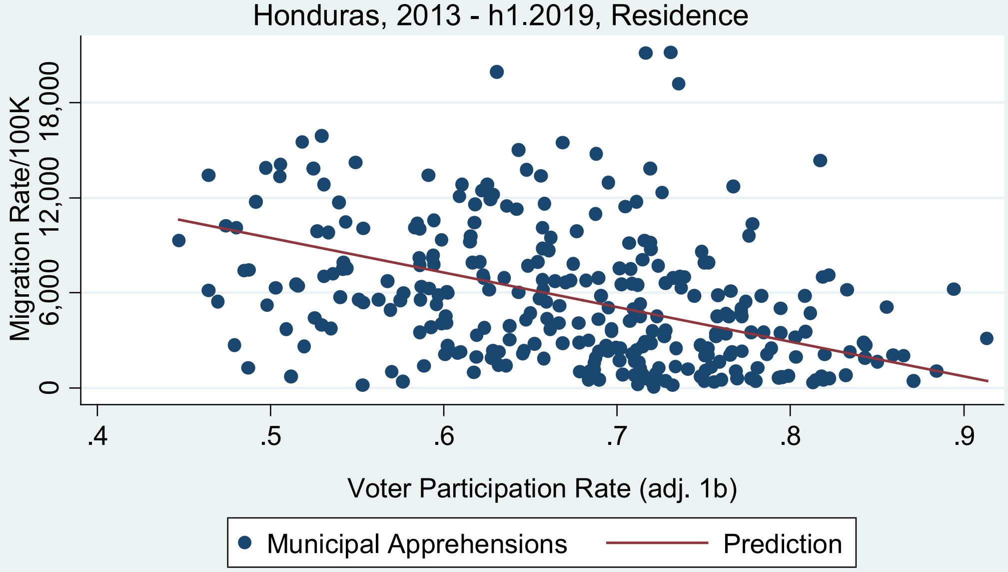


Note: Unadjusted participation rate, 2013 and 2017 average. Linear regression with fixed effects for department and control variables for poverty and population.

Sources: DHS; TSE voter file, 2013 and 2017. Analysis and elaboration by author.

Figure 1b. Civic Engagement and Migrant Apprehension Rate

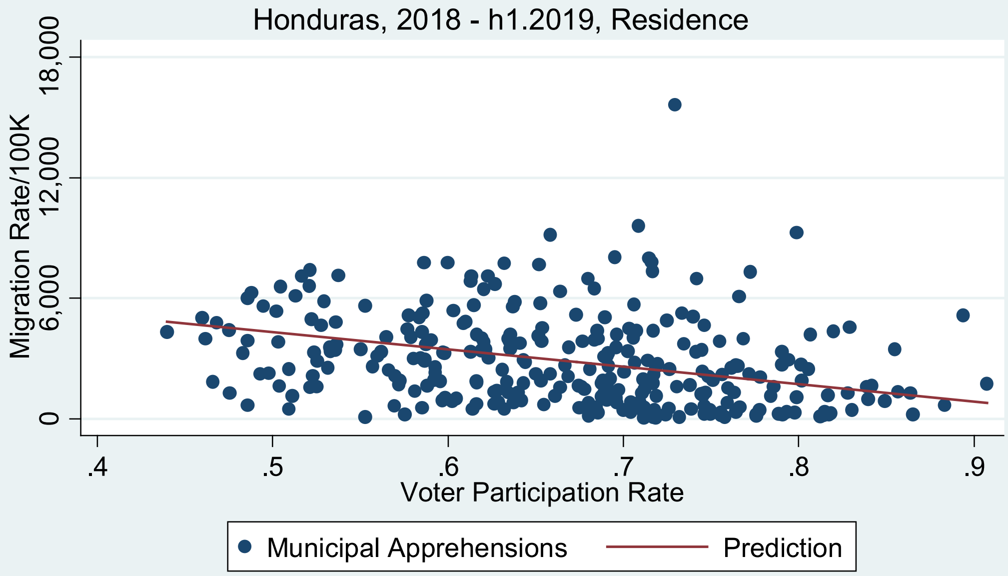
Honduras, 2013 - h1.2019, Residence



Note: Adjusted participation rate, 2013 and 2017 average. Linear regression with fixed effects for department and control variables for poverty and population.

Sources: DHS; TSE voter file, 2013 and 2017. Analysis and elaboration by author.

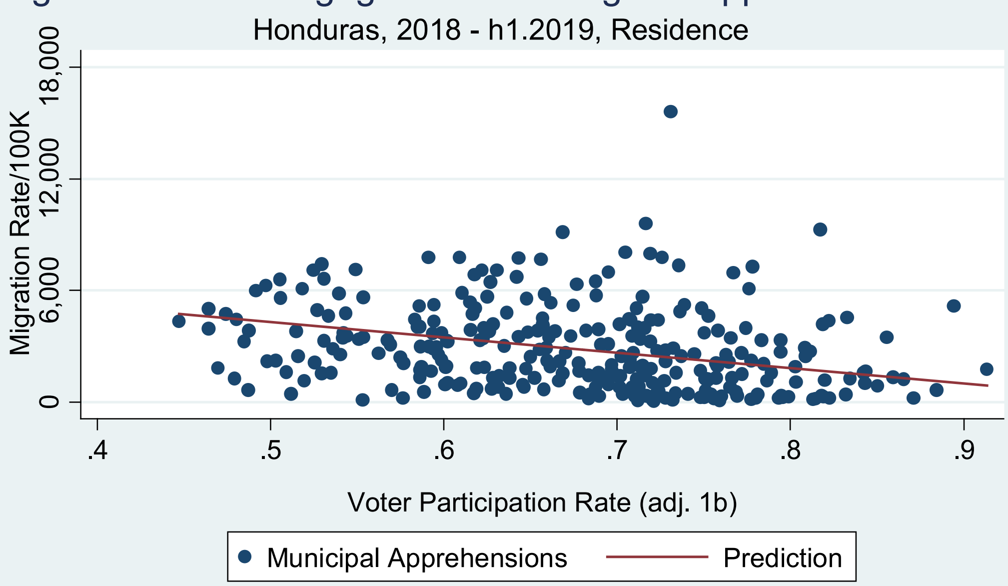
Figure 2a. Civic Engagement and Migrant Apprehension Rate



Note: Unadjusted participation rate, 2013 and 2017 average. Linear regression with fixed effects for department and control variables for poverty and population.

Sources: DHS; TSE voter file, 2013 and 2017. Analysis and elaboration by author.

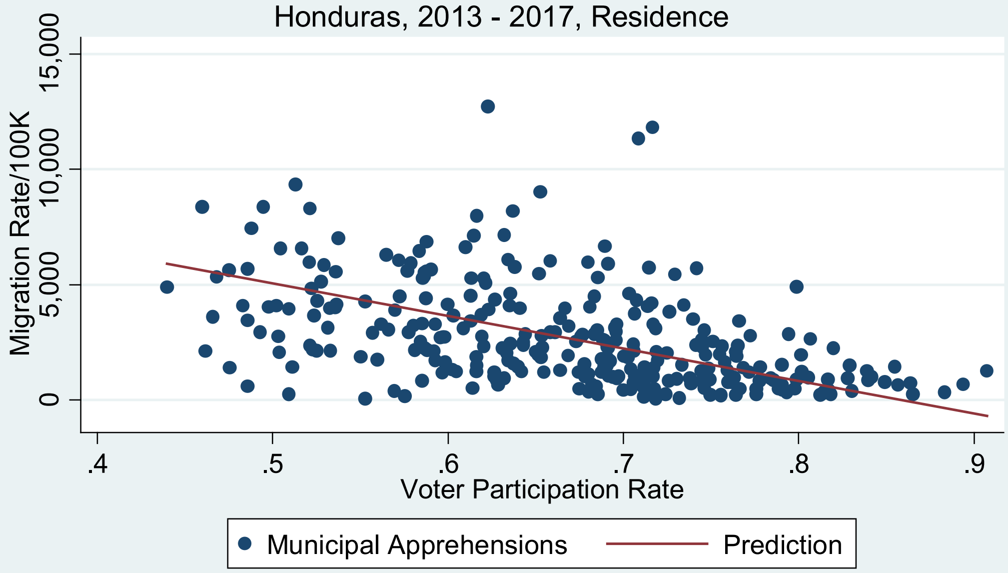
Figure 2b. Civic Engagement and Migrant Apprehension Rate



Note: Adjusted participation rate, 2013 and 2017 average. Linear regression with fixed effects for department and control variables for poverty and population.

