INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
IFPRI

WORKING PAPER DECEMBER 2024

External and Internal Migration Propensity Index (MPI) for Honduras

Out-of-sample Validation

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December 5th, 2024

Abstract

The e-MPI and the 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 effectiveness fully out of sample. We find good predictive power of each of these indices in terms of the respective type of migration they attempt to anticipate. Moreover, they perform well against alternative measures, work reasonably well for both rural and urban areas and in departments not included in the original calibration data, and appear to capture distinct aspects around households' decisions to migrate domestically and abroad. Overall, the MPI seems to be an important addition to policymakers' toolkit.

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 are the regions that receive most emigrants. 51% of migrants are men and roughly one third have between 15 and 34 years old. In addition, a large share of emigrants comes from rural areas, which receive around 40% of international remittances according to the Food and Agriculture Organization (2018). Even though COVID-19 has greatly halted international migration —reducing the number of international migrants by around 2 million globally by mid-2020—, this probably constitutes only a temporary disruption of the underlying growth trend (McAuliffe and Triandafyllidou, 2022).

Migration is a complex, multidimensional phenomenon determined by a wide set of factors, including push factors —encouraging people to move out of their current location— and pull factors —attracting people to move into a new location (Rubenstein, 2017)—. These factors are typically 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 potential factors, 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]

Identifying migration drivers thus requires a comprehensive and holistic approach. Migration decisions are normally influenced by various factors at the individual, household, local, regional, and national levels, and are typically interrelated, vary over time, often reinforce one another, and are not always directly observable, adding complexity to the analysis. 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 of an individual to migrate may depend on his network outside the community and abroad (Carrington et al, 1996; Munshi, 2003).[2] 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).

[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] See Skeldon (1997) for an extensive review of the determinants of migration.

In 2019, the International Food Policy Research Institute (IFPRI) proposed the MPI (hereafter the e-MPI), a **tool to objectively estimate and track the probability that individuals from a given household will migrate abroad in the near future**. The central idea is to identify and keep track of a small subset of household indicators and conditions that highly correlate with the (latent) decision to migrate abroad. The index was developed and calibrated for the case of Guatemala (Ceballos and Hernandez, 2020) and, later on, for Honduras (Almanzar et al. 2022). In addition, Ceballos et al. (2023) calibrated an i-MPI to predict internal (domestic) migration for both Guatemala and Honduras. The i-MPI was a natural extension to the e-MPI, given that internal migration is often regarded as an intermediate step to external migration —where individuals relocate internally before leaving their countries (Cattaneo & Robinson, 2019; McAuliffe & Triandafyllidou, 2021)— and that it relates to a host of important policy issues such as urbanization, shifting livelihoods, dietary changes, and increased mental stress, among others. To date, the MPI indices have been piloted and implemented across numerous field surveys in both countries, in person and over the phone.

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 they are 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 the potential factors correlated with these decisions, and tested through cross-validation procedures focusing on the out-of-sample predictive power of the index; and
4. Can help for both monitoring and targeting purposes, including monitoring (direct or indirect) beneficiaries of programs and/or for targeting purposes of new programs to populations of interest at risk to migrate.

The MPI is in essence similar to the Progress Out of Poverty/Poverty Probability Index (PPI), originally developed by the Grameen Foundation and currently implemented by Innovations for Poverty Action (IPA) across several countries.[4] The PPI relies on ten specific household characteristics and asset ownership questions to estimate the likelihood that a household is living below the poverty line (Schreiner, 2013). Such a tool allows for targeting of social programs by field staff in real time, eliminating the need for lengthy, in-depth income or expenditure surveys or more complex poverty mapping exercises. Naturally, the increased simplicity and immediacy of the approach comes at the cost of reduced accuracy.

[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.

[4] https://www.povertyindex.org/.

Understanding migration decisions, however, imposes different and additional challenges given the nature and potential factors driving these decisions. In particular, the decision to migrate should be regarded as a latent (hidden) decision process that can be correlated with multiple factors, some of which ultimately push an individual to migrate; and these conditions or circumstances that trigger someone to migrate may (or may not) periodically change over time. In this line, we modified the PPI approach to model the latent migration decision, with the goal of obtaining a reliable, simple, concise, and statistically sound migration scoring index that can help donors, policy makers, and program implementors better approximate and track the probability of migration among the population of interest.

In this paper, we test the e-MPI and i-MPI for Honduras fully out of sample in a real-world environment. To do this, we rely on longitudinal data collected in nine Honduran departments during 2023 and 2024 and assess whether a household's MPI at a given point in time helps predict actual instances of migration in the subsequent 12 months. In addition, during the baseline 2023 survey we collected a wealth of additional data on dimensions potentially related to the decision to migrate but not included in the original MPI calibration. Such data allows us to test the MPI's predictive capacity against competing alternatives.

We find that both the e-MPI (to anticipate external or cross-border migration) and the i-MPI (to anticipate internal or domestic migration) have an overall good predictive power on average, in terms of identifying households that have a higher or lower propensity to migrate. In the case of e-MPI, 8.2% of the households identified as being of high-propensity in 2023 had at least one member migrate abroad in the subsequent 12 months, compared to 5.6% and 1.5% in the medium- and low-propensity groups, respectively. In terms of the i-MPI, the pattern is even starker, with rates of effective domestic migration of 15.3% for the high-propensity group, compared to 4.3% and 0% for the medium- and low-propensity groups. These rates are similar to the ones found in Guatemala for external migration (Hernandez et al., 2022), at 7.4% for the high-propensity group, 4.0% for the medium-propensity group, and 1.6% for the low-propensity group.

In addition, both the e-MPI and the i-MPI turn out to be important predictors for, respectively, external and internal migration, in contrast to alternative measures that show no statistically-significant effects, including crime, perceptions, or food insecurity variables, important dimensions highlighted in the migration literature and in anecdotal evidence around migration in Honduras. In the case of external migration, aspirations turn out to be a second important predictor beyond the e-MPI, while in the case of internal migration having experienced a recent adverse weather event joins the i-MPI as a relevant predictor. Moreover, the MPIs show substantial explanatory power when controlling for local migration rates or when including fixed effects at the municipality or aldea levels, indicating that the indices are not simply acting as proxies of the strength of localized migration outflows. When conducting the analyses for the rural and urban subgroups, we find similar patterns across them, with the explanatory power of the MPI being seemingly higher for urban areas (in terms of its point estimate) but with a weaker statistical significance (arguably due to the much lower number of urban observations in the sample). Finally, we conduct placebo tests by jointly including the e-MPI and i-MPI and find that the placebo MPI does not provide additional explanatory power

beyond that of the main index, supporting the conclusion that both indices are indeed capturing distinct aspects around households' cross-border and domestic migration decisions.

The remainder of the paper is organized as follows. Section 2 describes the general methodology for calibrating the index, including the statistical methods and validation procedures used. Section 3 presents the current applications of the index, including the e-MPI and i-MPI. Section 4 discusses different validation exercises for both indices. Section 5 provides concluding remarks.

2. Brief overview of the MPI methodology

The overall goal of the MPI is to be a simple, concise, and statistically robust tool based on easily measurable, reliable household characteristics and conditions that can predict with reasonable confidence whether an individual in a household will migrate or not (cross-border or domestically) in the near future. We discuss each of these index attributes next.

First, given that the target group to use this index are donors, policy makers, and program implementors and that the index is basically meant for monitoring and targeting in real time, the index must be *simple*. In order to be readily adopted, practitioners must be able to grasp the inner workings of the index and trust its capacity to predict a phenomenon they already know reasonably well in qualitative terms. Complex statistical or machine learning models with non-linear effects and cross-interactions between variables are not always transparent or well suited to understanding and require an excessive amount of training data. In this regard, the MPIs are based on widely used statistical regression techniques and focus on key variables that would affect the propensity of an individual to migrate.

Second, information gathering in remote, rural areas is costly and faces numerous challenges. Conducting long household surveys in person may be cost-prohibitive in many cases. The index must thus be *concise*. The MPIs comprise twelve variables carefully selected to maximize its predictive capacity based on currently available data. Moreover, these variables must be *easy to measure* through direct, non-invasive questions and with minimal reporting bias. For instance, directly asking individuals about their intentions to migrate may possibly lead to underreporting — out of fear or mistrust—, or to refusals to respond. The MPIs must use indicators that can be measured with ease in the field and indirect enough to encourage honest (unbiased) responses. They must also contemplate the possibility of asking these questions over the phone, in order to significantly reduce costly transportation and logistics involved in sending a survey team to the field.

Third, if the indices are to be used with confidence to guide policy and intervention targeting, they must be *statistically robust*. Since the decision to migrate is dynamic in nature and since, particularly in the case of cross-border migration, the decision is followed by an influx of remittances into the migrant's household, model fit, and likely confounding effects (endogeneity problems) must be carefully considered to obtain a robust index with a high predictive power. The MPIs circumvent endogeneity problems by relying on a large, detailed panel survey of households from regions of interest, which, as discussed above, permits to compare a household's *ex ante* characteristics with their *ex post* decision to migrate. Furthermore, to avoid potential issues around model overfitting,

the MPIs are constructed and evaluated using cross-validation techniques, which split the working sample into two subsamples: one subsample for model fitting and the other subsample for evaluating the model's predictive capacity.

The next subsections describe the complete methodology for the construction and validation of the proposed MPIs.

