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Out-of-sample validation of the external and internal Migration Propensity Index (MPI) in Honduras

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Abstract

The external and internal Migration Propensity Indices (e-MPI and i-MPI) are tools to objectively estimate the probability that individuals from a given household will, respectively, migrate abroad or migrate domestically in the near future. We use new longitudinal data to test their predictive performance fully out of sample. We find that households classified as being of high-propensity to migrate by the e-MPI were significantly more likely to migrate abroad within 24 months (10.7%) than medium- and low-propensity groups (8.8% and 5.3%). For domestic migration, the i-MPI shows an even stronger gradient (19.6% versus 8.5% and 3.5%, respectively). Regression models confirm that both indices outperform alternative predictors—including income, climate shocks, crime, and migration intent—and maintain predictive power across rural and urban areas. Placebo tests indicate that the e-MPI and i-MPI capture distinct dimensions of migration behavior, validating their use for targeting and monitoring migration-related interventions. Overall, the MPIs emerge as simple yet statistically robust tools that reliably predict both international and domestic migration, offering a practical and scalable solution to help governments and development agencies anticipate migration trends and allocate resources strategically.

1. Introduction

International migration has grown faster than the world population over the last two decades. UN DESA (2020) estimates indicate a total of 281 million international migrants in 2020, or 3.6 percent of the world population, compared to 221 million in 2010 (a 27 percent increase). Western Europe and the United States receive the largest share of emigrants. About 51% of migrants are men, and roughly one-third are between 15 and 34 years of age. In addition, a large share of emigrants comes from rural areas, which account for approximately 40% of international remittances according to the Food and Agriculture Organization (2018). Even though COVID-19 significantly slowed international migration —reducing the global number of migrants by about 2 million by mid-2020— this likely represents only a temporary disruption of the underlying growth trend (McAuliffe and Triandafyllidou, 2022).

A complex, multidimensional phenomenon, migration is determined by a wide set of factors, including push factors —which encourage people to leave their current location— and pull factors —which attract people to a new location (Rubenstein, 2017). These factors can be grouped into four categories: economic (e.g., job opportunities, wages); environmental (e.g., food availability, weather); social (e.g., availability of services, quality of life); and safety/cultural (e.g., political stability, crime). Among these, The World Bank (2018) emphasizes the role of employment opportunities, wage differentials, and distance (whether physical or cultural) as important global factors shaping the observed international migration patterns. In the case of migration from the Northern Triangle (El Salvador, Guatemala, and Honduras) to the United States, additional factors include family reunification, vulnerability to natural disasters, and crime and insecurity (Cohn et al., 2017; Congressional Research Service, 2019a & 2019b; National Immigration Forum, 2019; Clemens, 2021).[1] Migration overall represents in many instances an adaptation strategy to help improve livelihoods, build resilience, and protect against fragility (Hernandez et al., 2023).

In this context, identifying migration drivers requires a comprehensive and holistic approach. Migration decisions are normally influenced by various factors at the individual, household, local, regional, and national levels, are typically interrelated, vary over time, often reinforce one another, and are not always directly observable, adding complexity to the analysis.[2] In 2019, Ceballos and Hernandez (2020) developed the Migration Propensity Index (MPI), a tool to objectively estimate and track the probability that individuals from a given household migrate in the near future. The MPI relies on a small subset of household-level indicators that are strongly correlated with the (latent) decision to migrate. The index was first designed and calibrated for the case of cross-border (external) migration (e-MPI) from Guatemala (Ceballos and Hernandez, 2020) and, later on, from Honduras

[1] A study from Creative Associates International (2019) identifies economic (unemployment, especially among youth; household economic hardship), transnational ties (having a relative living abroad; receiving remittances), and victimization (crime victim or relative/friend killed) as the three main drivers shaping international migration from the Northern Triangle.

[2] For instance, the decision to migrate is not necessarily an individual decision but is likely made together with other family members (Stark, 1991). Similarly, the potential opportunities for an individual to migrate may depend on their social network outside the community and abroad (Carrington et al, 1996; Munshi, 2003). More recent studies argue that migration may be an adaptation strategy to climate change (Jessoe et al., 2018) or a response strategy to natural disaster shocks where migrants' networks play an important role (Mahajan and Yang, 2020), and that higher education and credit constraints may not always drive international youth migration (Valentine et al., 2017; de Brauw, 2019). See Skeldon (1997) for an extensive review of the determinants of migration.

(Almanzar et al., 2022). In addition, Ceballos et al. (2023) calibrated the i-MPI to predict internal (domestic) migration for both countries, a natural extension given that domestic migration is often regarded as an intermediate step to migrating abroad (Cattaneo & Robinson, 2019; McAuliffe & Triandafyllidou, 2021). To date, all of the MPI indices have been piloted and implemented across numerous field surveys in the two countries, both in person and over the phone. Each version of the MPI employs a distinct questionnaire and weighting scheme, though risk thresholds and underlying migration probabilities are standardized across products.

As opposed to standard self-reported migration indicators that are likely subjective, inaccurate, and difficult to monitor over time, the MPI:

1. Avoids sensitive direct questions about attempts and intentions to migrate, which are prone to refusals or underreporting and may have undesired consequences if repeatedly asked over time to the same group of people,[3]
2. Is easy to implement and calculate in the field by relying on a concise set of simple, non-invasive questions that are easy to collect,
3. Is statistically robust, as it is derived using advanced statistical methods that account for the timing of migration decisions and potential correlated factors, and tested through cross-validation procedures focusing on out-of-sample predictive power; and
4. Can be used for both monitoring and targeting purposes, including monitoring beneficiaries of programs and/or targeting new programs to populations at risk of migrating.

In this paper, we test the e-MPI and i-MPI for Honduras fully out of sample in a real-world environment. We use longitudinal data from 1,209 households across nine Honduran departments collected during 2023–2025 to assess whether a household's MPI at baseline helps predict actual instances of migration in the subsequent 24 months. In addition, we test the MPI's predictive capacity against competing alternative indicators (measured at baseline) related to the decision to migrate but not included in the original MPI calibration.

Our analysis shows that both the e-MPI (which anticipates external or cross-border migration) and the i-MPI (which anticipates internal or domestic migration) are strong predictors of, respectively, international and domestic migration in Honduras. Households classified as high-propensity to migrate by the e-MPI were significantly more likely to experience cross-border migration within 24 months (10.7%) compared to medium- and low-propensity groups (8.8% and 5.3%, respectively), while the i-MPI exhibited an even steeper gradient for domestic migration (19.6% versus 8.5% and 3.5%). Multivariate regression models confirm that both indices outperform alternative predictors—including income, climate shocks, crime, and subjective migration intent—underscoring their robustness and practical utility. Importantly, the MPI retains predictive power across rural and urban areas and in departments beyond those used for calibration (confirming its external validity), and placebo tests indicate that the e-MPI and i-MPI capture distinct dimensions of migration behavior.

[3] For example, repeated sensitive questions to beneficiaries of a certain program every 6 or 12 months may result in people considering migration more seriously or opting out of the program.

These findings validate the MPI as a simple, statistically sound tool for anticipating migration and informing targeted interventions.

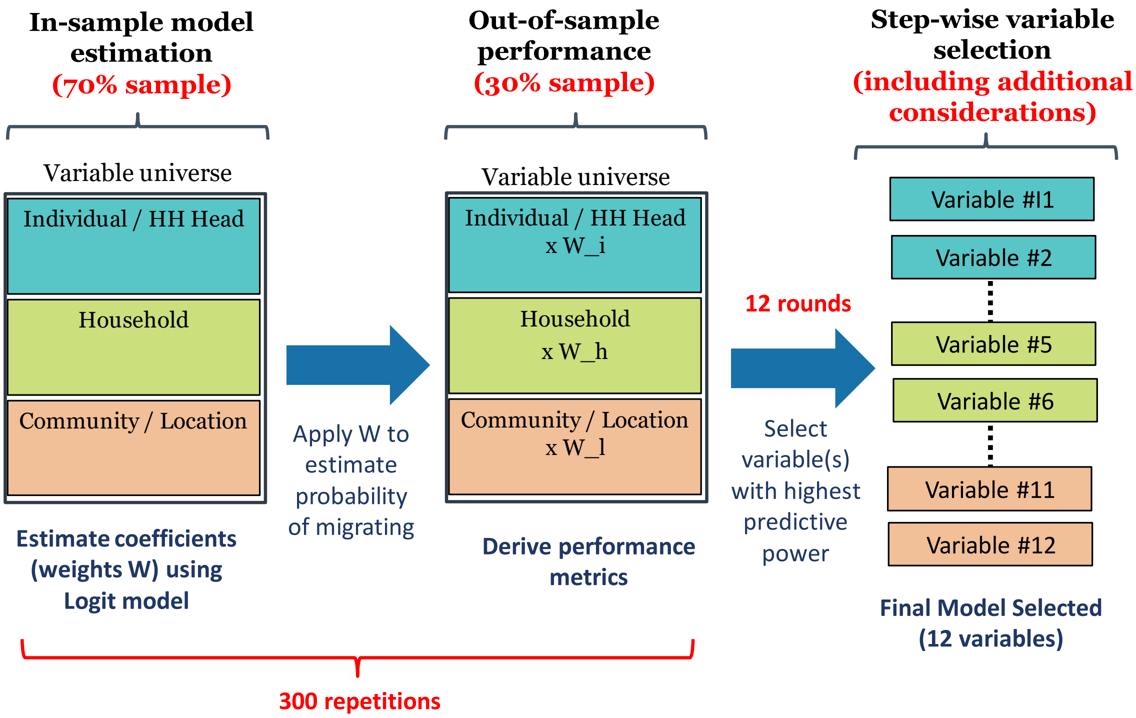
The remainder of the paper is organized as follows. Section 2 provides an overview of the general methodology for calibrating the index and introduces the current versions of the MPI. Section 3 introduces the data and methods used for the validation exercise and Section 4 discusses the results. Section 5 provides concluding remarks.