Sources: DHS; TSE voter file, 2013 and 2017. Analysis and elaboration by author.

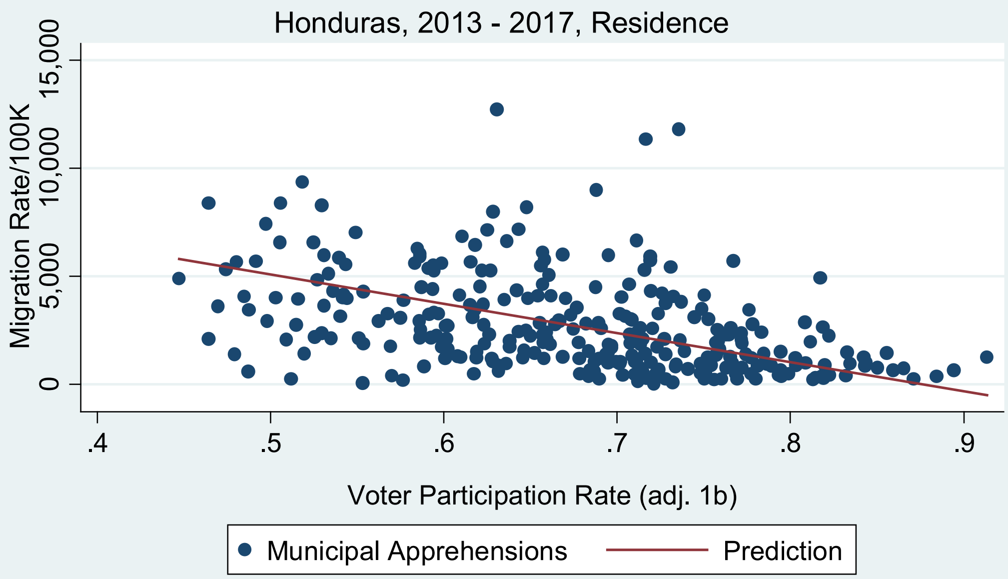
Figure 3a. Civic Engagement and Migrant Apprehension Rate



Note: Unadjusted participation rate, 2013 and 2017 average. Linear regression with fixed effects for department and control variables for poverty and population.

Sources: DHS; TSE voter file, 2013 and 2017. Analysis and elaboration by author.

Figure 3b. Civic Engagement and Migrant Apprehension Rate



Note: Adjusted participation rate, 2013 and 2017 average. Linear regression with fixed effects for department and control variables for poverty and population.

Sources: DHS; TSE voter file, 2013 and 2017. Analysis and elaboration by author.

Social Infrastructure

Table 5 shows the Pearson's correlation statistics for the three apprehension variables and six indicators or social infrastructure. These include, the number of schools as a percentage of youth population in a municipality, the health care deficit per 100,000 population, the number of health centers (per 100k), the number of cemeteries (per 100k), the number of churches (per 100k), and the number of soccer fields (per 100k). We expect higher endowments of social infrastructure to lead to less emigration; meaning we expect a negative correlation for each of these variables except for the health care deficit. In accordance with our expectations, the health care deficit had a positive relationship with apprehensions across both periods and the number of health centers had a negative relationship, but only from 2013 to 2017. Contrary to expectations, the number of churches, which we expect to explain greater community attachment, was positively associated with migration, but only from 2018 to 2019. In addition to exploring these variables independently, we construct a latent variable index of social infrastructure based on a principal components factor analysis of these variables. We transform the health care deficit variable by multiplying by -1 so that high values of each variable indicate higher levels of social infrastructure.[10] As reflected in Table 5, there is a nominally negative but not statistically significant relationship between social infrastructure and apprehensions across all three periods.

Table 5. Social Infrastructure and US Border Apprehensions
Pearson's Correlations

	Apprehensions/100k		
	2013-19	2013-17	2018-19
Schools (pct. of youth population)	-0.014	0.0226	-0.0468
Health Care Deficit (per 100K)	0.1659*	0.1719*	0.1417*
Health Centers (per 100K)	-0.1095	-0.1478*	-0.0525
Cemeteries (per 100K)	-0.0026	-0.0391	0.0396
Churches (per 100K)	0.0619	-0.0058	0.1296*
Soccer Fields (per 100K)	-0.004	-0.0908	0.0915
Social Infrastructure Index	-0.0612	0.0002	-0.108

* Statistically significant at the 0.05 level

Table 6a reports the results of three linear regression models including the social infrastructure variables individually, controls for poverty and population and fixed effects for department. After including these control variables, the positive relationship between health care deficit and apprehension rate remains significant. While this comports with our expectations, examining the distribution of this variable suggests that we should interpret this result with some caution. Figure 4a shows a scatter plot of the heath care deficit variable and the linear prediction of the full model. As can be seen, the bulk of municipalities do not have a health care deficit. The significant results remain when running this analysis without the high-end outliers in health care deficit (>20/100k) but not when excluding the all but 56 municipalities with a deficit of 0. The number of churches per 100,000 population, which was statistically significant in the positive direction—contrary to expectations—for the 2018-h1.2019 period emerges as statistically significant across all three models.

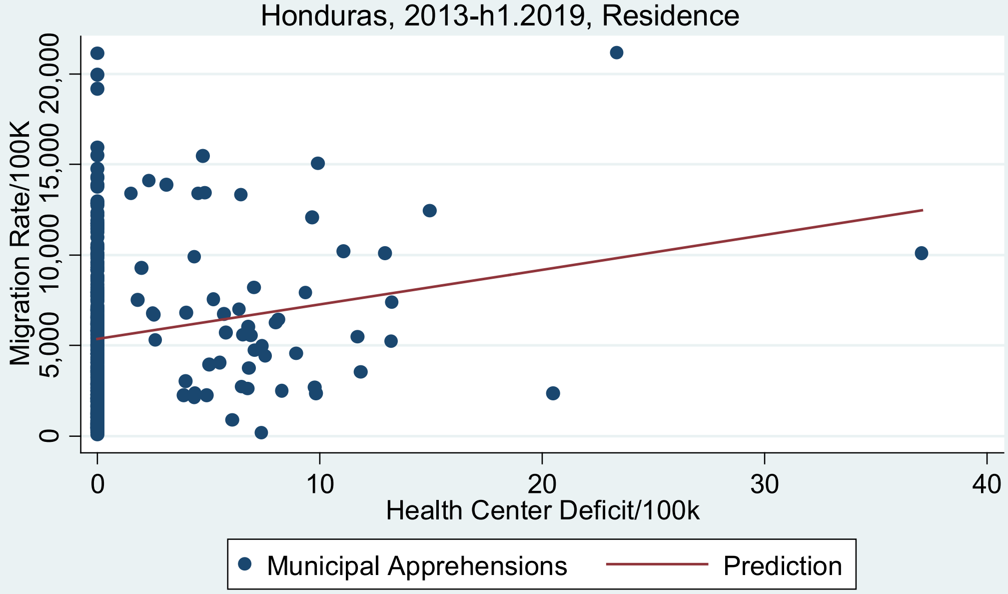
10 Eigenvalue = 1.56.