The model

Since the dependent variable, whether an individual in the household migrated (either abroad or domestically) during the last 24 months, is binary, we must rely on discrete choice statistical models. We work with a standard logistical regression model (Logit model), which allows to bound the outcome of the model to a probability range between 0 and 1. Since the propensity to migrate may vary according to local economic, social, and infrastructural conditions we must also control for these aggregated effects (shifters). To do this, and given that the underlying surveys used for calibration do not cover the entire country, department fixed effects are included in the specifications. In particular, a separate dummy for each of the six departments is included in the model:

- Copán
- Intibucá
- La Paz
- Lempira
- Ocotepeque
- Santa Bárbara

All specifications also include an indicator variable to distinguish rural from urban areas, according to the official classification of the nearest *caserío* from where the household is located. Since the sample was conducted at the *aldea* level, there was no *caserío* information, and therefore a *caserío* was assigned to each household using the household's GPS location coordinates, and the location coordinates of each *caserío*'s centroid point. For each household, the *caserío* at the closest straight-line distance was assigned. Finally, since some households are included twice in the working sample (i.e., when the household was interviewed across all three survey rounds), we cluster standard errors at the household level to account for the likely correlation in the observed outcomes within the same household.

Out-of-sample cross validation

The final model is selected using an out-of-sample cross-validation procedure, a standard statistical procedure to assess the predictive performance of a model. The idea is to assess how the model will perform when applied to new data. To achieve this, the data is randomly partitioned into two subsamples: 70% of the observations are used for estimating the model (i.e., model training); and the resulting coefficients are applied to the remaining 30% of the sample to test whether the model predictions match with actual observations (i.e., model predictive performance). To minimize

sampling bias, the procedure of splitting the sample is repeated 300 times.[5] In each of these repetitions, the coefficients of the model are estimated with 70% of the observations and the metrics on the model's predictive accuracy are calculated over the remaining 30% of observations. For each metric, we average the measures obtained across the 300 repetitions to derive an overall metric. Two metrics are considered for the model's construction:[6]

Root mean square error (RMSE): A usual metric to evaluate the fit of a statistical model, constructed by squaring the difference between the model's predicted probability and the observed outcome (either 0 or 1), averaging these across all observations, and taking the square root. It measures how far the model predictions are from the actual occurrences.[7]

Concordance statistic (C-Stat): This metric is commonly used for binary-choice models since it measures the concordance between the observed outcome and the model's predicted probability for that outcome across all observations. A model that maximizes this metric exhibits the most internally coherent array of predicted probabilities, in the sense that observations with a positive outcome (households having a migrant in our case) will have on average a higher predicted probability than those with a negative outcome.[8]

Stepwise variable selection

In order to maximize the objectiveness and unbiasedness of the final selected model, we rely on a stepwise statistical procedure to select the variables with the highest predictive power from amongst the universe of variables described in Section 2. We implement the following procedure:

1. Consider every possible one-variable model, constructed by only including one single variable from the universe, together with the department fixed effects and the rural indicator.[9]
2. Estimate each of these one-variable models and calculate their out-of-sample predictive-power metric.
3. Select the one-variable model with the highest predictive power.
4. Add one additional variable (from the remaining universe of variables) to the selected one-variable model, to construct all possible two-variable models.
5. Estimate each of these two-variable models and calculate their out-of-sample predictive power metric.
6. Select the two-variable model with the highest predictive power.

[5] These partitions naturally maintain the full-sample proportions of households with and without a migrant.

[6] We avoid using other standard metrics for the model construction, such as the correct classification rate or sensitivity and specificity measures, as these require converting the estimated probability outcomes into a binary regime prediction using a pre-determined (arbitrary) threshold.

[7] The RMSE ranges between 0 and 1. See Barnston (1992) for additional discussion on this measure.

[8] The C-Stat ranges from 0.5 to 1. See Hosmer and Lemeshow (2000) for further details on the interpretation of the C-Stat.

[9] As discussed above, the department fixed effects and rural indicator act as shifters and are included in all stepwise regressions.

7. Add one additional variable to the selected two-variable model (from the remaining universe of variables), to construct all possible three-variable models and repeat the selection process, adding one variable at a time and selecting the one with the highest predictive power in each round, until a 12-variable model is achieved.

Additional considerations

The above steps provide an objective procedure on which to build a statistically-sound model. However, in order to fulfill all index goals, we allow for a degree of subjectivity in the process. Besides considering variables that are simple and easy to measure, we need to ensure that they are (1) relatively dynamic over time, (2) add value to the model, and (3) cover key dimensions around the decision to migrate.

In terms of the first element, since one of the objectives of the index is to monitor the propensity of an individual in a household to migrate over time, it is important that at least a subset of the selected variables likely changes over time. For instance, the sex of the household head or his/her education would normally not change from one year to the next, while ownership of certain assets or exposure to natural shocks may. As for adding value to the model, we intend to avoid situations where two similar indicators (likely highly correlated) are jointly included. For instance, if the model already includes a variable capturing whether any of the household members in a certain age group has completed 5 or more years of education, additionally including whether any member has completed 6 or more years of education would not add real value. Finally, we must attempt to capture most key dimensions around the decision to migrate in the indicators proposed, including factors generally discussed in the broader migration literature and in studies specific to the Northern Triangle and Honduras.

To achieve this, the procedure described in the previous subsection is followed to select the optimal variable at each round but we further check if the new variable selected diverts from the objectives above; if so, this new variable is excluded, and the procedure is allowed to select the second-best variable for that round.[10] This process permits to have a final set of 12 variables that fulfill all the MPI objectives (plus the two location variables). Figure 1 summarizes the complete methodology.

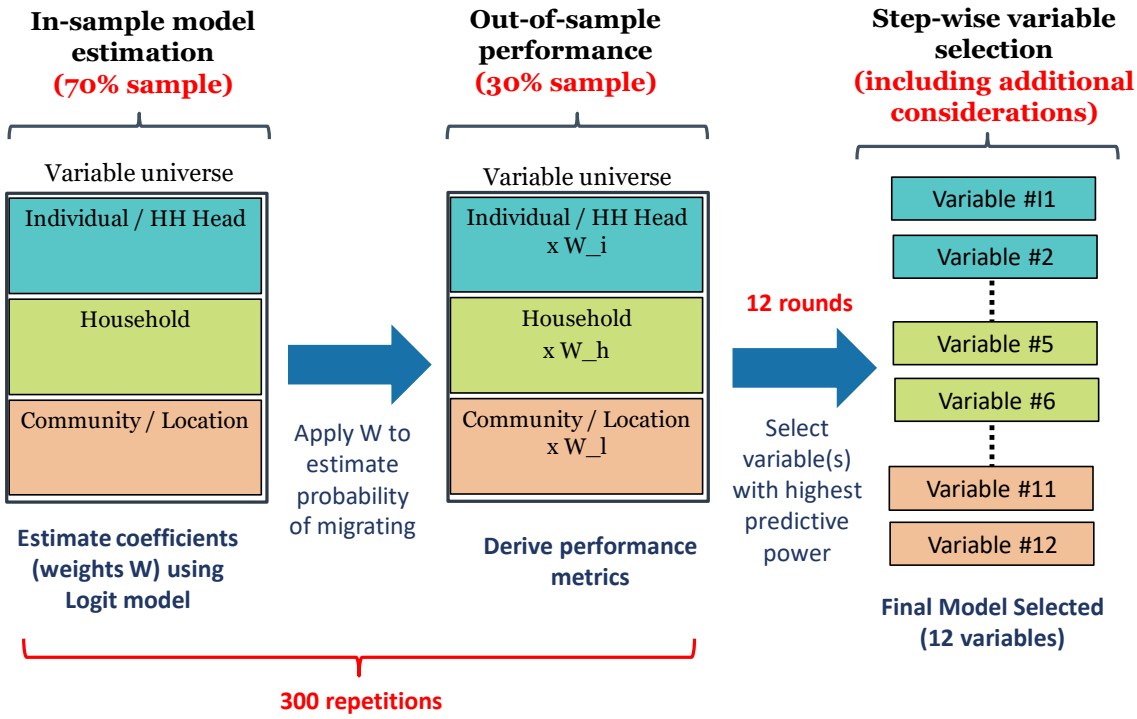
3. Applications

We rely on a panel dataset collected by IFPRI for the impact evaluation of USAID-ACCESO across three survey rounds in 2012, 2013, and 2015. The surveys encompassed six departments in western Honduras where activities under Feed the Future/USAID were taking place, i.e., Copán, Intibucá, La Paz, Lempira, Ocotepeque, and Santa Bárbara, and were designed to be representative at the department level. The surveys were implemented during Honduras' lean agricultural season, that spans the months from May to August, and included household socioeconomic characteristics, household income sources, employment, expenditures and assets, dwelling characteristics,

[10] The whole estimation process is documented and is available upon request.

access to services and credit, participation in social programs, hygiene and family health, nutrition, and household food consumption, among others.[11] Additionally, to consider climate-related dimensions, we included two variables calculated from external sources of whether the standardized precipitation index for any of the primera agricultural season months was below -1 or -1.5 (i.e., one or one and a half standard deviation below the historic average).[12] More details on the Honduras dataset are described in Almanzar et al. (2022).