2. Overview of the MPI Honduras

The Migration Propensity Index (MPI) is a streamlined, statistically sound tool designed to predict whether individuals in a household are likely to migrate domestically or internationally in the near future. It is designed to be practical and easy to implement, relying on household characteristics and conditions that are straightforward to measure. The MPI comprises 10–12 variables, selected to maximize predictive accuracy using available data. These variables can be collected through direct, non-invasive questions, minimizing reporting bias and ensuring the tool's applicability in diverse contexts.

The MPI is based on a standard logistic regression model and a stepwise model selection algorithm that relies on out-of-sample cross-validation to ensure predictive robustness. In particular, the data are randomly split into training (70%) and testing (30%) sets (repeated 300 times to minimize sampling bias), with each potential model calibrated in the training set and its predictive performance calculated from the testing set. To identify the most predictive variables, a stepwise forward selection procedure is applied, as follows. Predictive performance is first assessed for all single-variable models using the Concordance Statistic (c-stat), which evaluates how well predicted probabilities align with observed migration patterns. The model with the highest performance metric is retained, and additional variables are iteratively added in this way until a final specification with 10-12 variables is reached. While the process is data-driven, we incorporate judgment to ensure the final set of variables are distinct from each other, dynamic over time, and capture key dimensions around the decision to migrate. Figure 1 illustrates the overall methodology.

Figure 1. Outline of methodology to construct the Migration Propensity Index



The MPIs for Honduras were calibrated using a panel dataset collected by IFPRI for the USAID-ACCESO impact evaluation, which includes three survey rounds (2012, 2013, and 2015) across six departments in western Honduras and is representative at the department level.

Panel A in Table 1 lists the final 12 variables selected for the e-MPI (for predicting cross-border migration). Peer and network effects variables stand out as important predictors of the probability that someone in a household migrates. A higher prevalence of longer-term migrants in the community (as captured by the share of households in the community who received remittances from abroad during the last 12 months) has the largest positive effect on the probability that one of the members of a given household migrates. Additionally, whether the household has a migrant abroad (proxied by whether the household itself received remittances during the last 12 months) is another important pull factor positively influencing the propensity to migrate. Key demographic characteristics also turn out to be important factors: larger households as well as those with young members with some level of education are associated with a higher propensity to migrate. In terms of assets, owning any amount of agricultural land, a vehicle, or a television, as well as having a finished roof, are all associated with a higher propensity to migrate, while owning livestock is associated with a lower propensity to do so, possibly signaling very poor households not having the required means to migrate abroad. Finally, households that experienced a mild drought event in the previous (*primera*) agricultural season are associated to a higher probability to migrate.

Table 1. Final variables selected for the Migration Propensity Index

Panel A. External migration (e-MPI)

#	Indicator	Effect on probability to migrate
1	Community-level rate of migrants abroad	**Positive**
2	Household has received remittances (i.e., has a migrant abroad)	**Positive**
3	Household size	**Positive**
4	Men aged 15-29 with complete primary education or higher	**Positive**
5	Women aged 15-29 with at least one year of secondary education	**Positive**
6	Household head is male	**Negative**
7	Household owns agricultural land	**Positive**
8	Household owns livestock	**Negative**
9	Dwelling has finished roof (tiles/concrete)	**Positive**
10	Household owns a vehicle (car/motorcycle)	**Positive**
11	Household owns a television	**Positive**
12	Household experienced a drought event in the previous (*primera*) ag. season (SPI<-1)	**Positive**
+	**Rural and department indicators**	**(Shifters)**

Panel B. Internal migration (i-MPI)

#	Indicator	Effect on probability to migrate
1	Number of household members	**Positive**
2	At least one household member approved one year of secondary education	**Positive**
3	Age of household head in years	**Positive**
	Square of age of household head in years	**Negative**
4	Household experienced a drought event on previous (*primera*) ag. season (SPI<-1)	**Positive**
5	Household owns a vehicle (car/motorcycle)	**Negative**
6	At least one household member aged 15-29	**Positive**
7	At least one household member has a permanent disability	**Negative**
8	Household owns the house in which they live	**Negative**
9	Household owns a cellphone	**Positive**
10	Number of completed years of education of household head	**Positive**
	Square of number of completed years of education of household head	**Negative**
+	**Rural and department indicators**	**(Shifters)**

Panel B in the table shows the selected variables included in the i-MPI, to anticipate domestic migration. Unlike all other calibrated MPIs (including both the external and internal MPI for Guatemala) the calibration for the i-MPI Honduras did not select any pull factors, despite their inclusion in the variable universe. Instead, the i-MPI for Honduras leans more heavily on family composition, assets, and other demographic characteristics. Larger households, those with at least one member between 15-29 years of age, and those with at least one member having at least one year of secondary education are all associated with a larger propensity to migrate domestically. The head of household's age and years of education are included both in levels and squared, indicating the presence of non-linear effects of these variables on the probability to migrate. In particular, a positive effect in levels and a negative effect for the square indicates a positive association with the probability to migrate, which gradually diminishes over the range of values taken by each of these two indicators. The presence of a household member with a permanent disability or chronic condition (e.g., visual, hearing or mobility impairment, loss of limbs, or chronic illness) is negatively associated with a household's propensity to migrate. Having a cellphone is positively associated with the probability to migrate domestically, while ownership of a motorized vehicle (car or motorcycle) and owning the house where the household lives both reduce the likelihood that an individual in that household migrates. As in the case of the e-MPI, experiencing a mild drought event in the previous (*primera*) agricultural season is associated to a higher probability to migrate internally, with one of the largest marginal effects among the variables chosen, highlighting the importance of adverse climatic events in the decision to migrate domestically.

3. Data and methods

To conduct the validation exercise we rely on a set of three longitudinal surveys conducted one year apart from each other among a new sample of roughly 1,200 rural and urban households across nine departments. The main objective is to gauge to what extent the MPI scores at baseline predict actual migration instances in the 24 months between baseline and the two follow-up surveys. Moreover, the effectiveness of the MPI-Honduras is not only assessed on its own, but also against an array of other potential measures (also measured at baseline) likely associated to the decision to migrate.

The surveys were conducted in 2023, 2024, and 2025 across the six original departments used in the calibration (Copán, Intibucá, La Paz, Lempira, Ocotepeque, and Santa Bárbara) and three neighboring departments with more important urban centers (Comayagua, Francisco Morazán, and Cortés). The baseline survey reached 1,209 households and was designed to collect the questions needed to construct the MPI scores in addition to a broad range of indicators potentially related to migration. Sampled households were selected through a multi-stage cluster sampling strategy. First, 23 municipalities were selected with selection probability proportional to migration prevalence (using the 2022 rate of returnees relative to total population) and size (total population as per the 2013 Census).[4] Second, five *aldeas* were randomly drawn within each of the municipalities selected in the first step, with selection probability proportional to their total population during the 2013

[4] The oversampling of municipalities with a higher prevalence of cross-border migration was done with the objective of maximizing the chances of observing future migration events among interviewed households.

Census. Third, two *caseríos* or *barrios* were selected within each *aldea*.[5] Finally, in order to obtain a random sample of households within each community (*caserío* or *barrio*) —and in the absence of listing data—, we designed a procedure inspired by the EPI method (originally proposed by the World Health Organization's Expanded Program on Immunization).[6] Using GPS coordinates for each community (available from the Instituto Nacional de Estadística), six random locations were selected within a 5-kilometer radius of the community's coordinates.[7] Enumerators were instructed to travel to each of these random locations and identify the nearest structure where a household could be living in and attempt to interview that household, proceeding to neighboring structures until a household willing to participate was found.[8]

The two follow-up surveys were conducted 12 and 24 months after the baseline survey and re-interviewed, respectively, 1,094 and 1,078 of the original households, inquiring about actual (external and internal) migration instances of any of the household members during the previous 12 months. In addition, a tracking protocol was implemented for households that were not available for an interview or not found, which involved asking other family members outside of the household, neighbors, and/or community leaders whether anyone in that household had migrated either domestically or internationally. Such tracking data provides us with migration information on, respectively, 81 and 91 additional households in either round. Overall, we have migration data for a total of 1,175 households in the first follow up round and 1,169 households in the second one (around 97% of the original sample).

Migrants in each household were identified based on a survey question on whether someone in the household had migrated in the previous 12 months and a follow-up question on where they had migrated. Cross-border migration implies the migration of at least one individual to a destination outside of Honduras, while domestic migration captures instances where at least an individual within a household migrated to a different department within the country. While we have information on individual migrants and on the number of migrants within each household, since the MPI is defined only at the household level, we construct the migration indicators using the household as the unit of analysis. Note that a household may have experienced both cross-border and domestic migration, since different household members could have migrated to different locations.