Table 6a. Social Infrastructure and Migration Linear Regression Absorbing Department Effects, 2013- 2017			
VARIABLES	2013-h1.19	2013-17	2018-h1.19
Schools (pct. of youth population)	162.6	11.64	152.8*
	(163.1)	(88.50)	(85.70)
Health Care Deficit (per 100K)	157.6***	60.92**	96.49***
	(56.71)	(30.77)	(29.80)
Health Centers per-capita	-5.580	0.925	-6.326
	(14.08)	(7.642)	(7.400)
Cemeteries per-capita	-4.360	-0.0749	-4.147
	(7.971)	(4.326)	(4.189)
Churches per-capita	22.87***	15.60***	7.441*
	(8.169)	(4.433)	(4.293)
Soccer fields per-capita	7.874	6.195	1.715
	(8.349)	(4.531)	(4.387)
Probability Poor, 2013	-9,477***	-6,735***	-2,750
	(3,246)	(1,761)	(1,706)
Population	0.00183	0.00129	0.000518
	(0.00241)	(0.00131)	(0.00127)
Constant	6,762***	3,876***	2,803***
	(1,068)	(579.7)	(561.3)
Observations	298	298	298
R-squared	0.491	0.449	0.502
Adjusted R-squared	0.444	0.399	0.456

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 4a. Health Center Deficit and Migration

Honduras, 2013-h1.2019, Residence



Note: Linear regression with fixed effects for department and control variables for poverty and population.

Sources: DHS; SINIT geoportal. Analysis and elaboration by author.

We estimate an alternative and more parsimonious model with the social infrastructure index in the place of the individual variables. The models using this variable are reported in table 6b. Based on Akaike Information Criteria (AIC) comparison between both models suggests that the model in 6b (AIC= 5652.421) is "'considerably' more supported by the evidence" than the model presented in 6a (AIC= 5643.195).[11] This analysis shows that social infrastructure is positively associated with migration over the whole period and from 2013 through 2017. The relationship is positive but not statistically significant from 2018 through h1.2019. The relationship over the whole period is plotted in Figure 4b. This result contradicts our expectation that better social infrastructure should make populations less likely to emigrate, result that could have to do with development effects, as improvements in levels of development are expected to increase migration. Controlling for municipal-level poverty and department-level fixed effects should at least partially account for this.

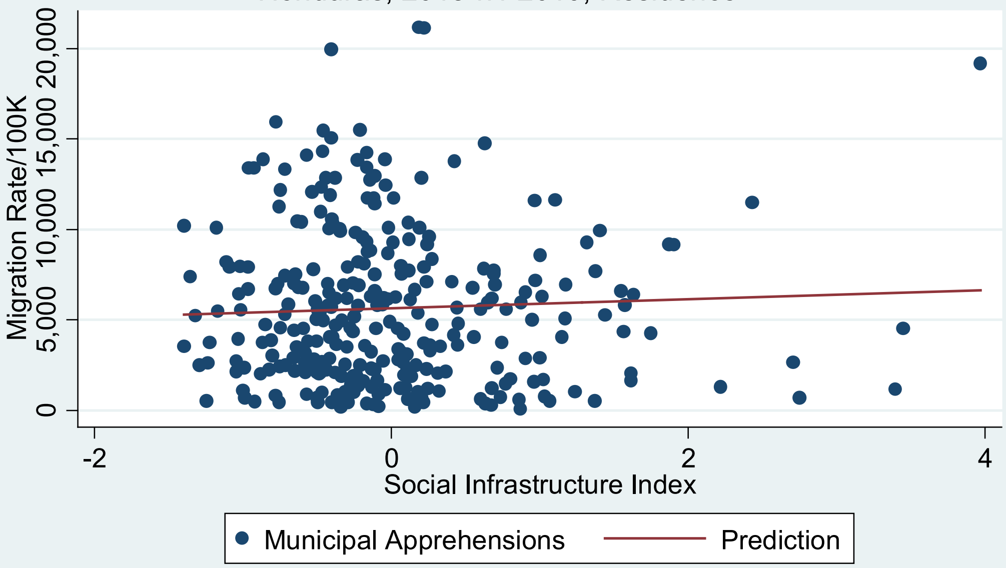
Table 6b. Social Infrastructure and Migration
Linear Regression Absorbing Department Effects, 2013- 2017

VARIABLES	2013-h1.19	2013-17	2018-h1.19
Social Infrastructure Index	489.5***	120.6	596.0**
	(138.5)	(135.2)	(256.1)
Probability Poor, 2013	-9,477***	-6,735***	-2,750
	(3,246)	(1,761)	(1,706)
Population	0.00183	0.00129	0.000518
	(0.00241)	(0.00131)	(0.00127)
Constant	6,762***	3,876***	2,803***
	(1,068)	(579.7)	(561.3)
Observations	298	298	298
R-squared	0.491	0.449	0.502
Adjusted R-squared	0.444	0.399	0.456

11 The information-theoretical criteria for selection (not a formal statistical test) suggest that if the AIC of one model is larger than that of another model, there is no empirical support for the former model (Cross-Validated 2017).

Figure 4b. Social Infrastructure and Migration

Honduras, 2013-h1.2019, Residence



Note: Linear regression with fixed effects for department and control variables for poverty and population.

Sources: DHS; SINIT geoportal. Analysis and elaboration by author.

HOME OWNERSHIP AND LAND USE

Table 7 shows the bivariate correlations between the home ownership rate and migration and the shares of municipal territory and changes in shares from 2014 to 2018 and the three apprehension rate variables. These variables get at different aspects of rootedness. We expect higher home ownership rates to be negatively related to migration, as owning a home is expected to bind a household to the place where they live. Regarding land use and change in land use, our working hypothesis is that productive investments will be negatively associated with emigration. That said, as noted above, there are counterhypotheses possible insofar as certain land use activities reduce labor demand or generate displacement due to land conflict. As expected, the home ownership rate was negatively related to migrant apprehensions, however this was most evident during the 2018-19 period.

Several land use variables were statistically significant. Percentage of land used for forests and savannahs was negatively related to migration, whereas African palm and industrialized agriculture were associated with higher rates of migration. Additionally, the change in the share of territory utilized for African palm was also positively related to migration. Next, we seek to sort out these relationships and the extent to which they hold when controlling for other variables.

Table 8 reports the results from three multivariate regression models that control for poverty and population and include departmental fixed effects. When running these models with the share and change of agriculture and African palm included, as well as the home ownership rate, the latter is the only variable that retains its statistical significance and does so across all three models. Figure 5 shows a scatter plot of this variable and the model's linear prediction for the full period studied.