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



To capture whether a household had an instance of international or domestic migration, we rely on differences between household members' lists between two consecutive survey rounds and on a follow-up question inquiring about the reason for which an individual that used to be a member of the household is no longer present, as follows:

- Why is [previous member] no longer a household member?
    1. *He/she passed away*
    2. *He/she was never a member; was in the roster by mistake*
    3. *He/she moved to another HH inside this village*
    4. *He/she moved to a different municipality*

[11] The MPI calibration procedure uses 56 explanatory variables available for the 2,839 households in the panel. See Almanzar et al. (2022) Appendix B with the variable universe, together with each variable's definition and type of measure.

[12] A household is considered to have suffered a drought event if for any of the months that comprise the last primera agricultural season (May to Semptember) prior to the moment of the survey the SPI (Standard Precipitation Index) was lower than -1 (in the case of the mild drought variable) or lower than -1.5 (in the case of the moderate drought variable). The monthly SPI was estimated using 20 years of historic precipitation data (2000-2020), at the municipality level, from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS).

5. *He/she moved to Tegucigalpa*
6. *He/she moved to a different department*
7. *He/she moved to a different country (specify the country)*

We define a household as having had a migrant since the previous survey round if there is at least one individual that belonged to the household during the previous survey round and that is no longer a member of the household in this survey wave. Migrants that moved to a different country (answer option 7) are considered international migrants, while those who moved to Tegucigalpa or a different department (answer options 5 or 6) are considered domestic migrants. Indicator variables are then constructed at the household level (our unit of observation) for external and internal migration, that take a value of 1 if the household had at least one individual who migrated internationally or domestically, respectively. Note that a household may be classified as both having had an international and a domestic migrant.

Table 1 lists the final 12 variables selected for the e-MPI (panel A) and i-MPI (panel B), in the order in which they were selected based on the C-Stat metric. The 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 decision factors. First, larger household size is associated with a larger propensity to migrate, as well as having youth with some level of education in the household (female or male members between 15 and 29 years of age with, respectively, at least one year of secondary education or complete primary). This is consistent with much of the existing literature on migration, which finds youth as the main age group migrating abroad, usually with a moderate level of education and skills. In contrast, being a male-headed household is negatively correlated with the decision 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, as captured by the standardized precipitation index being smaller than -1, are associated to a higher probability to migrate.

Table 1. Final variables selected for 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)**

In terms of external migration, the final e-MPI includes variables proxying for pull factors —such as the rate of households with migrants abroad and whether the household itself has a migrant abroad—, as crucial indicators for the propensity of an individual in a household migrating in the near future (i.e. with a relatively high partial contribution to the overall MPI score). The index also includes variables relating to household demographics, such as the gender of the household head and the presence of individuals from the same age group (15 to 29 years of age) with some level of education (complete primary). The index also identifies asset ownership (such as land or a television) and dwelling characteristics as further predictors of the probability to migrate. Finally, the index includes a question for whether the household experienced a recent drought.[13]

Panel B shows the selected variables when it comes to anticipating internal migration. It is worth noticing that, unlike all other calibrated MPIs (including both the external and internal MPI for Guatemala) the model calibration 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 calibration procedure selected the head of household's age and years of education 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. Finally, 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. Finally, and similarly to 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.

It is worth noting that the variable universe in the underlying surveys includes a large set of variables capturing different employment dimensions for the different members of the household, in terms of independent/dependent status, employment sectors, and various work dependency ratios. Despite such factors being normally mentioned as important determinants of migration in the literature, none of these was chosen by the variable selection algorithm. Of course, given that there is a high degree of correlation between household-level variables, the exclusion of employment indicators

[13] Reassuringly, the final list of variables for the e-MPI for Honduras shares many similarities with that for the e-MPI Guatemala. Since the calibrations for both indices are fully data driven, and as such completely agnostic of the variables selected in the other index, we interpret these similarities as strong evidence for the methodology's value in predicting potential migration in the context of the Northern Triangle.

from the final index does not imply that these are unimportant, but rather that they did not add sufficient predictive power to the model so as to warrant their inclusion.

Both models show a good predictive performance, in terms of the models sensitivity (or their ability to correctly predict positive cases, i.e. households where members end up migrating) and specificity (or their ability to correctly predict negative cases.[14] It is worth noting that the asymmetries between the predictive power of positive cases (i.e., correctly identifying a migrant) and negative cases (i.e., correctly identifying a non-migrant) are determined by the low prevalence of emigrants in the population or working sample (3.4% of households reported a cross-border migrant and 7% reported a domestic migrant). When the prevalence of the modeled variable is low, the predictive power of positive cases is lower as there are likely more false-positive outcomes due to a lower population (sample) probability; likewise, the predictive power of negative cases is higher as there are likely much less false-negative outcomes. Both the sensitivity and specificity metrics are very important for policymaking and targeting purposes. Correctly identifying households with future migrants is relevant for accurately targeting programs aimed at curbing or improving the conditions for migration. Correctly identifying non-migrating households is pertinent to better allocate program resources, which can be used in more efficient ways or to achieve other objectives not related to potential migrants.

Finally, considerations regarding implementation of the index on the field that are important to mention are that the questions around the number of households in the community and the number of these households with a recent migrant are meant to provide rough household-level estimates for the proportion of households in a community with a recent migrant, so as to avoid the need to interview all households in a community. Now, when the community under consideration is fairly large, this question could focus on a narrower definition of the community, such as those households with whom the interviewee normally interacts with (as this variable is mainly intended to proxy for potential peer or network effects in migration decisions); or could be replaced altogether by community-level estimates of the corresponding proportion, in case these data were available. Similarly, the question on whether there was a month in the previous primera season (in Honduras) when it rained considerably less than usual could be replaced by an indicator calculated from external sources. Such approaches could help to reduce some of the measurement error in the calculation of the index.[15]

4. Validation

While the MPIs were constructed using out-of-sample cross-validation techniques, we set out to test the ability of the tools to predict actual instances of external and internal migration truly out-of-sample. To begin with, since the original surveys used to calibrate the MPIs for Honduras were

[14] For technical details on the model's fit the reader is referred to Almanzar et al. (2022) and Ceballos et al. (2023).

[15] However, whether this is a positive or negative feature of the proposed index remains to be assessed, since the implicit measurement error in household self-reports around the size of their community and the number of households with recent migrants or about their perceptions around having faced a drought in the last primera agricultural season may plausibly be correlated with households' propensity to migrate in the near future.

conducted in 2013-15, the question remains whether the underlying determinants of migration that the tool is proxying for remain valid a decade later. In addition, the MPIs for Honduras were calibrated using available longitudinal data from 6 departments (as described above), so it is an open question whether such a calibration is externally valid to other departments in the country.

In order to quantitatively validate the MPI, we rely on two surveys among a new sample of roughly 1,200 rural and urban households. The main idea is to gauge whether actual migration instances in the 12 months between the baseline and the follow-up survey are associated to the MPI scores at baseline, in addition to an array of indicators potentially linked to the decision to migrate. Such an exercise can serve to assess the effectiveness of the MPI-Honduras on its own and against other potential measures to predict migration.

The baseline and follow-up surveys were conducted in, respectively, 2023 and 2024 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 questions underlying the MPI scores in addition to a broad range of data related to potential migration factors. The baseline survey sample was selected through a multi-stage cluster sampling strategy. In a first step, 23 municipalities were selected with selection probability proportional to migration prevalence (using the 2022 rate of returnees to total population) and size (total population as per the 2013 Census). 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. In a second step, 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 Census. In the third step, two caseríos or barrios were selected within each aldea.[16] 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).[17] 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.[18] 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

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

[17] 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.

[18] 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.

interview that household, proceeding to neighboring structures until a household willing to participate was found.[19]

The follow-up survey was conducted 12 months after the baseline survey and re-interviewed 1,094 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 to be interviewed, which attempted to find out through other family members outside of the household, neighbors, and/or community leaders whether anyone in the household had migrated either domestically or internationally. Such an exercise provides us with migration information on 82 additional households, for a total of 1,176 households (or 97% of the baseline sample) with data on migration, our main outcome of interest.

Migrants in each household were identified based on a survey question on whether someone in the household migrated in the previous 12 months and a follow-up question on where they migrated. External migration captures any migration outside of Honduras, while internal migration captures instances where at least an individual within a household migrated to a different department within Honduras. 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 migration indicator using the household as the unit of analysis. Note that a household may thus exhibit both external and internal migration, since different household members could have migrated to different locations.

Table 2 shows basic summary statistics on the study sample reached during the baseline and follow-up surveys and on effective migration captured during the follow-up survey. Of the 1,209 households interviewed during the baseline survey, almost a third were located in an urban or peri-urban area.[20] At follow-up, we found and re-interviewed 1,094 households, but obtained migration data about 82 additional households by calling contact phone numbers collected at baseline and/or inquiring with neighbors and community leaders. Thus, we count with baseline and outcome data (i.e. whether at least one member of the household migrated, either domestically or abroad) for 1,176 households, or more than 97% of the original baseline sample. All in all, 124 households (or 10.5% of the sample) had at least one migrant between 2023 and 2024, with 71 of them reporting cross-border migration (or 6% of the total sample) and 55 reporting domestic migration (4.8% of the total sample). Only 4 households reported both an instance of cross-border and of domestic migration, indicating that the simultaneous occurrence of these is rare. In terms of migrants' characteristics (panel B), we observe 79 cross-border and 59 domestic migrants, roughly equally split between male and female in the case of cross-border migrants but with about two thirds of migrants being female in the case of domestic migration. Most migrants are between 15 and 30 years of age (with a median of 22) and

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

[20] 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.

they typically have finished primary school, with little differences between cross-border and domestic migration in terms of these dimensions.