Table 2 shows basic summary statistics on the study sample covered during the baseline and both follow-up surveys, in addition to any migration instances identified during the follow-up surveys. Of the 1,209 households interviewed during the baseline survey, almost a third were located in an urban

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[5] Since sampling was conducted with replacement, the number of aldeas (caseríos/barrios) selected within each municipality (aldea) is not exactly 5 (2) in practice, but rather fluctuates around these numbers. The total number of aldeas (caseríos/barrios) in the study sample is 111 (207).

[6] The EPI method has many variants, but it can be loosely described as follows. In a selected community, (i) select a location near the centre of the community, (ii) choose a random direction (often defined in the field by spinning a bottle or pen), and (iii) identify a random household along the chosen direction pointing outwards from the centre of the community to its boundary. In subsequent steps, the procedure above is repeated, identifying a new household in each iteration until the required number of households is surveyed.

[7] These locations were manually checked against satellite imagery to ensure they fell near a structure. In the cases where they did not, a new random replacement location was drawn.

[8] Overall, this procedure worked quite well in practice, with little to no complications reported from enumerators, with only a few exceptions.

or peri-urban area.[9] While during the 2024 (2025) follow-up we found and re-interviewed 1,094 (1,078) households, we still count with migration data for 1,175 (1,169) households due to tracking information. All in all, a total of 201 households (or 16.7% of the sample) had at least one migrant between 2023 and 2025, with 109 of them reporting cross-border migration (or 9.1% of the total sample) and 107 reporting domestic migration (8.9% of the total sample). Only 15 households reported both an instance of cross-border and one of domestic migration, indicating that the simultaneous occurrence of these is relatively rare.

In terms of migrants' characteristics (panel B), we observe 117 cross-border and 107 domestic migrants, roughly equally split between male and female in the case of cross-border migrants but with a substantially higher proportion of women when it comes to domestic migration. Most migrants are between 16 and 32 years of age (with a median of 22) and they typically have finished primary school, with little differences between cross-border and domestic migrants along these dimensions.

[9] Since an official community-level rural-urban classification is not available in Honduras, we overlay household GPS coordinates with GHS-SMOD raster data, which relies on a harmonized global definition based on a combination of population size and population density to define the degree of urbanization of 1km. x 1km. pixels (Schiavina, Melchiorri, and Pesaresi, 2023). In particular, we consider households falling in GHS-SMOD pixels classified as "Very low density rural", "Low density rural", or "Rural cluster" as being rural, and those classified as "Suburban or peri-urban", "Semi-dense urban", "Dense urban", or "Urban" as being peri-urban/urban.

Table 2. Effective migration in the study sample between the baseline and follow-up surveys

Panel A. Interviewed households and effective migration

HOUSEHOLD SAMPLE	Total		Rural		Urban/ Peri-urban	
	#	%	#	%	#	%
Baseline survey (2023)						
Interviewed	1,209		862	*71.3%*	347	*28.7%*
1st follow-up survey (2024)						
With migration data	1,175		845	*71.9%*	331	*28.1%*
Re-interviewed	1,094					
Tracking	81					
2nd follow-up survey (2025)						
With migration data	1,169		839	*71.8%*	330	*28.2%*
Re-interviewed	1,078					
Tracking	91					
HOUSEHOLDS WITH AT LEAST ONE MIGRANT						
Months 1-12 after baseline survey	124	*10.5%*	87	*70.2%*	37	*29.9%*
Cross-border	71	*6.0%*	48	*67.6%*	23	*32.4%*
Domestic	57	*4.8%*	42	*73.7%*	15	*26.3%*
Months 13-24 after baseline survey	95	*10.5%*	67	*70.5%*	28	*29.5%*
Cross-border	48	*4.1%*	34	*70.8%*	14	*29.2%*
Domestic	56	*4.8%*	41	*73.2%*	15	*26.8%*
Total (months 1-24 after baseline survey)	201	*16.7%*	141	*70.1%*	60	*29.9%*
Cross-border	109	*9.1%*	77	*70.6%*	32	*29.4%*
Domestic	107	*8.9%*	77	*72.0%*	30	*28.0%*

Panel B. Individual migrants (24 months after baseline survey)

	Cross-border	Domestic
Number of individual migrants	117	107
Male	63	41
Female	54	66
Age		
25th percentile	16	16
Median	22	22
75th percentile	32	32
Years of schooling		
25th percentile	6	4
Median	6	6
75th percentile	12	11

4. Results

This section assesses the predictive performance and practical utility of the Migration Propensity Index (MPI) using recent longitudinal data. We examine whether the MPIs for Honduras accurately anticipate actual international and domestic migration events and assess their potential as a targeting tool at the community and household levels. The analysis proceeds in three steps: first, we present descriptive evidence on the relationship between MPI scores and observed migration patterns; second, we conduct formal econometric tests and compare the MPIs to alternative plausible predictors; and third, we conduct robustness checks and subgroup analyses to evaluate our findings' external validity and confirm that the external and internal MPI variants capture distinct dimensions of migration behavior.

Descriptive evidence on the MPI's effectiveness and targeting potential

We first assess the MPI's broad ability to predict migration, in terms of whether it classifies a household as being of high-, medium-, or low-propensity to migrate. Figure 2 shows effective rates of cross-border (panel A) and domestic (panel B) migration in the 24 months after the baseline survey among households in different migration propensity categories, as captured by, respectively, the e-MPI and i-MPI scores at baseline. For cross-border migration (panel A), the e-MPI seems to be somewhat effective at predicting actual migration instances: households in the high-propensity group exhibit a migration rate of 10.7%, compared to 8.8% and 5.3% in, respectively, the medium- and low-propensity groups.[10] These patterns are similar to those documented in Guatemala, where Hernandez et al. (2022) report migration rates (after 12 months) of 7.4%, 4.0%, and 1.6% among high-, medium-, and low-propensity households. For internal migration (panel B), the gradient is even stronger: 19.6% of high-propensity households experienced a migration instance after 24 months, versus 8.5% and 3.5%, respectively, for the medium- and low-propensity categories. In summary, our findings indicate that the MPI category in which households fall is indeed related to *ex post* effective migration rates, a relationship that seems to be stronger in the case of the i-MPI.

The next relevant questions are to what extent the MPIs serve as a targeting tool to (a) identify communities where migration is more prevalent, and (b) identify specific households more prone to migrate within a given community? To tackle the first question, we calculate the effective rate of migration in each surveyed *aldea* and plot it against the average MPI across all households at baseline.[11] Figure 3 shows the resulting scatterplots, with each point in the figure representing a single *aldea*. Overall, the average MPI at the *aldea*-level is positively —albeit weakly— associated with effective cross-border (panel A) and domestic (panel B) migration rates. In particular, *aldeas* with higher average MPI scores seem to exhibit slightly higher migration rates than those with lower scores. The fit is arguably not strong, but statistically significant in the case of domestic migration

[10] Appendix Figure 1 shows a similar exercise based on attempted cross-border migration, including both successful and unsuccessful attempts. The results are qualitatively similar, with 17.0%, 16.4%, and 14.3% effective migration rates for, respectively, the high-, medium-, and low-propensity groups.

[11] For this exercise, as well as the regression specifications below, we transform MPI scores to the underlying probability implicit in the base logit calibration model. Since the probability is a non-linear function of the score, such an approach is better suited to the linear nature of OLS models.

and barely not statistically significant at conventional levels for cross-border migration (p-value = 0.123).[12] The positive-yet-weak association may be due to a considerable number of *aldeas* showing no instances of migration, which could in part reflect a relatively low sample size of sampled and interviewed households at that administrative level.

Figure 4, in turn, focuses on the MPI's within-community predictive ability, or more specifically on whether the MPI can serve as a good proxy to identify households within a community that have a higher likelihood of migration. Each bar in the figure represents a migrant household —that is, a household where at least one of its members migrated abroad (panel A) or domestically (panel B) in the last 24 months—, with the vertical axis showing the within-*aldea* percentile for each of these migrant households. In other words, the height of the bar captures where in the *aldea*'s MPI distribution at baseline a given household was located, with a value of 100 indicating that that household had the highest MPI within the sample of households in the *aldea*. In the case of external migration, the figure shows that approximately 65% of migrant households (in both rural and urban areas) had an e-MPI that was above the median e-MPI at their *aldea*, while about 45% of migrant households had an e-MPI above the 75th percentile. These results are even stronger in the case of internal migration, with approximately three quarters of households with migrants having an i-MPI above the median i-MPI in their *aldea*, and more than half with an i-MPI above the 75th percentile. In the case of domestic migration, these patterns are slightly stronger in urban than in rural areas. All in all, we take this as indicative evidence that the MPI can be a helpful tool to identify which households within a community are more likely to migrate.