Table 7. Home Ownership and Land Use Pearson's Correlations

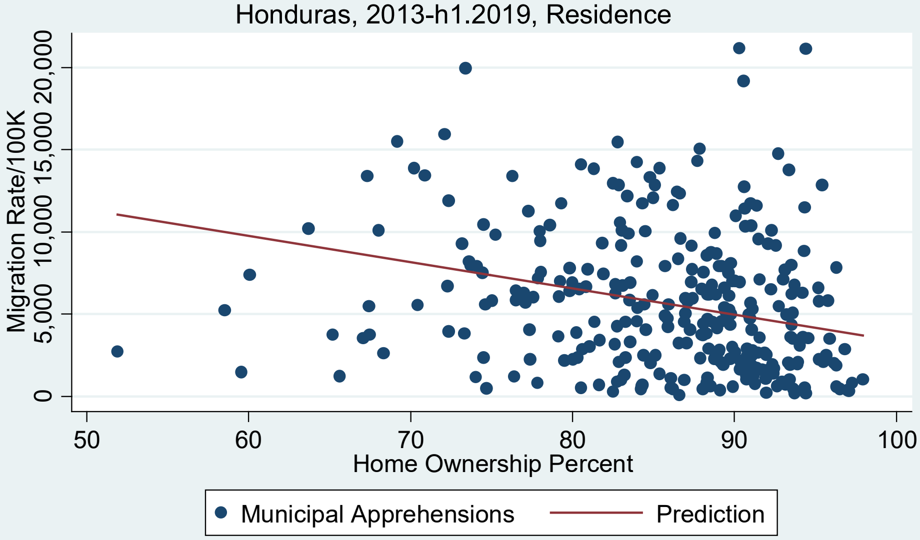
	Apprehensions/100k		
	2013-19	2013-17	2018-19
Percent who own their home (2013 census)	-0.1926*	-0.2369*	-0.1266*
Pct. Forests	-0.2332*	-0.1635*	-0.2689*
Pct. Change Forests	-0.085	-0.0905	-0.0688
Pct. Savannahs	-0.1491*	-0.1323*	-0.1476*
Pct. Change Savannahs	0.0807	0.0842	0.0678
Pct. Industrialized Agriculture	0.2073*	0.1104	0.2715*
Pct. Change Industrialized Agriculture	0.0323	0.0274	0.0319
Pct. African Palm	0.2186*	0.2523*	0.1620*
Pct. Change African Palm	0.1512*	0.1695*	0.1170*
Pct. Water ways, lagoons, etc.	-0.0842	-0.053	-0.1037
Pct. Change Water ways, lagoons, etc.	-0.0896	-0.1209*	-0.0496
Pct. Urban	0.0847	0.1275*	0.0325
Pct. Change Urban	-0.0154	-0.0123	-0.0164

* Statistically significant at the 0.05 level

Table 8. Home Ownership, Land Use, and Migration Linear Regression Absorbing Department Effects, 2013- 2017			
VARIABLES	2013-h1.19	2013-17	2018-h1.19
Percent who own their home (2013 census)	-109.5**	-60.23**	-47.14**
	(43.38)	(23.70)	(22.83)
Pct. Industrialized Agriculture	-1.861	-6.753	4.706
	(18.30)	(9.998)	(9.632)
Pct. Change Industrialized Agriculture	-30.79	-16.28	-14.71
	(29.04)	(15.86)	(15.28)
Pct. African Palm	87.91	61.89	25.37
	(80.45)	(43.95)	(42.34)
Pct. Change African Palm	-79.37	-97.17	17.30
	(172.8)	(94.41)	(90.95)
Probability Poor, 2013	-6,355*	-5,534***	-915.8
	(3,510)	(1,917)	(1,847)
Population	-0.000535	-0.000635	8.41e-05
	(0.00249)	(0.00136)	(0.00131)
Constant	16,829***	9,713***	6,905***
	(3,406)	(1,861)	(1,793)
Observations	298	298	298
R-squared	0.465	0.414	0.475
Adjusted R-squared	0.418	0.362	0.428

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 5. Home Ownership and Migration
Honduras, 2013-h1.2019, Residence



Note: Linear regression with fixed effects for department and control variables for poverty and population.
Sources: DHS; INE 2013. Analysis and elaboration by author.

COMMUNITY ROOTS AND (IM)MOBILITY

Table 9 shows the bivariate relationships between a series of variables measuring the depth of local roots and general mobility of the municipal population. In addition to the set of individual variables, we use a factor analysis to construct three latent variable index variables. The first we call "immobile", which is generated using the percentages of the municipal population that 1) were born in the same municipality and 2) that lived in the same village or neighborhood 5 years earlier (Eigenvalue=1.3). The second factor variable is called "internal" and is based on 1) the percentage of the population that was born in a different Honduran municipality and 2) the percentage that lived elsewhere in Honduras 5 years earlier (Eigenvalue=1.3). Finally, we generate a latent variable "global" based on 1) international migrants as a percentage of the municipal population, 2) the percent living abroad 5 years earlier, and 3) the percent born abroad (Eigenvalue=1.6). We expect that populations that are have moved less to move less in the future. As such, we would expect "immobile" and its component variables to be negatively related to subsequent migration flow; while we expect internal and global (and their component variables) to be positively associated with subsequent migration.

Surprisingly, neither the variables measuring immobility nor internal mobility are significantly associated with US border apprehensions. In accordance with expectations our "global" index and its component variables are all positively associated with migration flow as measured by apprehensions across all three periods.

Table 9. Community Roots and (Im)mobility
Pearson's Correlations

	Apprehensions/100k		
	2013-19	2013-17	2018-19
Pct. Born in Municipality (2013)	-0.0113	-0.0471	0.0253
Pct. in Same Village/Neighborhood in 2008 (2013)	0.047	0.0617	0.0313
Immobility Index	0.0192	0.0078	0.0304
Pct. Born in Other Municipality (2013)	0.0024	0.0359	-0.0309
Pct. elsewhere in Honduras in 2008 (2013)	-0.0821	-0.1006	-0.0586
Internal Migration Index	-0.0428	-0.0348	-0.0481
Pct. Born Abroad (2013)	0.1730*	0.2228*	0.1055
Pct. in Another Country in 2008 (2013)	0.3447*	0.3810*	0.2694*
Migrants as Percent of Population (2013)	0.5024*	0.6051*	0.3518*
Global Index	0.3710*	0.4317*	0.2710*

* Statistically significant at the 0.05 level

We next estimate three multivariate regression models, including the immobility and internal migration indices, as well as the variable for migrants as a percentage of the population and the control variables used in the previous models (see Table 10). There is reason to expect that the effects of these variables are moderated by the international migration networks, so we estimate the interaction effect of each index with the number of migrants from households in each municipality as a percentage of the population.[12] Not surprisingly, the migration variable is statistically significant in the positive direction

12 We also run a model with a three-way interaction—(migration)*(internal index)*(immobility index)—but this model does not improve upon the selected model with two two-way interaction. The two are equivalent based on a likelihood ratio test and the adjusted-R2 of the selected model is slightly smaller.

across all periods.[13] Somewhat surprisingly, when previous migration rates are high, immobility is positively related to the apprehension rate. Similarly, though not surprisingly, where previous migration rates are high, internal migration is positively associated with apprehensions. When previous migration is lower, however, both internal migration and immobility were negatively related to apprehensions. In interpreting these results it is important to keep in mind that, since the level of analysis is municipal, it does not follow that those who were immobile for their whole lives and in the previous 5 years when asked in 2013 became international migrants subsequently. That is, the migrants could have been drawn from the mobile minorities of these populations. Figure 6a plots the model prediction and scatter plot of the migration rate over the whole period. Figure 6b plots the predicted migration rate at different levels of previous migration, with all other variables held at their means.