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

Panel A. Interviewed households and migration rates

Number of municipalities		23	
Number of caseríos		208	
Baseline survey (2023)	Interviewed	1,209	
	Rural	862	*71.3%*
	Urban/Peri-urban	347	*28.7%*
Follow-up survey (2024)	Re-interviewed	1,094	
	Tracking data	82	
	With migration data	1,176	
	Rural	845	*71.9%*
	Urban/Peri-urban	331	*28.1%*
	With at least one migrant	124	*10.5%*
	Cross-border	71	*6.0%*
	Domestic	57	*4.8%*

Panel B. Individual migrants

	Cross-border	**Domestic**
Number of individual migrants	79	59
Male	41	22
Female	38	37
Age		
25th percentile	15	16
Median	22	22
75th percentile	32	28
Years of schooling		
25th percentile	6	4
Median	6	6
75th percentile	11	11

Figure 2 shows the effective rates of external migration (panel A) and internal migration (panel B) in the 12 months between the baseline and follow-up survey among households with a low, medium, or high propensity to migrate as per the MPI elicited during the baseline survey (either external, e-

MPI, or internal, i-MPI). In terms of cross-border migration, the e-MPI seems to do an overall good job predicting actual migration instances, with 8.2 % of the households in the high-propensity group having at least one member migrate abroad, compared to 5.6% and 1.5% in the medium- and low-propensity groups, respectively.[21] When it comes to internal migration, the pattern is even starker, with rates of effective domestic migration of 15.3% for the high-propensity group, compared to 4.3% and 0% for the medium- and low-propensity groups. These findings are similar to the ones in Guatemala for external migration, where Hernandez et al. (2022) find an effective migration rate of 7.4% among households with an initial high propensity to migrate, and rates of 4.0% and 1.6%, respectively, among those with a medium and low migration propensity in a sample of 1,170 re-interviewed households.

Next, we assess the MPI's between-community predictive ability; in other words, can the MPI help to prioritize communities with a higher propensity of migration? We tackle this question by calculating the effective rate of migration and the average MPI at the community level (proxied by the Aldea administrative unit).[22] Figure 3 shows scatterplots for these two variables, with the Aldea as the unit of observation.[23] Overall, the average MPI at the community-level is positively —but weakly— associated to effective external (panel A) and internal (panel B) migration rates. In particular, aldeas with higher average MPI scores seem to exhibit slightly higher migration than those with lower scores, with a statistically-significant association. The fit is arguably not strong due to a considerable number of Aldeas that show no instances of migration among sampled households, which could reflect a relatively low sample size at this administrative level or that migration may take longer to materialize than one single year.

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 are at a higher propensity to migrate. 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 12 months. The vertical axis shows the within-aldea percentile of migrant households; in other words, it captures where in the aldea's MPI distribution, that household's MPI was located. In the case of external migration, the figure shows that almost 65% of migrant households had an e-MPI that was above the median MPI at their aldea, while more than 40% of migrant households were above the 75th percentile. These results are even stronger in the case of internal migration, with more than three quarters of migrant households above the median MPI in the aldea, and almost 60% above the 75th percentile. While the figure shows these distributions separately for rural and urban areas, we do not find substantial differences between these in either panel. All in all, we take this as

[21] Appendix Figure 1 shows a similar exercise considering attempted external migration, that is including both successful and unsuccessful attempts to migrate abroad. The results are qualitatively similar, with 12.2%, 10.4%, and 7.7% effective migration rates for, respectively, the high-, medium-, and low-propensity groups.

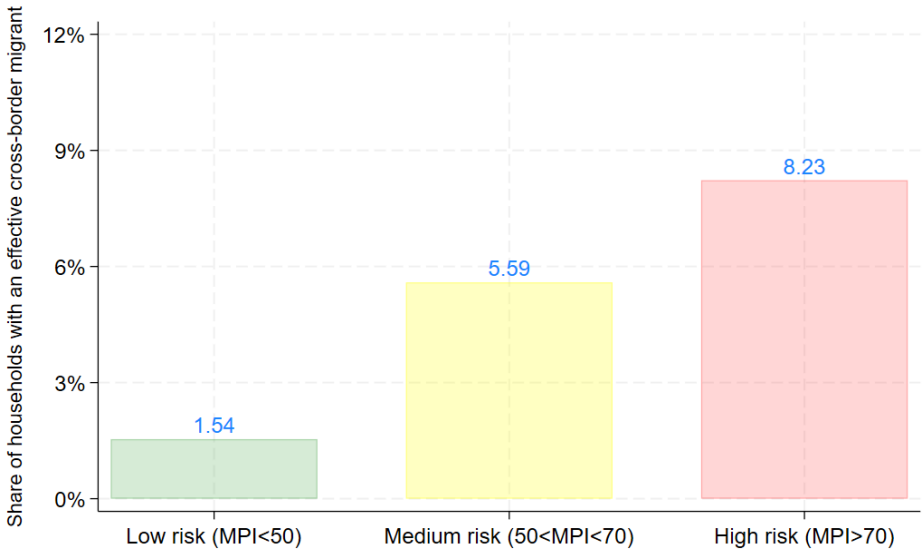
[22] For this exercise, as well as the regression specifications below, we transform MPI scores to the underlying probability implicit in the base logit calibration model. Since the probability is a non-linear function of the score, such an approach is better suited to the linear nature of OLS models.

[23] Appendix Figure 2 considers attempted external migration, with similar results.

indicative evidence that the MPI can be a helpful tool to identify which households within a community are more likely to migrate.

Figure 2. Effective migration rates by MPI group

Panel A. External migration



Panel B. Internal migration

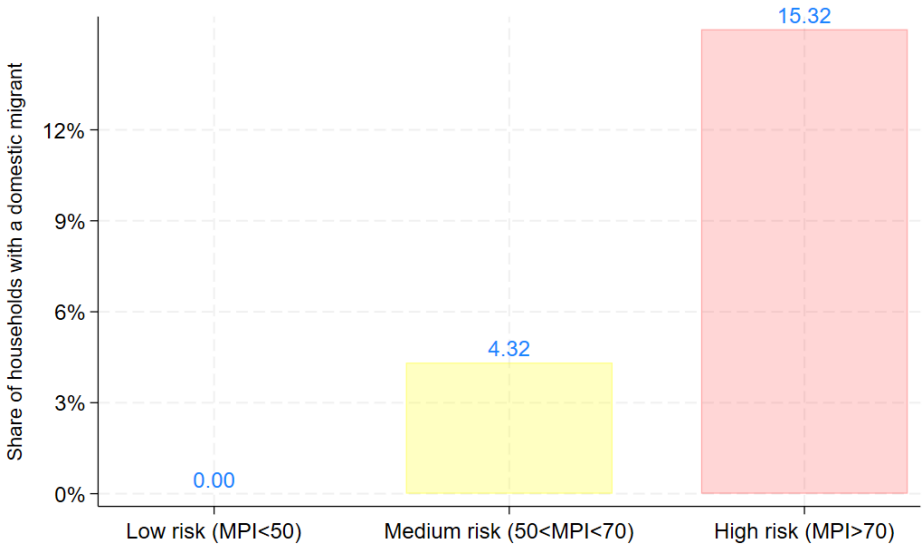
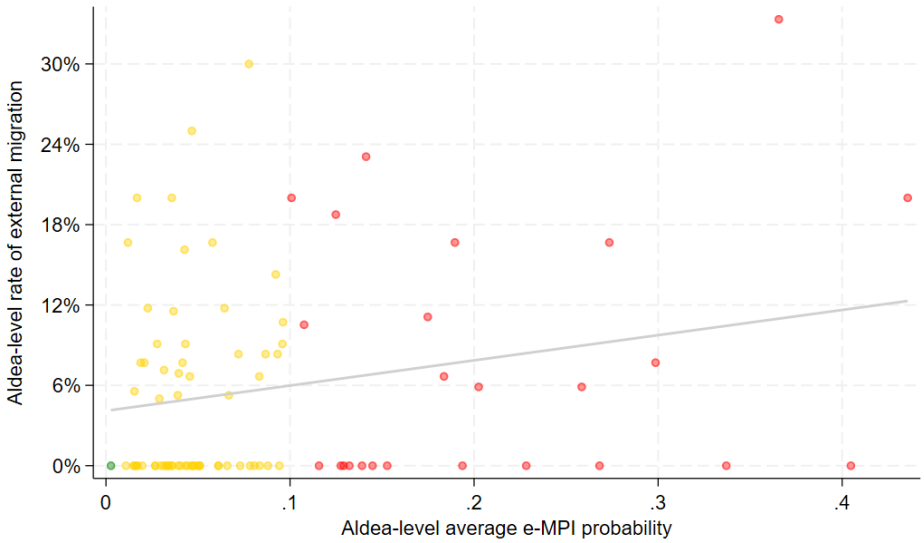