Regression models for testing MPI's effectiveness

To formally evaluate out-of-sample predictive performance, we estimate OLS models regressing a binary indicator identifying migrant households (i.e., if at least an individual in the household migrated since baseline) on the MPI at baseline and alternative predictors drawn from the migration literature. These include household income (in terciles, with the richest tercile included as a base category), financial stress, engagement in agricultural production, exposure to climate shocks, food insecurity, crime incidence, perceived insecurity levels in the community, income aspirations (gap between actual and desired income, in logs), and attitudes toward institutions and social cohesion. All indicators were measured at baseline, but the results are robust to including updated indicators for recent climate shocks and food insecurity instances from the follow-up surveys.[13] While the MPI calibrations incorporated some of these dimensions, others—such as crime and perceptions—were excluded due to data limitations, making this exercise a useful test of potential omissions. All specifications rely on ordinary least squares with robust standard errors, allowing for an easier interpretation of coefficients than logit or probit regressions.[14]

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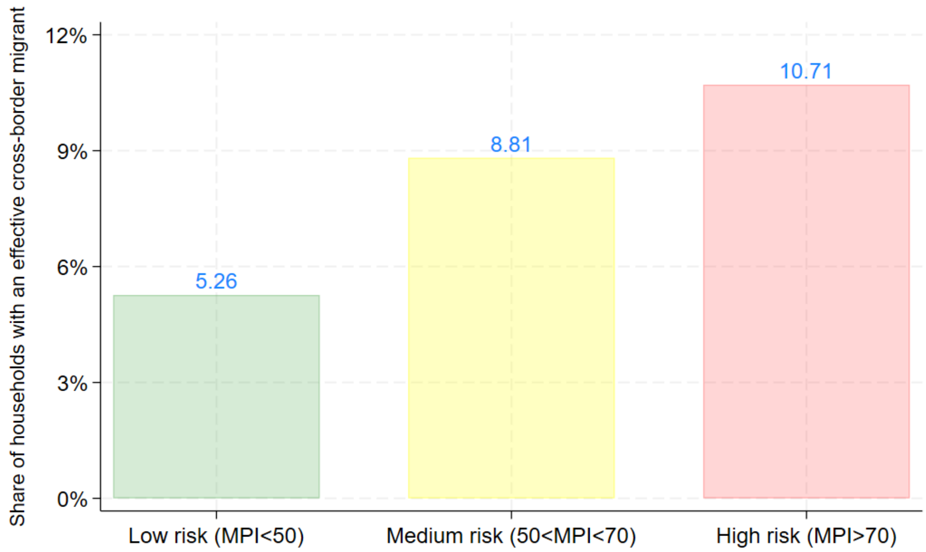
[12] Appendix Figure 2 considers attempted cross-border migration, with similar results and a statistically-significant association.

[13] We report the model with the measures at baseline, since the number of observations is higher than that for the alternative model with the updated indicators. This is because, as discussed above, not all households were re-interviewed during both follow-up surveys.

[14] The results are however qualitatively unchanged when we use these alternative models, which are available upon request.

Figure 2. Effective migration rates by MPI group

Panel A. External migration



Panel B. Internal migration

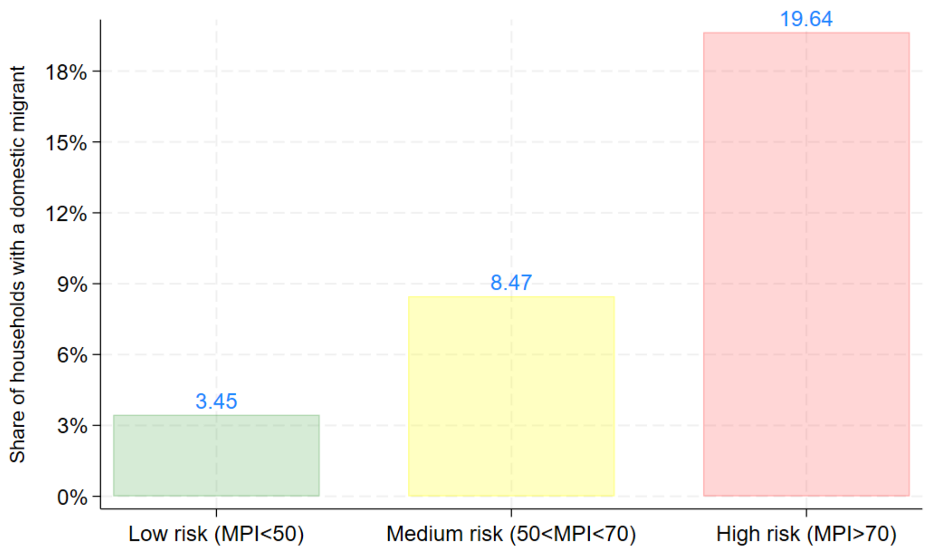
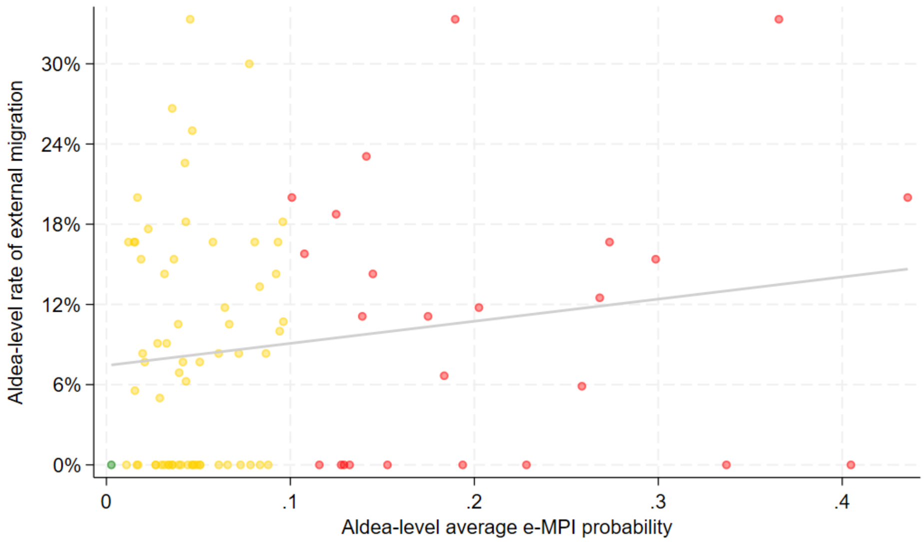


Figure 3. MPI predictive ability between-community

Panel A. External migration



Panel B. Internal migration

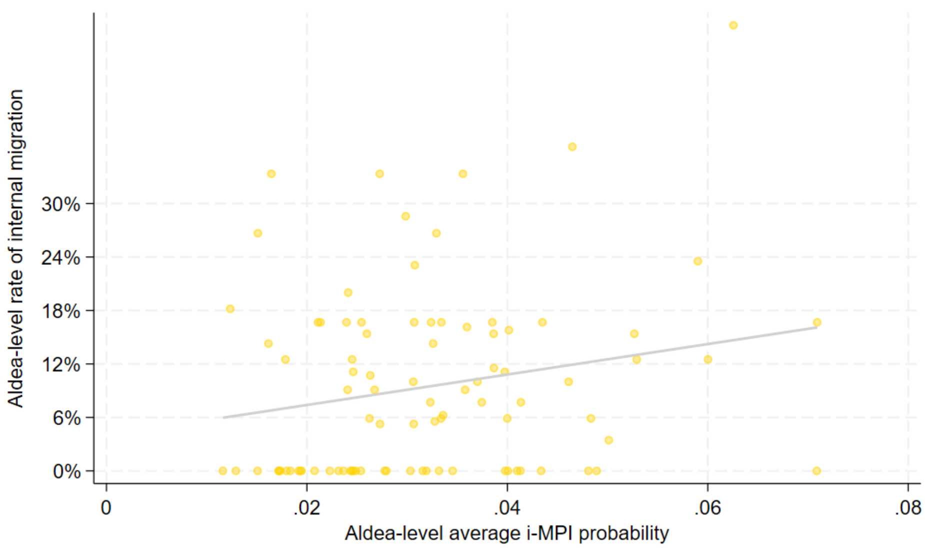
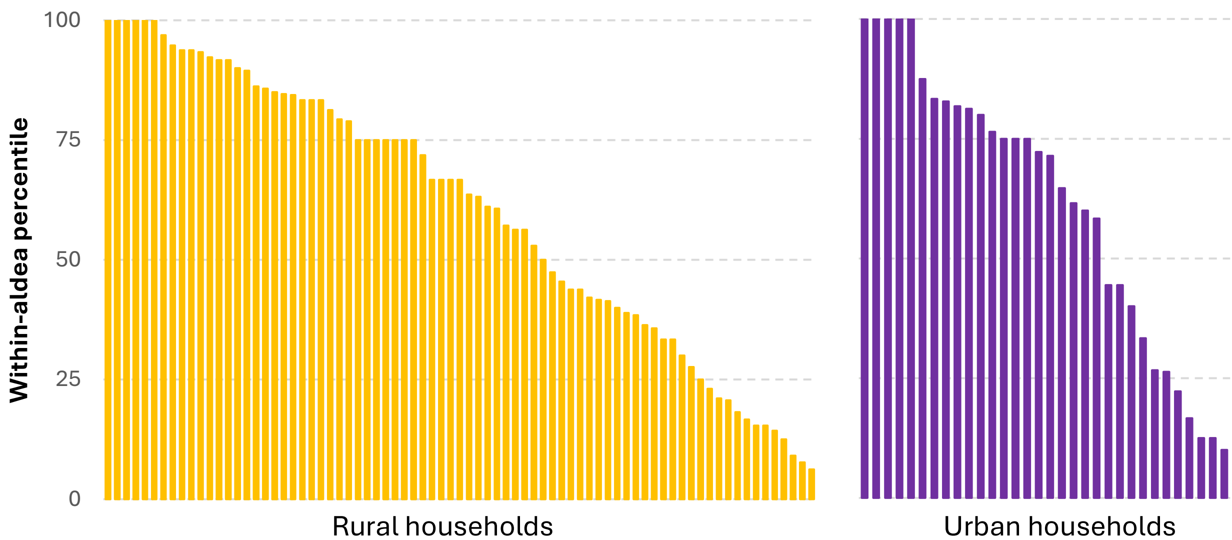