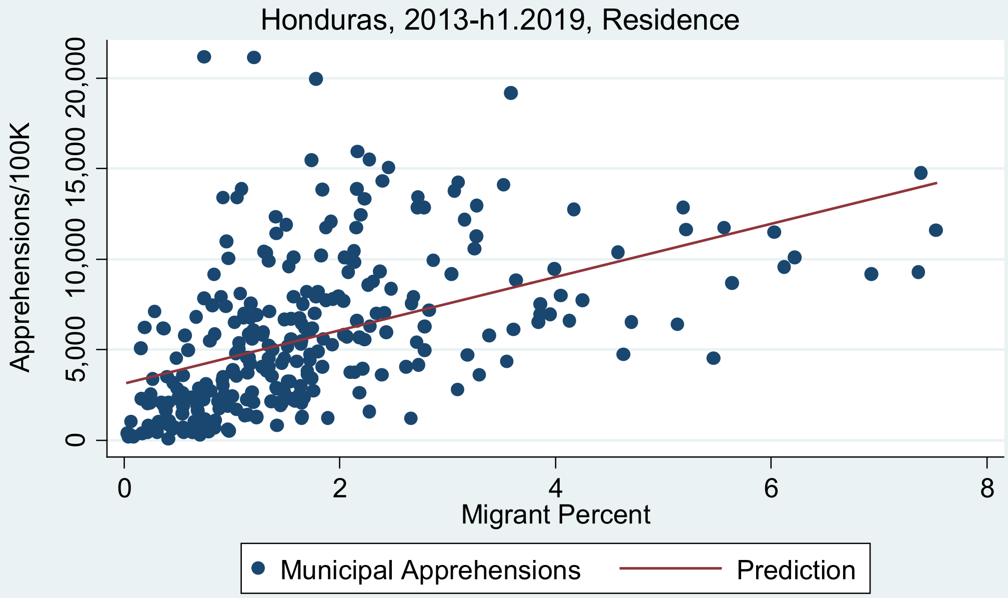
Table 10. (Im)mobility and Apprehensions
Linear Regression Absorbing Department Effects, 2013- 2017

VARIABLES	2013-h1.19	2013-17	2018-h1.19
Migrants as % of Pop.	1,487***	596.3***	893.5***
	(190.0)	(109.6)	(97.09)
Immobility Index	-15,327***	-9,402***	-5,523*
	(5,574)	(3,215)	(2,849)
Migrants*Immobility	4,289***	2,782***	1,406*
	(1,501)	(866.1)	(767.4)
Internal Migration Index	-15,804***	-9,728***	-5,680**
	(5,559)	(3,207)	(2,841)
Migrants*Internal	4,232***	2,790***	1,344*
	(1,474)	(850.3)	(753.3)
Probability Poor, 2013	-5,596**	-1,161	-4,462***
	(2,753)	(1,588)	(1,407)
Population	0.00261	0.00111	0.00145
	(0.00197)	(0.00113)	(0.00101)
Constant	4,923***	2,301***	2,558***
	(952.4)	(549.4)	(486.8)
Observations	298	298	298
R-squared	0.635	0.570	0.650
Adjusted R-squared	0.603	0.532	0.619

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

13 Ran similar models using the global index, however, since two of the component variables in that index (percent foreign born and percent living in another country 5 years earlier) are perfect complements to the component variables from the Immobility and Internal Migration indices, it is prudent to leave these out.

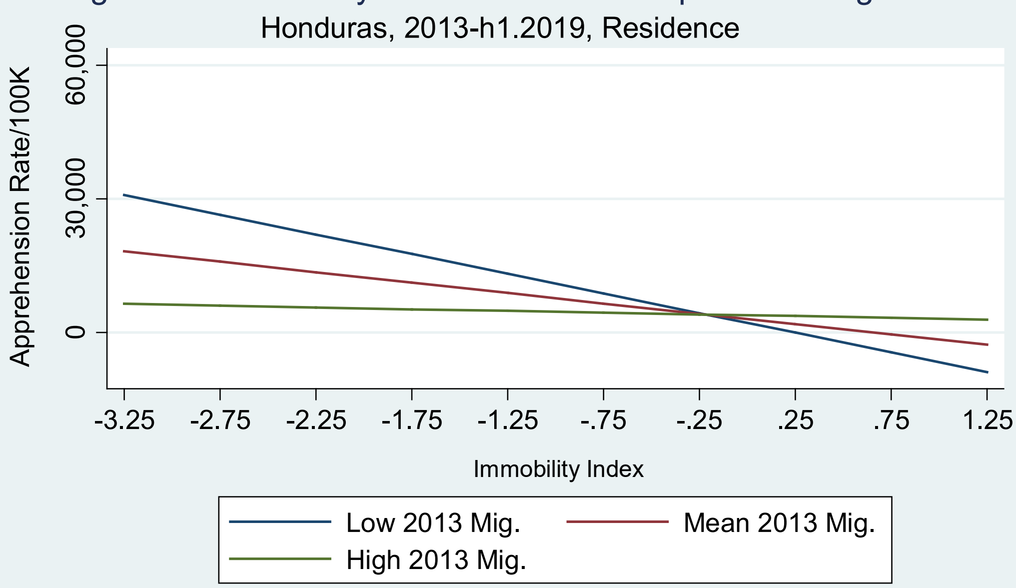
Figure 6a. Migrants as a Percentage of Population (2013)



Note: Linear regression with fixed effects for department and control variables for poverty and population.

Sources: DHS; INE 2013. Analysis and elaboration by author.

Figure 6b. Immobility at different levels of pre-2013 Migration



Note: Linear regression with fixed effects for department and control variables for poverty and population. High = mean - s.d; Low = mean + sd.

Sources: DHS; INE 2013. Analysis and elaboration by author.

STRENGTH OF CULTURAL TIES

Table 11 shows bivariate correlations between the municipal percentage of self-identified indigenous, Garifuna, and English-speaking Afro-Honduran populations at the municipal level. We also include a variable that includes all indigenous communities together and all Afro-Honduran populations together. The bivariate results show a negative relationship between apprehensions and Lenca, Miskito, and Indigenous population percentage across all time periods. It is important to note that the Lenca community is by far the most numerous, with 1,400 people identifying as Lenca in the average municipality (15%), followed by Miskito and Garifuna (255 and 123, respectively). For this reason, in the multivariate analysis include the variable grouping all indigenous pueblos together as well as the variable for the percentage of municipal population that identifies as Garifuna.

Table 11. Indigenous and Garifuna Pueblos (2013)
Pearson's Correlations

	Apprehensions/100k		
	2013-19	2013-17	2018-19
Pct. Maya-Chortí	0.0185	0.0087	0.0252
Pct. Lenca	-0.1929*	-0.1627*	-0.1990*
Pct. Miskito	-0.1737*	-0.1619*	-0.1643*
Pct. Nahua	0.0582	0.0131	0.094
Pct. Pech	0.034	0.021	0.0431
Pct. Tolupán	0.0224	0.0289	0.0125
Pct. Tawahka	-0.0726	-0.0674	-0.0689
Pct. Garifuna	0.0515	0.0355	0.0616
Pct. English-Speaking Black	-0.0943	-0.0877	-0.0899
Pct. Other	0.1044	0.1252*	0.0736
Pct. Indigenous	-0.2380*	-0.2063*	-0.2403*
Pct. Afro-Honduran	-0.0079	-0.0147	0.0007