Figure 3. MPI predictive ability between-community

Panel A. External migration



Panel B. Internal migration

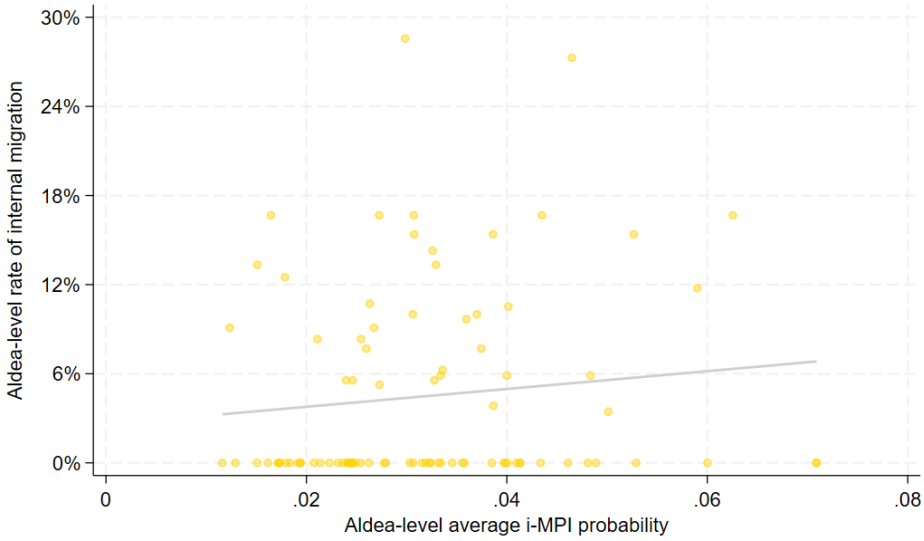
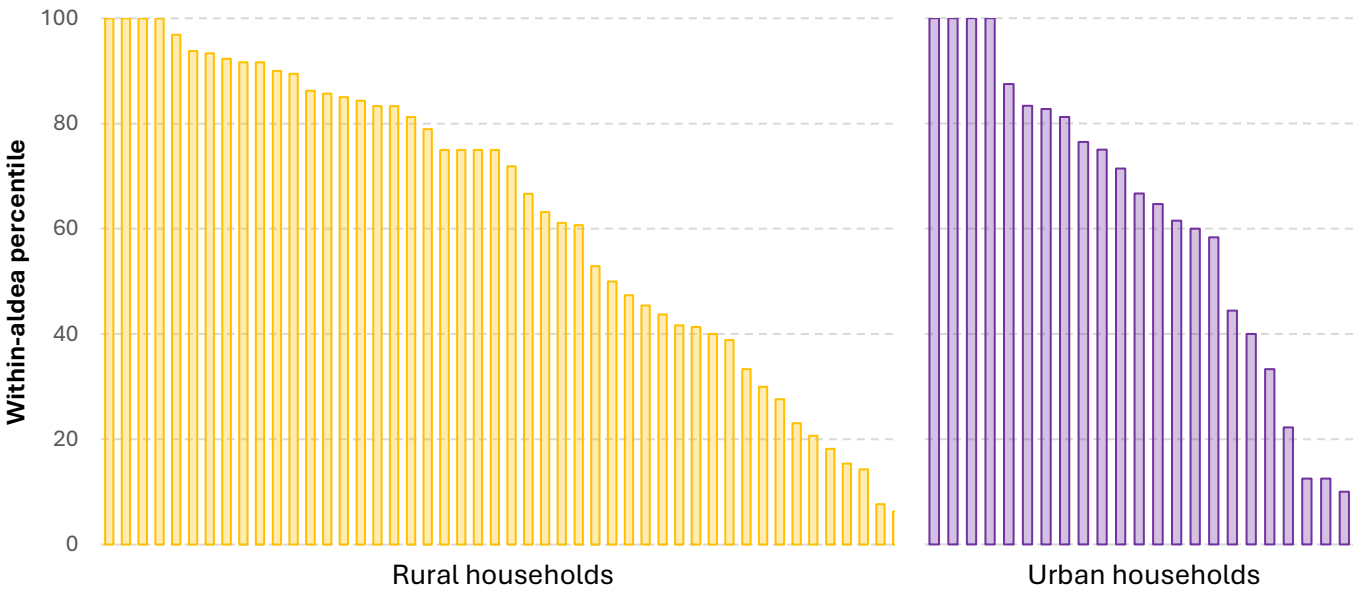
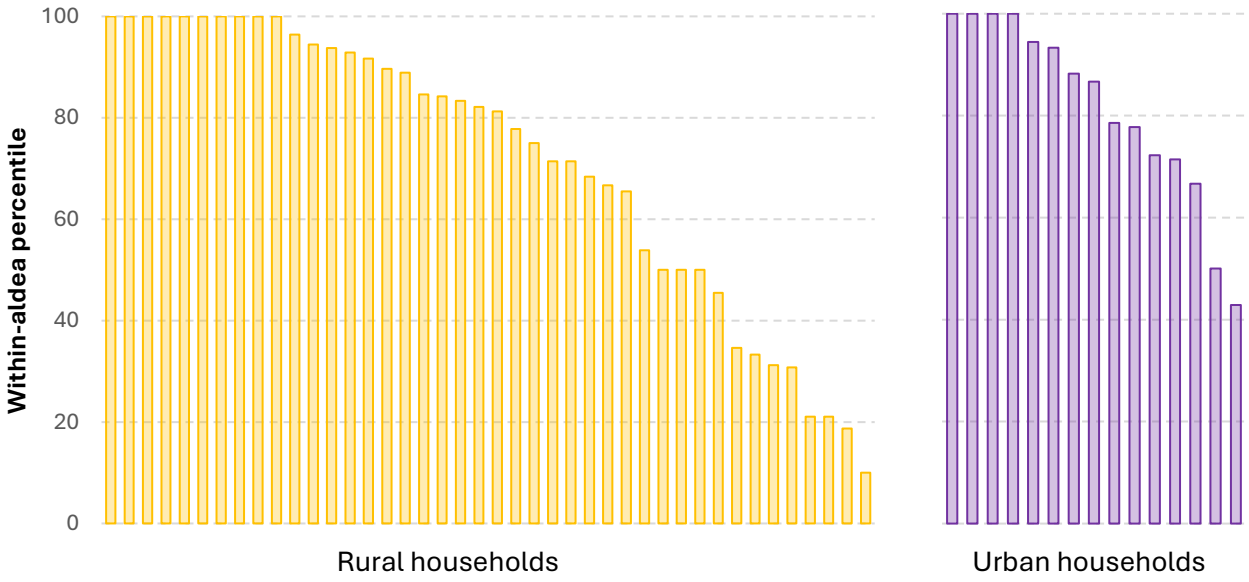


Figure 4. MPI predictive ability within-community

Panel A. External migration



Panel B. Internal migration



Finally, we conduct a more formal exercise to determine the out-of-sample predictive power of the MPI and contrast it to alternative indicators. Tables 3 and 4 show different specifications modelling a binary indicator identifying migrant households (if at least an individual in the household migrated) against the MPI and a range of other measures potentially related to the decision to migrate. For the latter, we consider several dimensions highlighted in the migration literature such as household income (in terciles, with the richest tercile included as a base category; in addition to an indicator

variable capturing households that report having financial difficulties to reach the end of the month), indicator variables for whether a household engages in agricultural production, faced an adverse weather event or mild, moderate, or severe food insecurity in the last 12 months, suffered any type of crime and the number of crime instances in the last 12 months, perceives high levels of insecurity in the community, a measure for a household's income aspirations (defined as the gap between the actual income and the desired one, expressed in logs), and a range of variables capturing a household's perceptions and attitudes around various topics such as trust in local authorities and in the police and the justice system, availability of opportunities to thrive economically, and social cohesion and trust in other people. All indicators, including the MPI, were elicited at baseline and should thus be unaffected by the recent migration instance, with the exception of the climate shocks and food insecurity variables, which were updated at follow-up (the results do not change when we include these variables measured at baseline). Importantly, while the MPI calibrations considered some of the dimensions above, such as income, engagement in agriculture, adverse weather events, or food insecurity, it excluded other important dimensions such as crime and perceptions due to a lack of data availability in the original surveys used. Thus, these specifications serve as an opportunity to test whether the omission of these seemingly relevant variables reduced the quality of the resulting MPI. All specifications rely on ordinary least squares (OLS) using robust standard errors, since this allows for an easier interpretation of coefficients than logit or probit regressions.[24]

Table 3 presents the results for external migration, assessing the e-MPI's predictive ability for migration instances. Column (1) shows the base specification, including the e-MPI and variables capturing all other dimensions described above. Interestingly, the e-MPI and the aspirations' gap are the only variables that turn out to be statistically-significant predictors of actual migration instances among our sample. 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 1.6 percentage points. While this effect is not that large in economic terms, the e-MPI rises as one of the only significant predictors of migration in our sample. The income aspirations gap is also an important predictor of households observing migration, with a 1 percent increase in this gap raising the probability of observing a migration instance by the same order of magnitude. Importantly, however, none of the crime, perceptions, or food insecurity variables, important 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. Column (2), in turn, includes the subjective indicator (captured 12 months prior, at baseline) of whether someone in that household intended to migrate, a question commonly asked when attempting to assess migration sentiment. The ability of this indicator to predict actual migration is statistically indistinguishable from zero, and its inclusion barely changes the e-MPI's predictive ability. This is an important finding; asking the non-invasive, indirect e-MPI questions does a much better job at predicting migration than asking the more invasive, direct question on whether someone in the household intends to migrate.