Figure 4. MPI predictive ability within-community

Panel A. External migration



Panel B. Internal migration

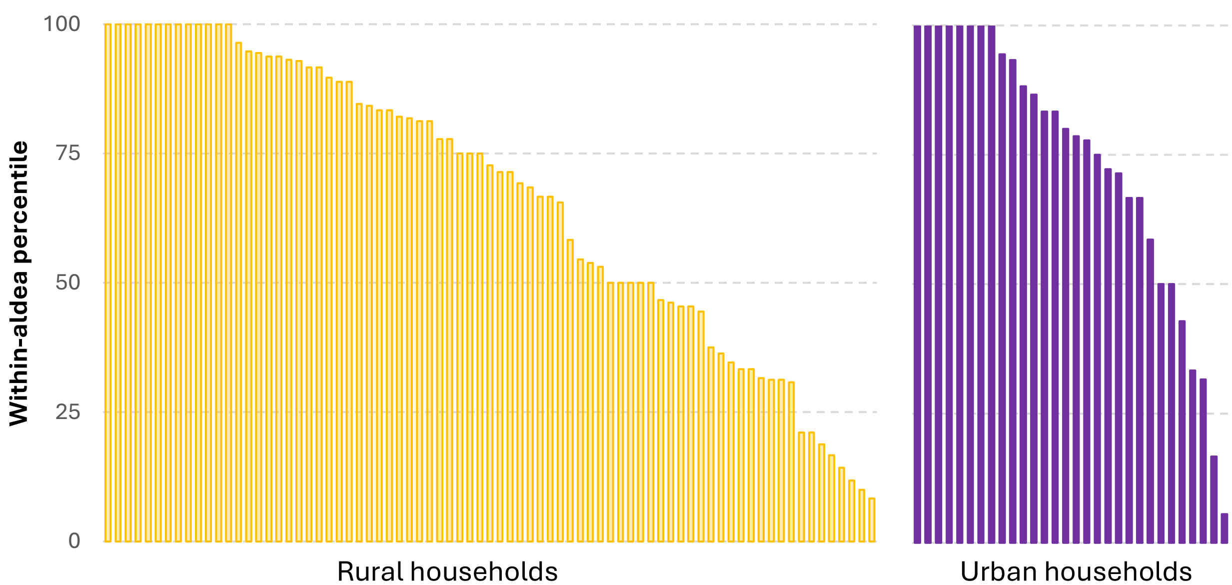


Table 3 presents the results in the case of cross-border migration, assessing the e-MPI's ability to predict instances of migration outside of Honduras. In the base specification (Column 1), the e-MPI and the income aspirations gap emerge as the only statistically significant predictors of migration. In particular, an increase in the e-MPI's probability of 10 percentage points (equivalent to 10 points in the MPI score around the medium-propensity MPI range or to 4 points in the score around the lower-end of the high-propensity range) increases the probability of observing an effective migration instance by around 1.6 percentage points. In turn, a 1 percent increase in the income aspirations gap is associated with a statistically significant, higher likelihood of migrating abroad by about the same order of magnitude. However, the squared semi-partial correlation coefficient (a measure of the relative explanatory power of an indicator) is substantially lower for the income aspirations gap in comparison to that of the e-MPI. Importantly, however, none of the crime, perceptions, or food insecurity variables, key dimensions highlighted in the migration literature and in anecdotal evidence around migration in Honduras, turn out to be effective predictors of cross-border migration beyond the e-MPI.[15] Ultimately, while the explanatory power of the MPI is modest in economic terms, it is still notable given the lack of significance for other variables, arising as the best predictor out of all possible alternatives measured in this study.

Column 2 adds a subjective migration-intent indicator (measured at baseline), commonly used to gauge migration sentiment in practice. While such indicator is also a statistically significant predictor of effective migration, its inclusion barely alters the e-MPI coefficient and its squared semi-partial correlation coefficient is less than half that of the e-MPI. This finding underscores the advantage of the MPI's indirect, non-invasive approach over direct intent questions.

Columns 1 and 2 in Appendix Table 1 show the same set of specifications considering an extended measure of external migration, which includes cross-border migration attempts in addition to actual successful ones. The results are similar to the ones in Table 3, but the e-MPI coefficient is smaller in magnitude and some statistically-significant effects arise in terms of the second income quartile and the indicator variable for whether a household faced an adverse weather event in the last 12 months, implying a stronger effect of climate variability and in line with existing literature (Dillon, Mueller, & Salau, 2011, Gray & Mueller, 2012a, 2012b; Dallmann & Millock, 2017; Colmer, 2021; Ibáñez et al., 2022; Alverio, Sowers, & Weinthal, 2023). Nevertheless, considering that failed attempts to migrate may involve different subjective interpretations of what a migration attempt is, and that these interpretations may also drive households' answers about future intentions to migrate, these results should be taken with caution.

Column 1 in Table 4 shows the results in the case of domestic migration, testing the baseline i-MPI's ability to predict instances where at least one individual in a household migrated domestically in the subsequent 24 months. Interestingly, the i-MPI exhibits a coefficient nearly four times larger than that for the e-MPI, consistent with the descriptive patterns in Figure 2. In addition, and in contrast to Table 3, the i-MPI is the only statistically significant indicator for identifying households with a domestic migrant, with the only exception of households who experienced a severe food insecurity instance at baseline showing a lower likelihood to migrate (again with a substantially lower square semi-partial correlation coefficient in relation to that of the i-MPI).

[15] This does not imply, however, that these variables are irrelevant to the decision to migrate, but instead that they do not provide additional explanatory power beyond what is captured by the e-MPI.

Table 3. Determinants of external migration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full sample	Full sample	Full sample	Municipality fixed effects	*Aldea* fixed effects	Rural households	Urban households	6 original departments	3 new departments	Placebo
e-MPI (probability)	0.155**	0.152**	0.167***	0.148**	0.148**	0.183**	0.130	0.125*	0.248	0.159**
	(0.062)	(0.062)	(0.063)	(0.066)	(0.071)	(0.079)	(0.100)	(0.070)	(0.151)	(0.063)
Reported intention to migrate at baseline		0.043**								
		(0.020)								
Rate of returnees 2021-22			-3.609***							
			(1.390)							
i-MPI (probability)										-0.143
										(0.189)
Income p.c. - First quartile (i.e. Poorest)	0.037	0.037	0.037	0.047*	0.039	0.055*	0.016	0.055*	0.028	0.039
	(0.025)	(0.025)	(0.025)	(0.025)	(0.027)	(0.030)	(0.049)	(0.030)	(0.045)	(0.025)
Income p.c. - Second quartile	0.024	0.023	0.023	0.027	0.022	0.034	0.014	0.046	-0.013	0.026
	(0.024)	(0.024)	(0.024)	(0.023)	(0.026)	(0.028)	(0.047)	(0.030)	(0.044)	(0.024)
Income p.c. - Third quartile	0.019	0.019	0.019	0.022	0.016	0.031	0.006	0.036	-0.003	0.021
	(0.023)	(0.022)	(0.023)	(0.023)	(0.024)	(0.027)	(0.040)	(0.028)	(0.039)	(0.023)
Reports financial difficulties to reach the end of the month	0.028	0.026	0.031	0.030	0.047*	0.039	0.012	0.045	-0.004	0.029
	(0.025)	(0.025)	(0.025)	(0.025)	(0.027)	(0.031)	(0.044)	(0.031)	(0.043)	(0.025)
Engaged in agricultural production	0.003	0.005	0.007	0.009	0.011	0.011	-0.014	0.044*	-0.062**	0.004
	(0.017)	(0.017)	(0.017)	(0.017)	(0.020)	(0.020)	(0.032)	(0.022)	(0.024)	(0.017)
Faced adverse climate event in last 12m	0.013	0.012	0.009	0.004	-0.004	0.026	-0.038	0.000	0.025	0.014
	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.020)	(0.034)	(0.022)	(0.027)	(0.017)
Faced mild food insecurity in last 12m	-0.018	-0.021	-0.016	-0.013	-0.008	0.001	-0.081**	-0.010	-0.023	-0.020
	(0.025)	(0.026)	(0.025)	(0.026)	(0.029)	(0.032)	(0.040)	(0.033)	(0.041)	(0.025)
Faced moderate food insecurity in last 12m	0.011	0.014	0.010	0.005	-0.002	-0.007	0.072	0.001	0.025	0.013
	(0.027)	(0.027)	(0.027)	(0.027)	(0.029)	(0.032)	(0.046)	(0.033)	(0.046)	(0.026)
Faced severe food insecurity in last 12m	-0.029	-0.031	-0.029	-0.028	-0.022	-0.043	-0.004	-0.044	-0.006	-0.029
	(0.022)	(0.022)	(0.022)	(0.022)	(0.024)	(0.026)	(0.040)	(0.029)	(0.033)	(0.022)
Suffered from crime in last 12m	-0.009	-0.015	-0.009	-0.009	-0.012	0.026	-0.078**	-0.000	-0.039	-0.009
	(0.025)	(0.025)	(0.025)	(0.025)	(0.027)	(0.033)	(0.036)	(0.033)	(0.040)	(0.025)
Perceives high level of insecurity in community	0.003	0.005	-0.001	0.005	0.018	0.004	0.003	0.003	-0.012	0.003
	(0.024)	(0.024)	(0.024)	(0.025)	(0.027)	(0.032)	(0.038)	(0.028)	(0.046)	(0.024)
Aspirations: (Income goal - actual), in logs	0.012*	0.012*	0.011*	0.012*	0.008	0.018**	0.003	0.014*	0.008	0.012*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.013)	(0.008)	(0.010)	(0.006)
Perceptions: ''In case of a problem I can go to local authorities for help''	-0.006	-0.007	-0.002	-0.005	-0.007	-0.014	0.011	-0.009	-0.015	-0.005
	(0.020)	(0.020)	(0.020)	(0.021)	(0.022)	(0.024)	(0.038)	(0.025)	(0.039)	(0.020)