* Statistically significant at the 0.05 level

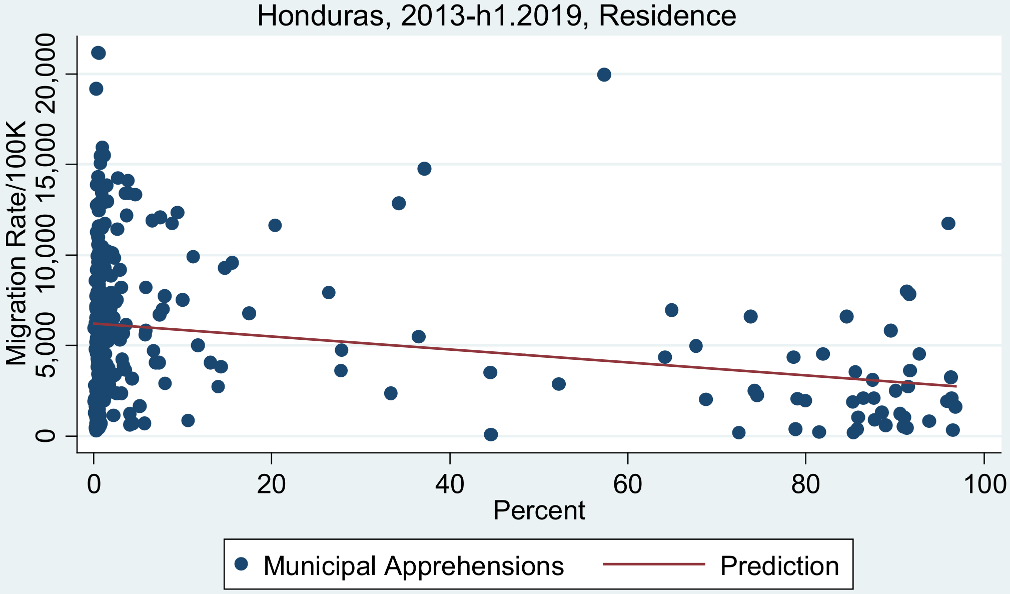
As Table 12 shows, the statistically significant negative relationship between indigenous percentage and apprehensions remains after including control variables for poverty, population, and departmental fixed effect. The relationship is present in all three periods, but strongest during the 2018-2019 period. Despite having a positive, albeit not statistically significant, bivariate relationship to migrant apprehensions, when controlling for other factors, the percentage of the population identifying as Garifuna had a slightly negative relationship with apprehensions from 2013 to 2017 ($p<0.1$). Figure 7 graphs a scatterplot of the relationship between indigenous percentage and apprehensions from 2013 through h1.2019 and includes the linear prediction estimated by the model.

Table 12. Indigenous and Garifuna Population and Migration Linear Regression Absorbing Department Effects, 2013-2017			
VARIABLES	2013-h1.19	2013-17	2018-h1.19
Pct. Indigenous	-23.21**	-9.454*	-13.37**
	(10.22)	(5.606)	(5.350)
Pct. Garifuna	-146.0	-100.0*	-45.27
	(110.0)	(60.38)	(57.62)
Probability Poor, 2013	-7,846**	-6,725***	-1,174
	(3,324)	(1,824)	(1,741)
Population	0.00198	0.000780	0.00114
	(0.00234)	(0.00128)	(0.00122)
Constant	8,388***	4,920***	3,416***
	(986.1)	(541.1)	(516.5)
Observations	298	298	298
R-squared	0.459	0.402	0.474
Adjusted R-squared	0.418	0.357	0.434

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 7. Percent Indigenous

Honduras, 2013-h1.2019, Residence



Note: Linear regression with fixed effects for department and control variables for poverty and population.

Sources: DHS; INE 2013. Analysis and elaboration by author.

FULL MODEL

The final section reports a full model including key variables from each of the above categories. Likelihood ratio tests were conducted to select the best model. As Table 13 shows, after including all the variables in the model, many of the relationships identified in the individual models reported above hold. The analysis of civic engagement held, but it is evident that the participation rate and the change in participation rate from 2013 to 2017 are negatively related to apprehensions; however, this relationship loses statistical significance for the 2018-2019 period. Municipalities that swung in favor of the incumbent, President Juan Orlando Hernandez from 2013 to 2017 were less likely to be apprehended at the US border from 2013 to 2017, as were those that voted solidly for the president in both elections. As with the participation rate, however, these relationships lost statistical significance during the 2018 to 2019 period.

Notably, in the full model, social infrastructure loses statistical significance from 2018-2019 and over the whole period (in the social infrastructure model reported in Table 6b, there was no statistically significant relationship from 2013 to 2017). The home ownership percentages retained statistical significance (weakly) in the 2013 to 2017 period and over the whole period, but not from 2018 to 2019. The series of interaction variables measuring mobility and immobility, internally and internationally, retained the same relationships as in the simple models but at lower levels of statistical significance. Not surprisingly, municipalities with more migrants as a percent of their population in 2013 were more likely to have their members apprehended at the US border over the whole period of study. Indeed, the inclusion of this influential variable likely explains the weakening relationships observed in the full model for other variables. Finally, and on that note, the percentage of the municipal population identifying with an indigenous or the Garifuna community lost statistical significance in the full model.

Table 13. U.S. Border Apprehension Rates of Honduran Municipalities: Full Models Linear Regression Absorbing Department Effects, 2013- 2017			
	2013-h1.19	2013-2017	2018-h1.2019
Participation Rate, 2013&17[14]	-5,964*	-4,267***	-1,699
	(3,091)	(1,551)	(1,811)
Change in Participation Rate, 2013-17	-6,237*	-3,039*	-3,156
	(3,542)	(1,778)	(2,075)
Swing Direction (+=toward JOH)	-511.6	-342.8*	-161.3
	(407.2)	(204.4)	(238.6)
Municipal Party Alignment[15]			
Swing	82.26	39.36	45.58
	(532.9)	(267.5)	(312.2)
Solid JOH	-792.3*	-530.5**	-260.6
	(475.6)	(238.7)	(278.6)
Social Infrastructure Index	33.79	150.9	-105.8
	(238.3)	(119.6)	(139.6)
Percent who own their home (2013)	-78.44*	-40.39*	-36.57
	(43.10)	(21.64)	(25.25)
Immobility Index	-10,255*	-2,172	-7,728**
	(5,648)	(2,835)	(3,309)
Migrants as % of Pop.	1,289***	767.1***	526.0***
	(208.9)	(104.8)	(122.4)
Migrants*Immobility	3,341**	880.6	2,378***
	(1,511)	(758.4)	(885.2)
Internal Migration Index	-10,799*	-2,327	-8,118**
	(5,635)	(2,828)	(3,301)
Migrants*Internal	3,270**	799.8	2,391***
	(1,492)	(748.9)	(874.2)
Pct. Indigenous	-0.348	5.948	-5.795
	(8.673)	(4.353)	(5.081)
Pct. Garifuna	-53.10	-56.49	2.834
	(93.10)	(46.73)	(54.54)
Probability Poor, 2013	-1,398	-2,809*	1,261
	(3,288)	(1,650)	(1,926)
Population	-0.000348	-1.31e-05	-0.000329
	(0.00214)	(0.00108)	(0.00126)
Constant	15,142***	8,805***	6,173***
	(3,411)	(1,712)	(1,999)
Observations	298	298	298
R-squared	0.665	0.690	0.592
Adjusted R-squared	0.623	0.651	0.541

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

14 For the full model, we use the adjusted participation rate reported in column 2 of tables 2, 3, and 4.
15 Base category is opposition aligned in 2013 and 2017.

ANNEX A: SOURCES AND MEASUREMENT METHODS FOR VARIABLES

I. Civic Engagement

MESCLA downloaded 2017 presidential and deputy general election and the 2013 presidential election voting data from the *Tribunal Supremo Electoral* (TSE) at the level of the *Mesa Electoral Receptora* (MER). Among other variables, these data include variables for the number of **total votes**, the number of **valid votes** (total votes less nullified and blank votes), and the number of **ballots received**. We assume that the number of ballots received at each MER is a good estimate of the number of eligible registered voters, and thus the baseline denominator to calculate the participation rate.[16] However, due to irregularities and allegations of fraud, the 2017 electoral results were challenged and there was a recount and review of results in 5,755 MERs (more than 30% of the total). In these MERs, the number of ballots received is recorded as 0. To deal with this problem, we draw upon the number of **ballots** received for the Chamber of Deputies election and use this value when the value is 0 in the presidential file.