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

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)	0.163***	0.162***	0.167***	0.163***	0.122*	0.163**	0.194*	0.144**	0.170	0.157***
	(0.058)	(0.058)	(0.058)	(0.061)	(0.064)	(0.067)	(0.115)	(0.066)	(0.132)	(0.058)
Reported intention to migrate 12m ago		0.025								
		(0.017)								
Rate of returnees 2021-22			-1.335							
			(1.159)							
i-MPI (probability)										0.186
										(0.180)
Income p.c. - Lowest tercile	0.021	0.019	0.021	0.021	0.022	0.023	0.031	0.029	0.016	0.019
	(0.018)	(0.018)	(0.018)	(0.019)	(0.021)	(0.021)	(0.039)	(0.023)	(0.034)	(0.018)
Income p.c. - Middle tercile	0.021	0.020	0.021	0.014	0.017	0.035	-0.011	0.043*	-0.016	0.019
	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.022)	(0.030)	(0.023)	(0.026)	(0.017)
Reports financial difficulties to reach the end of the month	0.003	0.002	0.004	-0.001	0.011	-0.002	0.020	0.009	-0.015	0.001
	(0.019)	(0.019)	(0.019)	(0.019)	(0.021)	(0.024)	(0.032)	(0.024)	(0.034)	(0.019)
Engaged in agricultural production	0.022	0.023	0.023	0.018	0.009	0.023	0.025	0.038**	-0.013	0.022
	(0.015)	(0.015)	(0.015)	(0.014)	(0.017)	(0.016)	(0.033)	(0.018)	(0.025)	(0.015)
Faced adverse climate event in last 12m	-0.010	-0.005	-0.011	-0.002	-0.011	-0.057	0.054	-0.079	0.065**	-0.010
	(0.056)	(0.055)	(0.056)	(0.060)	(0.061)	(0.082)	(0.044)	(0.125)	(0.029)	(0.056)
Faced mild food insecurity in last 12m	0.021	0.021	0.021	0.028	0.029	0.038	-0.026	0.008	0.050	0.020
	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)	(0.024)	(0.043)	(0.025)	(0.031)	(0.020)
Faced moderate food insecurity in last 12m	-0.024	-0.025	-0.023	-0.026	-0.043**	-0.032	0.017	-0.022	-0.029	-0.024
	(0.018)	(0.017)	(0.018)	(0.018)	(0.020)	(0.021)	(0.038)	(0.022)	(0.032)	(0.018)
Faced severe food insecurity in last 12m	-0.012	-0.011	-0.011	-0.006	-0.005	-0.022	-0.001	-0.008	-0.021	-0.012
	(0.019)	(0.019)	(0.019)	(0.019)	(0.021)	(0.020)	(0.044)	(0.026)	(0.026)	(0.019)
Suffered from crime in last 12m	0.008	0.007	0.006	-0.002	-0.012	0.047	-0.083***	0.029	-0.039**	0.009
	(0.028)	(0.028)	(0.028)	(0.028)	(0.030)	(0.043)	(0.028)	(0.045)	(0.018)	(0.028)
Number of crime instances in last 12m	-0.008*	-0.008*	-0.008*	-0.009*	-0.005	-0.012*	0.005	-0.010	-0.001	-0.009*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)	(0.005)
Perceives high level of insecurity in community	0.014	0.014	0.012	0.023	0.026	0.002	0.014	0.013	0.001	0.015
	(0.021)	(0.021)	(0.022)	(0.023)	(0.026)	(0.027)	(0.032)	(0.025)	(0.044)	(0.021)
Aspirations: (Income goal - actual), in logs	0.010**	0.009**	0.010**	0.010**	0.009**	0.012**	0.005	0.011*	0.007	0.010**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.008)	(0.006)	(0.004)	(0.004)

Perceptions: ''In case of a problem I can go to local authorities for help''	-0.006	-0.007	-0.005	-0.003	-0.011	-0.003	-0.008	-0.001	-0.007	-0.007
	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)	(0.041)	(0.024)	(0.036)	(0.020)
Perceptions: ''Police and the justice system protect honest citizens''	-0.005	-0.005	-0.005	-0.003	-0.003	-0.004	-0.013	-0.009	-0.006	-0.006
	(0.016)	(0.015)	(0.015)	(0.016)	(0.017)	(0.019)	(0.031)	(0.020)	(0.024)	(0.016)
Perceptions: ''If I am victim of a crime I always denounce it to authorities''	-0.016	-0.016	-0.016	-0.015	-0.014	-0.002	-0.065	-0.026	0.003	-0.017
	(0.018)	(0.018)	(0.018)	(0.018)	(0.021)	(0.020)	(0.041)	(0.021)	(0.043)	(0.018)
Perceptions: ''In my country there are plenty of opportunities to thrive''	0.014	0.015	0.014	0.014	0.011	0.022	0.007	-0.002	0.049	0.015
	(0.017)	(0.017)	(0.017)	(0.017)	(0.019)	(0.021)	(0.030)	(0.021)	(0.031)	(0.017)
Perceptions: ''I feel included in my community's social activities''	0.023	0.022	0.023	0.015	0.017	0.021	0.038	0.025	0.013	0.021
	(0.015)	(0.015)	(0.015)	(0.016)	(0.018)	(0.019)	(0.030)	(0.019)	(0.028)	(0.016)
Perceptions: ''I usually trust other people''	0.023	0.026	0.023	0.023	0.017	0.020	0.021	0.002	0.059	0.023
	(0.021)	(0.021)	(0.021)	(0.022)	(0.024)	(0.025)	(0.041)	(0.025)	(0.042)	(0.021)
A member of the household is mentally or physically impaired	-0.023	-0.021	-0.023	-0.026	-0.011	-0.013	-0.040	-0.035*	0.010	-0.023
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.022)	(0.032)	(0.020)	(0.036)	(0.018)
Constant	-0.082	-0.086	-0.059	-0.085	-0.060	-0.081	-0.064	-0.028	-0.120	-0.088
	(0.073)	(0.073)	(0.075)	(0.079)	(0.081)	(0.097)	(0.112)	(0.136)	(0.081)	(0.073)
Number of observations	1,003	1,003	1,003	1,003	1,003	723	280	678	325	1,003
R-squared	0.034	0.036	0.035	0.064	0.146	0.037	0.076	0.043	0.060	0.035

A potential criticism for the MPI is that it simply serves as a proxy for observed migration rates in the community or the municipality. This is more crucial given that the fraction of households receiving remittances in the community constitutes a quantitatively important component in the MPI score. To test this idea more formally, column (3) includes the ratio of the total number of returnees during 2021 and 2022 in a given municipality as a percentage of the population in that municipality (as per the latest 2013 census). This is the best available data on migration outflows at a disaggregated level 2021 and 2022 in a given municipality as a percentage of the population in that municipality (as per the latest 2013 census). This is the best available data on migration outflows at a disaggregated level and come from the Secretaría de Desarrollo Social de Honduras. Again, the e-MPI stands unchanged as a predictor of migration, with the effect of the rate of returnees not being distinguishable from zero (and a negative point estimate). Columns (4) and (5), in turn, test this hypothesis further by including fixed effects at the municipality and aldea levels. Even in this case, the e-MPI still holds explanatory power for predicting migration instances ex post, with a coefficient of similar magnitude when considering fixed effects at the municipality level, and only slightly lower (though still statistically significant) in the case of fixed effects at the aldea level. In other words, the MPI continues to be a useful predictor of migration when considering only within-municipality or within-aldea variability in migration.

Columns (6) and (7) in Table 3 show the results of this exercise for, respectively, the subgroups of rural and urban households in our sample. Overall, the patterns described above remain for both groups. Though the explanatory power of the MPI seems to be slightly higher for urban areas than for rural areas, the coefficient is statistically significant only at the 10% level. In other words, these results seem to validate the ability of the MPI to predict migration instances in both rural and urban areas, though this conclusion is based on a relatively low number of observations for urban households so they should be taken with caution. Columns (8) and (9) do the same for the subgroups of households in the six original departments where the e-MPI was originally calibrated and those in the three departments not included in the calibration yet interviewed during this survey. Similarly to the rural-urban subgroups, the e-MPI remains highly predictive of migration in the six original departments, and seems to have a slightly higher predictive power in the three new departments, even though the coefficient is not statistically significant in this case, arguably due to the small number of observations in that subgroup.

Appendix Table 1 shows the same set of specifications considering our extended measure of external migration, which includes cross-border migration attempts in addition to actual successful ones. The results are overall quite similar to those in Table 3, with the exception that the e-MPI coefficient does not turn out statistically significant in the aldea fixed effects specification (column 5) or in the urban subsample (though it does show a coefficient of a similar magnitude to that in Table 3). The subjective indicator on intention to migrate at baseline, however, is higher and statistically significant in these specifications (seemingly without taking away from the e-MPI's predictive ability). 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, we suggest taking this finding with caution. Finally, it is important to note that the aspirations variable loses statistical significance in most of these specifications.