Perceptions: ''Police and the justice system protect honest citizens''	-0.008	-0.005	-0.006	-0.005	0.000	0.009	-0.044	-0.020	0.022	-0.007
	(0.019)	(0.019)	(0.019)	(0.020)	(0.021)	(0.024)	(0.032)	(0.024)	(0.028)	(0.019)
Perceptions: ''If I am victim of a crime I always denounce it to authorities''	-0.004	-0.004	-0.004	0.002	0.003	0.023	-0.064*	0.003	-0.013	-0.003
	(0.019)	(0.019)	(0.019)	(0.020)	(0.022)	(0.023)	(0.037)	(0.023)	(0.038)	(0.019)
Perceptions: ''In my country there are plenty of opportunities to thrive''	0.019	0.020	0.018	0.020	0.009	0.029	-0.005	0.014	0.027	0.018
	(0.020)	(0.020)	(0.020)	(0.020)	(0.023)	(0.024)	(0.033)	(0.025)	(0.035)	(0.020)
Perceptions: ''I feel included in my community's social activities''	0.028	0.027	0.027	0.021	0.011	0.027	0.046	0.028	0.005	0.028
	(0.018)	(0.018)	(0.018)	(0.019)	(0.021)	(0.022)	(0.033)	(0.023)	(0.031)	(0.018)
Perceptions: ''I usually trust other people''	0.014	0.019	0.015	0.015	0.029	0.004	0.029	0.001	0.022	0.014
	(0.023)	(0.023)	(0.023)	(0.023)	(0.026)	(0.026)	(0.046)	(0.029)	(0.040)	(0.023)
Constant	-0.087	-0.095	-0.020	-0.085	-0.062	-0.193***	0.084	-0.135*	0.002	-0.083
	(0.068)	(0.069)	(0.077)	(0.067)	(0.069)	(0.073)	(0.144)	(0.080)	(0.127)	(0.069)
Number of observations	1,193	1,193	1,193	1,193	1,193	853	340	795	398	1,193
R-squared	0.020	0.025	0.026	0.053	0.123	0.036	0.052	0.029	0.037	0.021

Robustness and external validity

This subsection focuses on robustness tests and addresses additional empirical questions that are relevant in terms of the MPI's external validity.

First, given that the index is partly driven by pull factors such as the rate of households in the community that receive remittances (a proxy for having a migrant abroad), a reasonable concern is for the MPI to simply be a proxy for local migration rates. To test whether this is the case, we pursue three different strategies. Column 3 in Table 3 controls for the most recent rate of returnees in a municipality (defined as the total number of returnees during 2021 and 2022, from the Secretaría de Desarrollo Social de Honduras, as a percentage of the population, as per the latest 2013 census). This is the best available data on disaggregated migration outflows. Notably, the coefficient for the e-MPI is unchanged, and the effect of the rate of returnees is negative. Columns 4 and 5, in turn, provide alternative tests for this hypothesis by including fixed effects at the municipality and *aldea* levels, exploring whether the MPI can effectively serve to identify migrants within those administrative levels. Indeed, the e-MPI holds predictive power, with a coefficient of similar magnitude and statistical significance to previous specifications. Appendix Table 1 extends the analysis to include migration attempts; with broadly similar results (except for a lower coefficient when including *aldea* fixed effects). Columns 2 through 4 in Table 4 do the same for domestic migration, and the i-MPI remains strongly effective across all three alternative specifications. In other words, both the e-MPI and i-MPI continue to be useful predictors of, respectively, cross-border and domestic migration even after considering overall migration flows in the municipality or *aldea*.

Next, we focus on subgroup analyses to inform the external validity of the MPI indices. Several external validity questions motivate this analysis. First, given that the original surveys used to calibrate the MPIs for Honduras covered only six departments, a relevant question is whether the MPIs can be effectively applied in other regions. Second, since these surveys over-represented rural areas within these six departments, an important question is whether the underlying mechanisms (implicitly captured by the MPIs) are also relevant for urban populations.

The results of these subgroup analyses in the remaining columns of Tables 3 and 4 indicate that both the e-MPI and i-MPI remain valid when applied in other departments in Honduras and across urban populations. In particular, the MPIs' regression coefficients tend to be larger in the case of the urban subgroup and that for households located in the 3 new departments, even though in some cases the lower sample size results in a loss of statistical significance.[16] All in all, the findings seem to validate the ability of the MPIs to predict migration instances in both rural and urban areas, as well as both in the original departments used for calibration and in other departments, though these conclusions are based on a relatively low number of observations for the urban subgroups and the subgroup of households in new departments, so they should be taken with caution.

[16] In the case of cross-border migration, the e-MPI coefficient is actually smaller in magnitude (and statistically insignificant) for urban than for rural households, even though it is still of a comparable magnitude to the coefficient for the full sample. At the same time, however, when including migration attempts (Appendix Table 1) the coefficient is actually stronger in the case of the urban subgroup.

Finally, since some of the underlying questions in the e-MPI are similar to those in the i-MPI, it is reasonable to question whether these indices are indeed capturing distinct aspects around households' propensity to migrate either abroad and/or domestically or, alternatively, a general propensity to migrate (regardless of the destination). Column 10 in Table 3 and column 9 in Table 4 show the result of placebo specifications, where in addition to the primary MPI we include the alternative MPI as an explanatory variable. In both cases, the primary MPI retains its predictive ability, with the placebo MPI not providing any additional explanatory power. These findings support the conclusion that both indices are measuring different aspects of migration behavior.

Table 4. Determinants of internal migration

	(1) Full sample	(2) Full sample	(3) Municipality fixed effects	(4) Aldea fixed effects	(5) Rural households	(6) Urban households	(7) 6 original departments	(8) 3 new departments	(9) Placebo
i-MPI (probability)	0.990***	0.991***	1.099***	1.118***	0.933***	0.987**	0.831***	1.258***	0.963***
	(0.248)	(0.249)	(0.252)	(0.259)	(0.309)	(0.421)	(0.302)	(0.420)	(0.248)
Rate of returnees 2021-22		-0.482							
		(1.306)							
e-MPI (probability)									0.050
									(0.053)
Income p.c. - First quartile (i.e. Poorest)	0.033	0.033	0.025	0.024	0.057*	-0.016	0.041	0.026	0.035
	(0.027)	(0.027)	(0.027)	(0.030)	(0.032)	(0.049)	(0.032)	(0.049)	(0.027)
Income p.c. - Second quartile	-0.008	-0.008	-0.010	0.009	0.009	-0.036	-0.008	-0.001	-0.006
	(0.025)	(0.025)	(0.025)	(0.027)	(0.029)	(0.050)	(0.029)	(0.046)	(0.025)
Income p.c. - Third quartile	-0.018	-0.018	-0.020	-0.007	-0.008	-0.014	-0.020	-0.015	-0.016
	(0.022)	(0.022)	(0.022)	(0.024)	(0.026)	(0.038)	(0.026)	(0.039)	(0.022)
Reports financial difficulties to reach the end of the month	0.033	0.033	0.026	0.006	0.048*	0.005	0.035	0.019	0.032
	(0.024)	(0.023)	(0.023)	(0.024)	(0.028)	(0.043)	(0.025)	(0.053)	(0.024)
Engaged in agricultural production	-0.009	-0.008	-0.008	-0.012	0.001	-0.021	-0.003	-0.015	-0.009
	(0.018)	(0.018)	(0.020)	(0.022)	(0.022)	(0.032)	(0.023)	(0.034)	(0.018)
Faced adverse climate event in last 12m	-0.020	-0.020	-0.012	-0.008	-0.024	-0.025	0.007	-0.075**	-0.020
	(0.018)	(0.018)	(0.018)	(0.020)	(0.021)	(0.032)	(0.022)	(0.031)	(0.018)
Faced mild food insecurity in last 12m	0.040	0.040	0.041	0.038	-0.000	0.121***	0.043	0.053	0.040
	(0.025)	(0.025)	(0.025)	(0.027)	(0.030)	(0.046)	(0.030)	(0.045)	(0.025)
Faced moderate food insecurity in last 12m	0.002	0.002	0.007	-0.007	0.007	0.007	0.015	-0.038	0.003
	(0.027)	(0.027)	(0.027)	(0.029)	(0.032)	(0.048)	(0.031)	(0.048)	(0.027)
Faced severe food insecurity in last 12m	-0.044*	-0.045*	-0.049**	-0.032	-0.043	-0.048	-0.049	-0.033	-0.043*
	(0.024)	(0.024)	(0.025)	(0.026)	(0.027)	(0.047)	(0.030)	(0.042)	(0.024)
Suffered from crime in last 12m	0.007	0.007	0.005	0.021	0.029	-0.041	0.010	-0.015	0.007
	(0.026)	(0.026)	(0.026)	(0.028)	(0.033)	(0.037)	(0.031)	(0.048)	(0.026)
Perceives high level of insecurity in community	-0.025	-0.025	-0.032	-0.048*	-0.021	-0.029	-0.005	-0.073**	-0.028
	(0.020)	(0.020)	(0.021)	(0.025)	(0.026)	(0.032)	(0.024)	(0.036)	(0.020)
Aspirations: (Income goal - actual), in logs	-0.002	-0.002	-0.001	-0.003	-0.004	0.006	-0.001	-0.007	-0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.010)	(0.006)	(0.011)	(0.006)
Perceptions: ''In case of a problem I can go to local authorities for help''	0.017	0.018	0.021	0.034	0.024	-0.011	0.011	0.044	0.018
	(0.021)	(0.021)	(0.021)	(0.022)	(0.024)	(0.038)	(0.022)	(0.050)	(0.021)
Perceptions: ''Police and the justice system protect honest citizens''	-0.019	-0.019	-0.019	-0.018	0.008	-0.077**	-0.008	-0.065	-0.019
	(0.020)	(0.020)	(0.020)	(0.021)	(0.025)	(0.037)	(0.022)	(0.046)	(0.020)