With this starting point, we calculate the municipal-level participation rate using several different operationalizations. Most simply, the presidential election participation rate is calculated by dividing the number of **total votes** in the municipality (the sum of votes of all MERs in each municipality) by the imputed number of eligible voters.[17] We calculate seven alternatives to this estimate by adjusting the denominator in an effort to more accurately capture the true number of possible voters. Specifically, the estimated number of eligible voters is adjusted based on different assumptions of the number of migrants who have left the municipality in the years preceding the election. This adjustment is important to make because higher migration places, all else equal, will appear to be less participatory. As such, calculating the participation rate with an unadjusted denominator could bias the estimates in such a way that it would seem as though participation decreased the likelihood of migration (or that migration decreased the participation of those who stayed behind) when in fact there is simply a systematic overestimation of the number of eligible voters present in higher migration municipalities.

The alternative estimates of eligible voters all begin with the imputed estimate of eligible voters described above and subtracting the following:[18]

For 2013 and 2017 elections:

1) Using 2013 census data on migrant household members:
    a. The number of households with at least 1 migrant living abroad when asked in the 2013 census.
    b. The number of individual migrants living abroad from households in Honduras when asked in the 2013 census.
    c. The number of individual migrants living abroad who left in 2009 or later from households in Honduras when asked in 2013.

For 2017 election only:

16 For the purposed of measuring civil engagement and thus community attachment we believe that the most relevant numerator is the number of **total votes**, as the act of nullifying one's vote or leaving the ballot blank is a sign of civic engagement—in addition to being arguably an indicator of broad rejection of the political system (as opposed to one particular party). The rate of abstention is arguably also an indicator of this but reflects an arguably lower level of civic—or at least political system—engagement.

17 We also calculate similar quotients using valid votes as the numerator and using total and valid votes in the Chamber of Deputies election, though these results are not detailed here.

18 While the return migrant numbers used above all include Mexican deportations as well as US deportations, the apprehension numbers are only available for the US. As such, we may be underestimating the number of net migrants in some cases, specifically by not counting those migrants who left Honduras but remain in Mexico. Another alternative to explore draws on a completely different source for the original estimate of eligible voters by using census adult population estimates, though in some cases this number is smaller than the total number of votes.

2) [Adult US CBP apprehensions (2013-2017) (based on residence municipality)] – [Adult Returns (2016-17) (based on destination municipality)] / (average number of deportations, 2013-17)

3) [Adult US CBP apprehensions (2013-2017) (based on birth municipality)] – [Adult Returns (2016-17) (based on birth municipality)] / (average number of deportations, 2013-17)

4) [Adult US CBP apprehensions (2013-2017) (based on residence municipality)] – [All US Returns (2016-17) (based on residence municipality)] / (average number of deportations, 2013-17)

5) [Adult US CBP apprehensions (2013-2017) (based on birth municipality) – [All US Returns (2016-17) (based on birth municipality)]/ / (average number of deportations, 2016-17)

We divide by the average number of deportations of those deported in 2016 and 2017 to adjust for the fact that double counting might be greater in some municipalities than in others.[19] Specifically, the unit of analysis of the CBP data is apprehensions, not individuals. For the purposes of estimating the number of eligible voters in a municipality, however, the relevant number is individuals. A limit of the estimates using 2013 census data is that they do not capture cases where everyone from a household had migrated.

In addition to the above variables, we also compute the average and change in participation rates from 2013 to 2017.

II. Social Infrastructure

The data for social infrastructure variables were obtained from the *Sistema Nacional de Información Territorial* (SINIT). Shape file digital format maps is a layer of the mosaic of 236 topographic maps at 1:50,000 scale published in SINIT geoportal at www.sinit.hn. SINIT. Infrastructure is a layer of the 50,000 Maps. Honduras 1:50,000 Maps consists in 7 editions published in 2013, prepared within the cooperative program of the "Instituto Geográfico Nacional" of Honduras with the Inter-American Geodetic Service (IAGS) and the Army Map Service, United States. Includes various editions of some sheets. Some maps published by the Instituto Geográfico Nacional. Some maps published in English by Army Map Service. Some maps published with the collaboration of the United States Defense Mapping Agency. Some maps prepared and published by the United States Defense Mapping Agency, Topographic Center. Some maps reprinted by United States National Imagery and Mapping Agency. Original map compiled by photogrammetric methods.

The QGIS point polygon count algorithm was used to tabulate the infrastructure attributes as class fields "point count algorithm" using the municipal and infrastructure polygons as inputs. This algorithm takes a points layer and a polygon layer and counts the number of points from the first one in each polygon of the second one. A new polygons layer is generated, with the exact same content as the input polygons layer but containing an additional field with the points count corresponding to each polygon. Alternatively, a unique class field can be specified. If set, points are classified based on the selected attribute, and if several points with the same attribute value are within the municipal polygon, only one of them is counted. The final count of the point in a polygon is, therefore, the count of different classes that are found in it.

Using this method, we identified the number of Schools, Health Centers, Cemeteries, and Churches, and the Health Care Deficit in each municipality.

III. Home ownership

19 This is a very rough estimate, as some of the individuals answering these survey questions could have been deported many years ago rather than over the past few years or less.

The variable for the home ownership percentage comes from the "tenencia" variable from the 2013 Census of Population and Households (INE 2013) and was processed by the author using the following Redatam command:

```
RUNDEF
Job
   SELECTION ALL

TABLE AVar0
                TITLE
"Tenencia"
    AS AREALIST
        OF    MUNIC,    MUNIC.NMUNIC    64.0,
HOGAR.TENENCIA A1
    DECIMALS 2
     FOOTNOTE "Procesado con Redatam;Censo
2013 Ine-Honduras"
```

Based on the output, we calculate the number of homes that were owned (propia) as a percentage of all families (hogares).

IV. Land use and land use change

These variables are based on 2014 and 2018 data. For 2018, the data come from the Mapa Forestal y Cobertura de la Tierra of the Unidad de Monitoreo Forestal, Centro de Información y Patrimonio Forestal, Instituto Nacional de Conservación y Desarrollo Forestal, Áreas Protegidas y Vida Silvestre ICF. We use semi-automatic classification using the Google Earth Engine (GEE) platform for SENTINEL Multispectral images. The 2014 data come from the Mapa Forestal y Cobertura de la Tierra, Unidad de Monitoreo Forestal, Centro de Información y Patrimonio Forestal, Instituto Nacional de Conservación y Desarrollo Forestal, Áreas Protegidas y Vida Silvestre ICF. Processing and clasification of satelite images is done using the Sensor RapidEye TM 2012- 2013.

The QGIS Zonal histogram algorithm was used to tabulate the land use attributes. This algorithm adds fields that represent the number of each unique value in a raster layer contained within zones defined as municipal polygons.

V. Community roots

The community roots, or (im)mobility variables come from three different variables in the 2013 Census of Population and Households (INE 2013) and were processed by the author using Redatam. The first variable is based on the question asking where each person (5 years or older) lived 5 years prior (CTLRESANT) and was processed at the municipal level of aggregation using the following command:

```
RUNDEF Job
   SELECTION ALL

TABLE AVar0
    TITLE "Residencia 5 años atras"
    AS AREALIST
```

```
      OF    MUNIC,    MUNIC.NMUNIC    64.0,
PERSONA.CTLRESANT A1
     DECIMALS 2
     FOOTNOTE "Procesado con Redatam;Censo
2013 Ine-Honduras"
```

The second variable asked where each person was born (CTLNAC) and was processed using the following Redatam command:

```
RUNDEF Job
   SELECTION ALL

TABLE AVar0
     TITLE "Lugar de nacimiento"
     AS AREALIST
      OF    MUNIC,    MUNIC.NMUNIC    64.0,
PERSONA.CTLNAC A1
     DECIMALS 2
     FOOTNOTE "Procesado con Redatam;Censo
2013 Ine-Honduras"
```