Table 4 shows the results when taking into consideration internal migration, with an indicator variable of whether at least one individual in the household migrated domestically in the last 12 months, against the i-MPI underlying probability. It is interesting to note that the coefficient for the i-MPI is considerably higher than the one in Table 3 for the e-MPI, at almost a fourfold increase. This is in line with the stronger effects of the i-MPI seen in Figure 2. Similarly to the e-MPI, the i-MPI does not seem to solely proxy for local migration flows —columns (2) through (4)— and remains highly predictive of domestic migration in both the urban subsample and the subsample of households in the 3 departments not included in the calibration data. In this case, however, while the aspirations variable does not turn out to be statistically significant, the indicator variable for whether a household faced an adverse weather event in the last 12 months does. This implies a stronger effect of climate variability for internal migration (beyond that already captured by one of the components in the i-MPI, related to experiencing a drought during the last agricultural primera season), and is in line with the existing literature (Dillon, Mueller, & Salau, 2011, Gray & Mueller, 2012a, 2012b; Dallmann & Millock, 2017; Colmer, 2021; Ibáñez et al., 2022; Alverio, Sowers, & Weinthal, 2023). Clement et al. (2021), for instance, estimate that climate change could force the internal migration of more than 200 million people by 2050. Exploring the effect of specific adverse weather events remains as an important avenue for future research in this regard.

Finally, since some of the components in the e-MPI are similar to those in the i-MPI, it is reasonable to test whether these indices are capturing distinct aspects around households' propensity to migrate. Column (7) in both tables show the result of such a "placebo" exercise, where in addition to the e-MPI (i-MPI) we include the i-MPI (e-MPI) as an explanatory variable. In both cases, the main MPI retains its predictive ability, with the placebo MPI not being able to provide additional explanatory power, supporting the conclusion that both indices are indeed capturing distinct dimensions in households' decision to migrate.

Table 4. Determinants of internal migration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full sample	Full sample	Municipality fixed effects	Aldea fixed effects	Rural households	Urban households	6 original departments	3 new departments	Placebo
i-MPI (probability)	0.917***	0.919***	0.978***	0.969***	0.881***	1.109***	0.901***	0.968**	0.903***
	(0.236)	(0.236)	(0.242)	(0.237)	(0.291)	(0.424)	(0.284)	(0.435)	(0.232)
Rate of returnees 2021-22		-1.612							
		(1.049)							
e-MPI (probability)									0.026
									(0.043)
Income p.c. - Lowest tercile	0.013	0.013	0.007	0.010	0.013	-0.001	0.016	0.012	0.014
	(0.018)	(0.018)	(0.018)	(0.020)	(0.022)	(0.030)	(0.024)	(0.024)	(0.018)
Income p.c. - Middle tercile	-0.008	-0.008	-0.010	-0.001	-0.010	-0.010	-0.016	0.007	-0.007
	(0.017)	(0.017)	(0.017)	(0.019)	(0.020)	(0.030)	(0.021)	(0.029)	(0.017)
Reports financial difficulties to reach the end of the month	0.000	0.002	-0.002	-0.014	-0.002	0.008	0.006	-0.008	0.000
	(0.017)	(0.017)	(0.017)	(0.019)	(0.023)	(0.026)	(0.021)	(0.038)	(0.017)
Engaged in agricultural production	-0.013	-0.011	-0.012	-0.016	-0.020	0.011	-0.007	-0.017	-0.013
	(0.014)	(0.014)	(0.015)	(0.018)	(0.017)	(0.028)	(0.016)	(0.026)	(0.014)
Faced adverse climate event in last 12m	0.054***	0.052***	0.046**	0.023	0.053**	0.077*	0.048**	0.034	0.055***
	(0.015)	(0.015)	(0.018)	(0.019)	(0.023)	(0.040)	(0.020)	(0.035)	(0.016)
Faced mild food insecurity in last 12m	0.008	0.008	0.013	0.023	-0.005	0.042	0.027	-0.038	0.008
	(0.016)	(0.016)	(0.017)	(0.019)	(0.019)	(0.031)	(0.020)	(0.032)	(0.016)
Faced moderate food insecurity in last 12m	0.001	0.003	0.005	0.000	0.009	-0.020	-0.003	0.013	0.001
	(0.016)	(0.015)	(0.015)	(0.016)	(0.017)	(0.035)	(0.020)	(0.023)	(0.016)
Faced severe food insecurity in last 12m	-0.025	-0.024	-0.025	-0.031	-0.024	-0.022	-0.010	-0.042**	-0.024
	(0.018)	(0.018)	(0.018)	(0.022)	(0.022)	(0.034)	(0.026)	(0.019)	(0.018)
Suffered from crime in last 12m	-0.011	-0.013	-0.009	-0.014	-0.028	0.032	-0.046*	0.051	-0.011
	(0.029)	(0.030)	(0.030)	(0.033)	(0.036)	(0.053)	(0.024)	(0.069)	(0.029)
Number of crime instances in last 12m	0.008	0.008	0.008	0.014	0.016	-0.014	0.015	-0.011	0.008
	(0.011)	(0.011)	(0.011)	(0.014)	(0.016)	(0.012)	(0.014)	(0.018)	(0.011)
Perceives high level of insecurity in community	-0.000	-0.002	-0.005	-0.006	-0.009	0.020	0.001	0.012	-0.002
	(0.017)	(0.016)	(0.019)	(0.022)	(0.019)	(0.029)	(0.019)	(0.039)	(0.017)
Aspirations: (Income goal - actual), in logs	-0.012	-0.012	-0.012	-0.010	-0.022*	0.006	-0.003	-0.026	-0.012
	(0.008)	(0.008)	(0.008)	(0.009)	(0.012)	(0.004)	(0.004)	(0.019)	(0.008)

Perceptions: ''In case of a problem I can go to local authorities for help''	0.019	0.020	0.021	0.029	0.013	0.024	0.027	-0.015	0.019
	(0.017)	(0.017)	(0.017)	(0.018)	(0.020)	(0.034)	(0.018)	(0.043)	(0.017)
Perceptions: ''Police and the justice system protect honest citizens''	-0.013	-0.013	-0.010	-0.015	0.007	-0.062*	-0.007	-0.022	-0.014
	(0.016)	(0.016)	(0.015)	(0.017)	(0.018)	(0.033)	(0.017)	(0.037)	(0.016)
Perceptions: ''If I am victim of a crime I always denounce it to authorities''	-0.001	-0.001	-0.006	-0.011	-0.003	0.017	-0.007	0.022	-0.001
	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.033)	(0.018)	(0.034)	(0.016)
Perceptions: ''In my country there are plenty of opportunities to thrive''	0.008	0.007	0.007	0.006	-0.002	0.031	0.016	-0.010	0.009
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.033)	(0.019)	(0.025)	(0.015)
Perceptions: ''I feel included in my community's social activities''	-0.018	-0.018	-0.019	-0.013	-0.019	-0.017	-0.019	-0.016	-0.018
	(0.018)	(0.018)	(0.018)	(0.018)	(0.021)	(0.031)	(0.021)	(0.036)	(0.018)
Perceptions: ''I usually trust other people''	-0.019	-0.018	-0.020	-0.020	-0.018	-0.027	-0.010	-0.043	-0.018
	(0.017)	(0.017)	(0.018)	(0.021)	(0.022)	(0.029)	(0.022)	(0.028)	(0.017)
A member of the household is mentally or physically impaired	-0.006	-0.005	-0.003	-0.015	-0.017	0.011	-0.001	-0.020	-0.006
	(0.019)	(0.019)	(0.019)	(0.020)	(0.021)	(0.040)	(0.025)	(0.029)	(0.019)
Constant	0.062	0.092	0.070	0.076	0.168	-0.151**	-0.033	0.245	0.058
	(0.074)	(0.074)	(0.077)	(0.082)	(0.106)	(0.070)	(0.051)	(0.178)	(0.075)
Number of observations	1,003	1,003	1,003	1,003	723	280	678	325	1,003
R-squared	0.050	0.052	0.066	0.144	0.057	0.091	0.051	0.091	0.051

Association between migration and empowerment

This subsection explores the association between effective cross-border and domestic migration in a household with a theoretically-informed subset of indicators from the Women's Empowerment Metric for National Statistical Systems (WEMNS), identified as those most likely to be associated with migration based on a review of the literature.[25] The data to construct these indicators were collected during the follow-up survey from a single respondent in each household. The protocol was to administer this module to a woman between 18 and 49 years old, in the absence of which the module could be administered to a man in this same age range. The indicators are divided into four domains, intrinsic agency, instrumental agency, collective agency, and agency-enabling resources. In addition, we construct an index that aggregates all of the individual indicators into a single empowerment measure. Table 5 shows the indicators that we collected in addition to their conceptual definition and their weights, which are derived from the WEMNS weights.

Table 5. Selected empowerment indicators from WEMNS index

Indicator	Conceptual definition	Weights for female respondents	Weights for male respondents
Intrinsic agency:			
Endorsement of women's freedom in livelihood choices (female respondents only)	Believes that every woman has the right to attend school, pursue her preferred livelihood strategies, and use her money as she wishes as demonstrated by fully agreeing with each of a series of five statementsregarding women's rights in this domain	0.1364	-
Instrumental agency:			
Influence over time allocation	Has had a lot of influence on whether to spend their time on all activities in which they participated in the last 7 days (from among households duties, caring for household members, going to the market to purchase essential items, non-agricultural work activities, agricultural production for sale, agricultural production for household consumption)	0.1364	0.1579
Influence in spending decisions	Has a lot of influence on control over any source of income and over large household purchases	0.1364	0.1579
Influence in own health decisions	Has a lot of influence on own healthcare decisions	0.1364	0.1579
Collective agency:			
Participation in organizations	Participated in at least one type of community organization in the last 12 months (from among government councils or agencies, groups that provide local services, formal or informal savings or credit groups, groups related to livelihood activities, and other groups)	0.1364	0.1579

[25] WEMNS was developed by IFPRI, Emory University, and the Living Standards and Measurement Study Team at the World Bank. See Seymour et al. (2024).