Perceptions: ''If I am victim of a crime I always denounce it to authorities''	0.028	0.028	0.020	0.012	0.010	0.085**	0.023	0.055	0.028
	(0.021)	(0.021)	(0.021)	(0.022)	(0.024)	(0.043)	(0.024)	(0.043)	(0.021)
Perceptions: ''In my country there are plenty of opportunities to thrive''	0.015	0.015	0.013	0.027	-0.007	0.076*	0.006	0.037	0.017
	(0.019)	(0.019)	(0.019)	(0.021)	(0.021)	(0.041)	(0.022)	(0.038)	(0.019)
Perceptions: ''I feel included in my community's social activities''	-0.031	-0.031	-0.033	-0.025	-0.035	-0.019	-0.061**	0.015	-0.031
	(0.021)	(0.021)	(0.020)	(0.021)	(0.025)	(0.038)	(0.026)	(0.035)	(0.021)
Perceptions: ''I usually trust other people''	-0.035	-0.035	-0.035	-0.028	-0.043*	-0.015	0.012	-0.125***	-0.035
	(0.021)	(0.021)	(0.022)	(0.024)	(0.026)	(0.037)	(0.029)	(0.030)	(0.021)
Constant	0.046	0.055	0.049	0.059	0.058	-0.031	0.032	0.114	0.041
	(0.053)	(0.056)	(0.055)	(0.060)	(0.069)	(0.091)	(0.061)	(0.106)	(0.054)
Number of observations	1,193	1,193	1,193	1,193	853	340	795	398	1,193
R-squared	0.043	0.043	0.067	0.147	0.044	0.103	0.044	0.094	0.044

5. Conclusions

The Migration Propensity Index (MPI) is a suite of simple, practical tools designed to quickly assess the likelihood of someone in a household migrating either abroad or domestically in the near future, based on a small set of simple, non-invasive, and indirect questions. This paper tests the MPI's effectiveness fully out of sample and in a real-world environment, by relying on panel data from three survey rounds conducted among 1,209 households in nine departments of Honduras.

The paper first presents descriptive evidence on the predictive performance of the e-MPI (for cross-border migration) and the i-MPI (for domestic migration), examining their ability to predict actual migration instances across high-, medium-, and low-propensity household groups, as well as on the MPI's effectiveness as a tool to identify both communities with higher overall migration propensity and households more likely to migrate within a given community. In addition, the paper uses rich survey data collected at baseline to compare the MPI's reliability to alternative predictors of migration. Finally, it addresses a variety of empirical questions related to the index's nature and its external validity (assessing its predictive ability beyond the population profiles used for calibration).

The results show that both the e-MPI and the i-MPI are reliable indices to anticipate migration at the household level. Both indices show good predictive ability for identifying groups of households with a higher propensity to, respectively, migrate abroad and domestically, with the i-MPI showing a slightly better performance than the e-MPI. Moreover, both indices are effective at identifying communities where migration is more prominent (though these results are somewhat weaker, possibly due to the limited sample size of study communities) and at identifying households within a community that have a higher likelihood of observing an individual within that household migrate.

At the same time, while both MPI indices are far from being able to predict all migration instances, they still arise as the best *ex ante* predictors when compared to a host of other potential measures in a multivariate regression framework. In particular, when simultaneously including the MPI indices and a rich set of baseline indicators on multiple dimensions potentially related to migration (including indicators of crime, perceptions around corruption or opportunities, and food insecurity, some of which were missing in the calibration dataset), both the e-MPI and the i-MPI outperform all alternative measures. The only potential exception in terms of cross-border migration is a measure of economic aspirations at baseline — defined as the gap between a household's desired and actual income—, which is positively and statistically-significantly related to migration, yet with a much smaller squared semi-partial correlation coefficient than that of the e-MPI. In the case of domestic migration, having experienced an instance of severe food insecurity is negatively and significantly related to migrating, beyond what is explained by the i-MPI alone, though again with a substantially lower squared semi-partial correlation coefficient.

Since push factors are important contributors to the MPI scores (see Almanzar et al., 2022, and Ceballos et al., 2023), it could be hypothesized that the MPI's predictive power is just a direct consequence of it serving as a proxy of current migration rates in the community, which naturally relate to future migration rates. We find, however, that the MPI holds its predictive power even after controlling for local migration rates (proxied by the 2022-2023 rate of returnees) or after including fixed effects at the municipality or *aldea* levels. This, together with the fact that households with migrants in our sample tend to be on the higher end of the MPI distributions in their communities, suggests that the MPI is capturing specific features of the household and its members that makes them more prone to migrating.

In terms of external validity, both MPI indices perform similarly across rural and urban/peri-urban subgroups (despite being calibrated on a mostly rural dataset), with an even (slightly) stronger point estimate in urban/peri-urban areas. Both indices also retain their predictive power when applied in departments not included in the original calibration data, pointing to their applicability to the rest of Honduras.

Finally, it is reasonable to ask whether domestic and international migration stem from a similar underlying decision-making process. If this were the case, separately capturing the drivers of domestic and cross-border migration through the i-MPI and the e-MPI would be unnecessary. To test this hypothesis, we conduct placebo tests by jointly including the main MPI index (e.g., the e-MPI when modelling cross-border migration) in addition to the alternative MPI index. When doing so, we find that the i-MPI (e-MPI) retains its predictive ability when attempting to explain instances of domestic (cross-border) migration, with the alternative MPI not providing additional predictive power beyond that of the main index. This finding confirms that the two indices capture distinct aspects around households' migration behavior.

Overall, our results strongly support the idea that tracking 10-12 indirect questions can successfully inform the *ex ante* likelihood to migrate. Even with imperfect training data, both the i-MPI and the e-MPI for Honduras at baseline emerge as significant predictors of migration instances in the subsequent 24 months. Naturally, the MPI should be viewed as a probabilistic proxy that performs well *on average* rather than as a precise predictor at the household level. In this sense, its main value lies in identifying groups of households with a higher propensity to migrate. How best to leverage such indices for targeting development programs and monitoring migration sentiment among local communities remains an important avenue for future work.