The total number of migrants from each municipality (who were members of a family still living in Honduras) as a percentage of the municipal population was based on the variable MIG04 from the migration module in the census. The Redatam command used was the following:

```
RUNDEF Job
   SELECTION ALL

DEFINE MIGRACION.TMPVAR1
   AS RECODE MIGRACION.MIG04
   (1=1)
   ELSE 0
   TYPE INTEGER
   RANGE 1 - 1
   VARLABEL "Sexo"
   VALUELABELS
   1 "Hombre"

DEFINE MUNIC.QTSTOT2
   AS COUNT MIGRACION
   WEIGHT VIVIENDA.FACTORVI
   TYPE REAL
   VARLABEL "Total"
    DECIMALS 2

DEFINE MUNIC.QTSSEL3
   AS COUNT MIGRACION
   WEIGHT VIVIENDA.FACTORVI
   FOR MIGRACION.TMPVAR1 > 0
```

```
   TYPE REAL
   VARLABEL "Total Seleccionado"
    DECIMALS 2

DEFINE MUNIC.QTSPCTOT4
   AS ( MUNIC.QTSSEL3 / MUNIC.QTSTOT2 ) * 100
   FOR MUNIC.QTSTOT2 > 0
   TYPE REAL
   VARLABEL "Porcentaje"
    DECIMALS 2

TABLE TABLE1
    TITLE "Migracion"
    AS AREALIST
       OF MUNIC, MUNIC.NMUNIC 64.0, MUNIC.QTSTOT2,
MUNIC.QTSSEL3, MUNIC.QTSPCTOT4
    DECIMALS 2
    FOOTNOTE "Procesado con Redatam;Censo 2013 Ine-Honduras"
```

In addition to the number of total migrants in each municipality, this command generated the number of male and female migrants, however these variables were not used in this analysis.

VI. Strength of cultural ties

Finally, the numbers of people in each municipality identifying with different indigenous pueblos or as members of the Garifuna or English-speaking Afro-Honduran populations comes from the census questions about "pueblo indigena" (GRUPOBLA). The Redatam command used to generate this municipal-level table is the following:

```
RUNDEF Job
   SELECTION ALL

TABLE AVar0
    TITLE "Pueblo indígena"
    AS AREALIST
        OF MUNIC, MUNIC.NMUNIC 64.0,
PERSONA.GRUPOBLA A1
    TOTAL
    DECIMALS 2
     FOOTNOTE "Procesado con Redatam;Censo
2013 Ine-Honduras"
```

All of these tables can be reproduced by running the above code in the "Procesador Estadistico REDATAM" under the "Información General" tab at the following website: http://170.238.108.227/binhnd/RpWebEngine.exe/Portal?BASE=CPVHND2013NAC&lang=ESP

ANNEX B. DESCRIPTIVE STATISTICS: KEY VARIABLES

Variables	N	Mean	Std.Dev.	Min	Max
Cumulative Apps/100k (2018-h1-19)	298	2,866	2,266	22	15,611
Cumulative Apps/100k (2013-h1-19)	298	5,643	4,267	59	21,155
Cumulative Apps/100k (2013-17)	298	2,714	2,226	36	12,722
2013 Part. Rate	298	0.67	0.10	0.44	0.91
2013 Part. Rate (adj.1)	298	0.69	0.10	0.45	0.92
2013 Part. Rate (adj.1a)	298	0.69	0.10	0.45	0.92
2013 Part. Rate (adj.1b)	298	0.68	0.10	0.45	0.91
2017 Part. Rate	298	0.66	0.11	0.43	0.91
2017 Part. Rate (adj.1)	298	0.67	0.11	0.44	0.92
2017 Part. Rate (adj.1a)	298	0.67	0.10	0.44	0.92
2017 Part. Rate (adj.1b)	298	0.67	0.10	0.44	0.91
2017 Part. Rate (adj.2)	298	0.69	0.11	0.43	1.01
2017 Part. Rate (adj.3)	297	0.69	0.11	0.45	1.00
2017 Part. Rate (adj.4)	298	0.70	0.11	0.46	1.08
2017 Part. Rate (adj.5)	297	0.71	0.11	0.47	1.04
Avg. Part. Rate, 2013&17	298	0.67	0.10	0.44	0.91
Avg. Part. Rate, 2013&17 (adj. 1)	298	0.68	0.10	0.45	0.92
Avg. Part. Rate, 2013&17 (adj. 1a)	298	0.68	0.10	0.45	0.92
Avg. Part. Rate, 2013&17 (adj. 1b)	298	0.67	0.10	0.45	0.91
Change in Part Rate, 2013-2017	298	-0.01	0.05	-0.22	0.17
Change in Part. Rate, 2013-2017 (adj. 1)	298	-0.02	0.05	-0.23	0.17
Change in Part. Rate, 2013-2017 (adj. 1a)	298	-0.02	0.05	-0.23	0.17
Change in Part. Rate, 2013-2017 (adj. 1b)	298	-0.02	0.05	-0.23	0.17
Average competitiveness (2013&17)	298	0.15	0.10	0.01	0.50
Swing Direction (+=toward JOH)	298	0.06	0.46	-1.00	1.00
Political Alignment (High=JOH)	298	1.40	0.79	0.00	2.00
Schools (percent of youth population)	298	4.70	1.66	1.66	14.40
Health Care Deficit (per 100K)	298	1.47	3.95	0.00	37.09
Per-capita Health Centers (per 100K)	298	25.21	18.19	0.00	134.81
Per-capita Cemeteries (per 100K)	298	27.58	28.79	0.00	259.54
Per-capita Churches (per 100K)	298	34.96	29.74	0.00	211.85
Per-capita Soccer Fields (per 100K)	298	21.69	28.87	0.00	136.13
Percent who own their home (2013)	298	85.76	7.85	51.89	97.93
Land Use: Pct. Forests	298	59.77	17.84	3.43	93.93
Land Use: Pct. Change Forests	298	5.49	8.51	-20.83	39.73
Land Use: Pct. Savannahs	298	0.87	3.54	0.00	42.39
Land Use: Pct. Change Savannahs	298	-0.03	1.30	-9.16	12.57
Land Use: Pct. Industrialized Agriculture	298	35.91	16.99	0.59	87.21
Land Use: Pct. Change Ind. Agriculture	298	-4.43	8.24	-37.02	18.71

Variables	N	Mean	Std.Dev.	Min	Max
Land Use: Pct. African Palm	298	1.41	5.14	0.00	35.80
Land Use: Pct. Change African Palm	298	0.54	2.25	-7.10	17.09
Land Use: Pct. Water ways, lagoons, etc.	298	0.87	1.80	0.00	15.68
Land Use: Pct. Change Water ways	298	0.22	0.82	-4.55	6.04
Land Use: Pct. Urban	298	1.00	1.55	0.00	13.85
Land Use: Pct. Change Urban	298	0.11	0.44	-1.52	2.87
Pct. Born in Municipality (2013)	298	80.48	11.53	40.05	97.05
Pct. Born in Other Municipality (2013)	298	19.10	11.47	2.63	59.35
Pct. Born Abroad (2013)	298	0.42	0.59	0.00	4.95
Pct. in Same Village/Neighborhood in 2008 (2013)	298	94.66	3.20	80.89	99.42
Pct. somewhere else in Hond. in 2008 (2013)	298	4.96	3.14	0.53	18.90
Pct. in Another Country in 2008 (2013)	298	0.38	0.31	0.00	1.87
Pct. of workers in agriculture (2013)	298	65.11	21.08	3.01	94.10
Pct. of workers in extractive industries (2013)	298	0.27	1.04	0.00	12.02
Pct. Garifuna (2013)	298	0.39	2.17	0.00	25.38
Pct. Indigenous (2013)	298	15.67	30.22	0.05	96.82
Pct. Afro-Honduran	298	0.01	0.03	0.00	0.31
Pct. (ppi <$2.25) (2013)	298	0.30	0.08	0.14	0.48

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