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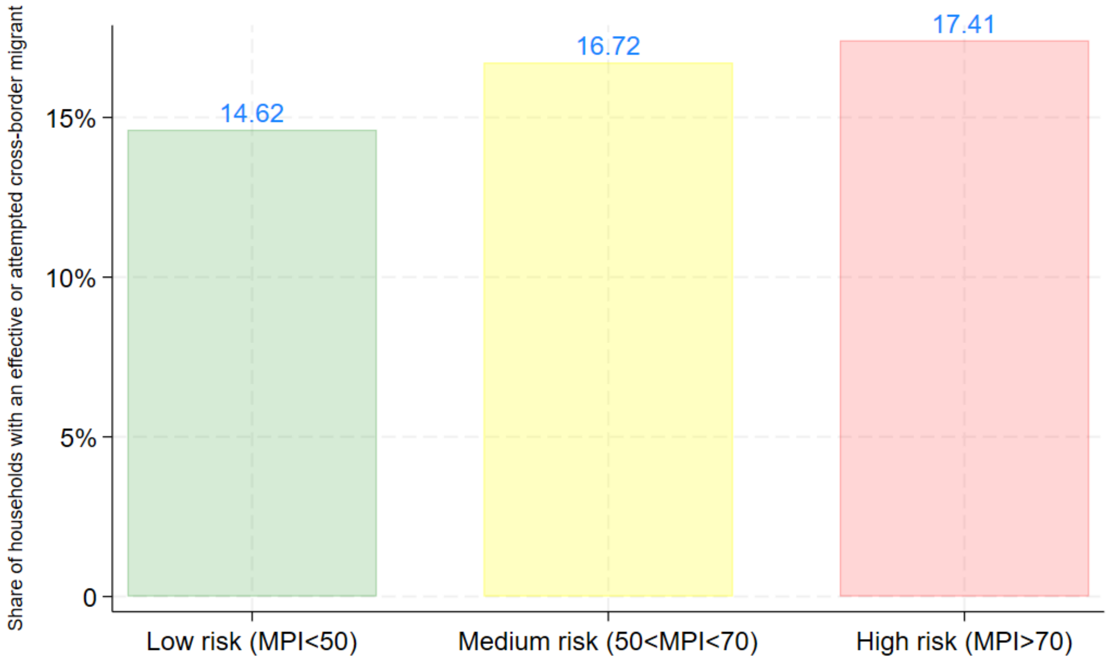
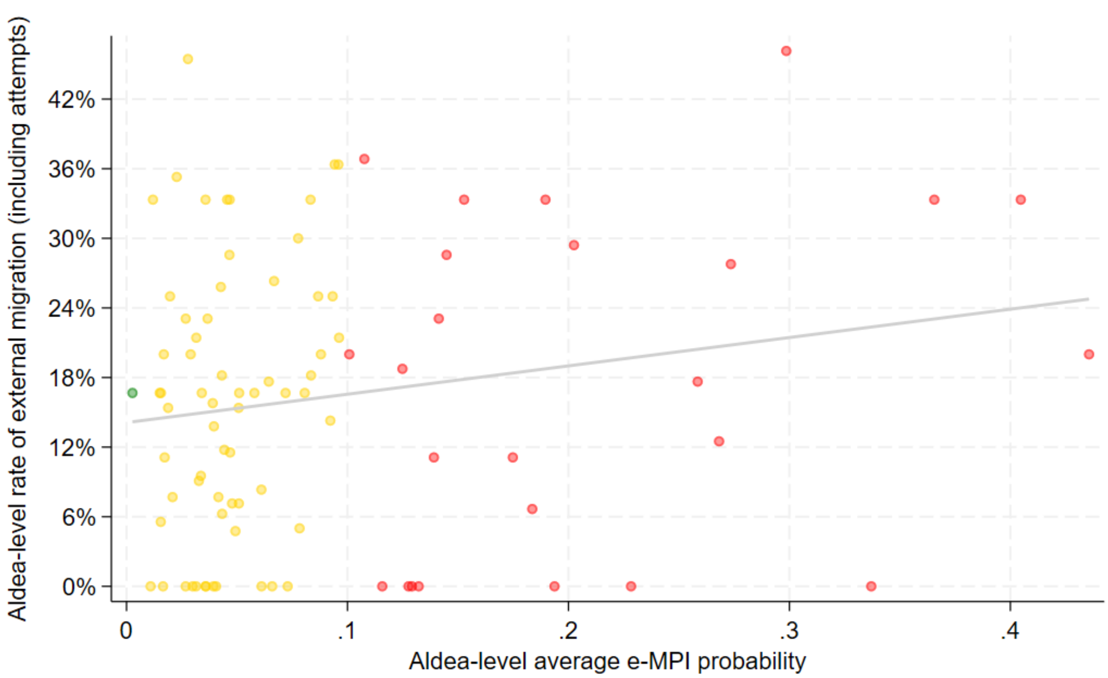
APPENDIX

Appendix Figure 1. Effective attempted external migration rates by MPI group



Appendix Figure 2. MPI predictive ability between-community – Attempted external migration



Appendix Table 1. Determinants of attempted external migration

	(1) Full sample	(2) Full sample	(3) Full sample	(4) Municipality fixed effects	(5) Aldea fixed effects	(6) Rural households	(7) Urban households	(8) 6 original departments	(9) 3 new departments	(10) Placebo
e-MPI (probability)	0.130*	0.124*	0.136*	0.126*	0.055	0.126	0.197*	0.129	0.151	0.133*
	(0.072)	(0.070)	(0.072)	(0.075)	(0.083)	(0.090)	(0.118)	(0.081)	(0.171)	(0.072)
Reported intention to migrate at baseline		0.124***								
		(0.026)								
Rate of returnees 2021-22			-1.630							
			(1.877)							
i-MPI (probability)										-0.090
										(0.269)
Income p.c. - First quartile (i.e. Poorest)	0.031	0.028	0.030	0.047	0.051	0.053	-0.008	0.039	0.066	0.031
	(0.033)	(0.032)	(0.032)	(0.033)	(0.035)	(0.039)	(0.060)	(0.038)	(0.063)	(0.033)
Income p.c. - Second quartile	0.064**	0.059*	0.063**	0.073**	0.070**	0.056	0.103	0.075**	0.076	0.064**
	(0.032)	(0.032)	(0.032)	(0.032)	(0.034)	(0.038)	(0.065)	(0.038)	(0.063)	(0.032)
Income p.c. - Third quartile	0.040	0.038	0.040	0.046	0.043	0.061*	-0.002	0.045	0.049	0.041
	(0.030)	(0.030)	(0.030)	(0.030)	(0.032)	(0.037)	(0.052)	(0.037)	(0.052)	(0.030)
Reports financial difficulties to reach the end of the month	0.003	-0.002	0.004	0.010	0.025	0.021	-0.037	0.024	-0.036	0.003
	(0.033)	(0.033)	(0.033)	(0.032)	(0.035)	(0.041)	(0.056)	(0.038)	(0.064)	(0.033)
Engaged in agricultural production	-0.005	-0.002	-0.003	0.012	0.010	0.023	-0.078*	0.049*	-0.078*	-0.005
	(0.023)	(0.023)	(0.023)	(0.024)	(0.026)	(0.027)	(0.043)	(0.028)	(0.040)	(0.023)
Faced adverse climate event in last 12m	0.052**	0.048**	0.051**	0.043*	0.032	0.056**	0.018	0.017	0.092**	0.053**
	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)	(0.028)	(0.043)	(0.028)	(0.040)	(0.023)
Faced mild food insecurity in last 12m	-0.027	-0.036	-0.026	-0.028	-0.020	-0.005	-0.100**	-0.015	-0.037	-0.028
	(0.034)	(0.034)	(0.034)	(0.034)	(0.038)	(0.042)	(0.050)	(0.041)	(0.063)	(0.033)
Faced moderate food insecurity in last 12m	0.030	0.038	0.029	0.027	0.004	0.003	0.113**	0.021	0.028	0.031
	(0.035)	(0.035)	(0.035)	(0.036)	(0.038)	(0.043)	(0.055)	(0.042)	(0.066)	(0.035)
Faced severe food insecurity in last 12m	0.003	-0.003	0.003	0.004	0.019	-0.014	0.024	-0.042	0.081*	0.002
	(0.028)	(0.028)	(0.028)	(0.029)	(0.032)	(0.034)	(0.053)	(0.035)	(0.048)	(0.028)
Suffered from crime in last 12m	0.018	0.002	0.018	0.021	0.021	0.056	-0.057	0.029	-0.019	0.018
	(0.035)	(0.034)	(0.035)	(0.035)	(0.037)	(0.044)	(0.058)	(0.043)	(0.062)	(0.035)
Perceives high level of insecurity in community	0.003	0.006	0.001	0.004	0.024	-0.022	0.036	-0.012	0.062	0.003
	(0.030)	(0.029)	(0.030)	(0.031)	(0.034)	(0.037)	(0.051)	(0.034)	(0.063)	(0.030)
Aspirations: (Income goal - actual), in logs	0.010	0.009	0.009	0.009	0.008	0.019**	-0.011	0.012	0.002	0.009
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.018)	(0.010)	(0.016)	(0.008)
Perceptions: ''In case of a problem I can go to local authorities for help''	-0.026	-0.029	-0.024	-0.029	-0.033	-0.044	0.017	-0.030	-0.043	-0.026
	(0.025)	(0.025)	(0.025)	(0.026)	(0.028)	(0.030)	(0.045)	(0.028)	(0.057)	(0.025)

Perceptions: ''Police and the justice system protect honest citizens''	0.003	0.009	0.003	0.008	0.006	0.033	-0.068	-0.016	0.038	0.003
	(0.025)	(0.025)	(0.025)	(0.026)	(0.028)	(0.031)	(0.044)	(0.029)	(0.052)	(0.025)
Perceptions: ''If I am victim of a crime I always denounce it to authorities''	-0.010	-0.012	-0.011	-0.004	-0.006	0.004	-0.024	-0.015	0.018	-0.010
	(0.025)	(0.025)	(0.025)	(0.026)	(0.028)	(0.030)	(0.048)	(0.028)	(0.059)	(0.025)
Perceptions: ''In my country there are plenty of opportunities to thrive''	-0.017	-0.015	-0.018	-0.017	-0.013	-0.015	-0.030	-0.025	-0.008	-0.018
	(0.024)	(0.024)	(0.024)	(0.025)	(0.027)	(0.029)	(0.043)	(0.029)	(0.049)	(0.024)
Perceptions: ''I feel included in my community's social activities''	0.059**	0.057**	0.058**	0.047*	0.044*	0.067**	0.050	0.051*	0.051	0.059**
	(0.024)	(0.024)	(0.024)	(0.024)	(0.026)	(0.028)	(0.046)	(0.029)	(0.045)	(0.024)
Perceptions: ''I usually trust other people''	0.006	0.019	0.006	0.010	0.026	-0.022	0.073	-0.007	0.002	0.006
	(0.030)	(0.030)	(0.030)	(0.030)	(0.032)	(0.033)	(0.060)	(0.035)	(0.055)	(0.030)
Constant	-0.021	-0.043	0.009	-0.026	-0.016	-0.153	0.234	-0.052	0.043	-0.018
	(0.088)	(0.088)	(0.099)	(0.088)	(0.088)	(0.094)	(0.190)	(0.102)	(0.174)	(0.089)
Number of observations	1,193	1,193	1,193	1,193	1,193	853	340	795	398	1,193
R-squared	0.021	0.043	0.022	0.046	0.120	0.032	0.068	0.032	0.044	0.021