Leadership in organizations	Acted as a leader in at least one type of community organization in the last 12 months (same groups as above)	0.1364	0.1579
Agency-enabling resources:			
Use of financial services	Has used at least one financial service in last 12 months	0.0682	0.0789
Access to credit	Believes would be able to take a loan from at least one formal or semi-formal lending source	0.0682	0.0789
Secure property rights	Name listed on ownership document for at least one land parcel or dwelling	0.0455	0.0526

Table 6 includes these empowerment indicators in the multivariate regression framework used in Tables 3 and 4, to explain cross-border (left panel) and domestic (right panel) migration instances in the sample. Odd-numbered columns include either the aggregate empowerment index or the set of individual indicators in addition to the e-MPI or i-MPI, while even-numbered columns include, in addition, the full set of control variables used in Tables 3 and 4. The aggregate empowerment index is positively and statistically significantly associated with effective cross-border migration, even after controlling for a broad set of additional control variables. However, when it comes to the individual empowerment indicators, the association is somewhat weaker, with only the coefficients for use of financial services and access to credit being statistically significant at conventional levels. It is worth noting, however, that all but one of the empowerment indicators has a positive trend. In the case of domestic migration, however, no association is observed with any of the empowerment indicators. It is interesting to note that the introduction of empowerment indicators slightly reduces the magnitude of the coefficient for the e-MPI (columns 1 through 4) and i-MPI (columns 5 through 8), indicating that empowerment could be an important aspect around migration that is indirectly but not perfectly captured by the MPI.[26]

Table 6. Cross-border and domestic migration and empowerment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cross-border migration				Domestic migration			
e-MPI or i-MPI (probability)	0.132**	0.127**	0.120**	0.117**	0.832***	0.855***	0.828***	0.859***
	(0.054)	(0.056)	(0.055)	(0.057)	(0.220)	(0.232)	(0.222)	(0.234)
Aggregate empowerment index (partial WEMNS)	0.172***	0.187***			0.020	0.031		
	(0.050)	(0.054)			(0.043)	(0.046)		
Influence over time allocation			-0.009	0.001			0.012	0.012
			(0.015)	(0.016)			(0.013)	(0.013)
Participation in organizations			0.022	0.020			0.012	0.006
			(0.016)	(0.017)			(0.016)	(0.016)
Leadership in organizations			0.022	0.018			-0.004	0.002
			(0.021)	(0.022)			(0.017)	(0.018)
Endorsement of women's freedom in livelihood choices			0.003	0.009			0.005	0.002
			(0.014)	(0.015)			(0.015)	(0.015)
Use of financial services			0.034**	0.033**			-0.009	-0.004
			(0.016)	(0.016)			(0.013)	(0.015)
Access to credit			0.024*	0.018			0.005	-0.000
			(0.013)	(0.013)			(0.015)	(0.017)

[26] One could argue that, when exploring the determinants of actual cross-border (domestic) migration, a cleaner comparison group would be households where no domestic (cross-border) migration took place. Specifications excluding these other households with a migrant show essentially the same results, so we present the specifications using the full sample for simplicity. These alternative specifications are however available upon request.

Secure property rights			0.013	0.011			-0.017	-0.020
			(0.014)	(0.015)			(0.016)	(0.017)
Influence in spending decisions			0.012	0.021			0.001	0.002
			(0.019)	(0.020)			(0.015)	(0.015)
Influence in own health decisions			0.011	0.006			-0.008	-0.002
			(0.015)	(0.016)			(0.015)	(0.016)
Income p.c. - Lowest tercile		0.025		0.030		0.017		0.014
		(0.019)		(0.019)		(0.019)		(0.019)
Income p.c. - Middle tercile		0.027		0.030*		-0.012		-0.013
		(0.018)		(0.018)		(0.017)		(0.017)
Reports financial difficulties to reach the end of the month		0.004		0.004		-0.001		-0.001
		(0.021)		(0.021)		(0.019)		(0.019)
Engaged in agricultural production		0.025*		0.023		-0.006		-0.003
		(0.015)		(0.015)		(0.014)		(0.014)
Faced adverse climate event in last 12m		-0.013		-0.015		0.054***		0.050***
		(0.058)		(0.058)		(0.016)		(0.017)
Faced mild food insecurity in last 12m		0.021		0.024		0.010		0.008
		(0.020)		(0.021)		(0.016)		(0.016)
Faced moderate food insecurity in last 12m		-0.025		-0.024		0.002		0.000
		(0.018)		(0.018)		(0.016)		(0.016)
Faced severe food insecurity in last 12m		-0.009		-0.010		-0.030*		-0.031*
		(0.020)		(0.020)		(0.017)		(0.017)
Suffered from crime in last 12m		0.015		0.015		-0.036		-0.038
		(0.030)		(0.030)		(0.027)		(0.028)
Number of crime instances in last 12m		-0.010*		-0.010*		0.012		0.012
		(0.005)		(0.006)		(0.013)		(0.013)
Perceives high level of insecurity in community		0.023		0.024		0.000		0.000
		(0.023)		(0.023)		(0.017)		(0.017)
Aspirations: (Income goal - actual), in logs		0.008**		0.008*		-0.014		-0.013
		(0.004)		(0.004)		(0.008)		(0.009)
Perceptions: ''In case of a problem I can go to local authorities for help''		-0.004		-0.003		0.015		0.015
		(0.020)		(0.019)		(0.016)		(0.016)
Perceptions: ''Police and the justice system protect honest citizens''		-0.006		-0.004		-0.012		-0.012
		(0.016)		(0.016)		(0.016)		(0.015)
Perceptions: ''If I am victim of a crime I always denounce it to authorities''		-0.022		-0.024		0.003		0.003
		(0.019)		(0.019)		(0.015)		(0.015)
Perceptions: ''In my country there are plenty of opportunities to thrive''		0.017		0.018		0.013		0.012
		(0.017)		(0.017)		(0.015)		(0.015)
Perceptions: ''I feel included in my community's social activities''		0.019		0.019		-0.025		-0.025
		(0.016)		(0.016)		(0.018)		(0.018)
Perceptions: ''I usually trust other people''		0.031		0.030		-0.016		-0.016
		(0.021)		(0.021)		(0.017)		(0.018)
A member of the household is mentally or physically impaired		-0.027		-0.028		-0.008		-0.005
		(0.018)		(0.018)		(0.019)		(0.019)
Constant	-0.022	-0.127	-0.029	-0.128	0.001	0.069	0.008	0.088
	(0.016)	(0.080)	(0.019)	(0.081)	(0.017)	(0.083)	(0.022)	(0.084)
Number of observations	1,044	960	1,044	960	1,044	960	1,044	960
R-squared	0.026	0.048	0.035	0.053	0.031	0.053	0.034	0.055

Given that the empowerment data stems from the follow-up survey, and that it was thus measured after the migration event took place in the household, the interpretation of these associations is tricky. One explanation might be that in households where someone has recently migrated empowerment has increased among the remaining household members. These are certainly reasonable explanations for the financial service and credit indicators that are significant on their own. Alternatively, if one assumes that the

empowerment levels of individuals in the same household are more similar and that the responses can serve as proxies, these findings suggest that more empowered individuals have a higher tendency to migrate, perhaps in search of better opportunities to reach their aspirations. Given the data at hand, it is not possible to distinguish between these two mechanisms, but this remains an important avenue for the following round of data collection, which will allow us to test to what extent empowerment levels captured during the 2024 surveys are predictive of migration in the subsequent 12 months, and to what extent observing a migration event between the 2024 and 2025 survey waves affects the empowerment levels of the same individual during that same period.

5. Conclusions

This paper sets out to test the predictive capacity of the Migration Propensity Index (MPI), fully out of sample and in a real-world environment. To do so, we rely on data from two survey rounds conducted with a panel of households in nine departments of Western Honduras. In particular, we test whether a household's MPI at baseline helps predict actual instances of migration in that household over the subsequent 12 months. We do this for two alternative indicators, the e-MPI, as a predictor of external or cross-border migration, and the i-MPI, as a predictor of internal or domestic migration.

Both the e-MPI and the i-MPI show good predictive power for identifying groups of households with a higher or lower propensity to migrate. In the case of the e-MPI, 8.2% of the households identified as being high-propensity in 2023 had at least one member migrate abroad in the subsequent 12 months, compared to 5.6% and 1.5% in the medium- and low-propensity groups, respectively. In terms of the i-MPI, the pattern is even starker, with rates of effective domestic migration of 15.3% for the high-propensity group, compared to 4.3% and 0% for the medium- and low-propensity groups.

We count with rich data collected at baseline across multiple dimensions potentially related to migration, allowing us to assess the MPI's predictive ability against that of competing indicators in a multivariate regression framework. In doing so, we find that both the e-MPI and the i-MPI outperform the large majority of alternative measures in predicting, respectively, cross-border and domestic migration, including indicators of crime, perceptions around corruption or opportunities, and food insecurity indicators, some of which were missing in the calibration dataset. The only exception in terms of cross-border migration is economic aspirations of interviewed households — defined as the gap between a household's desired and actual income at baseline, which is positively and statistically-significantly related to households experiencing migration of one of its members over the following year. In the case of domestic migration, having experienced an adverse weather event is also positively and significantly related to migrating, beyond what is explained by the i-MPI alone. This is despite the i-MPI already including having experienced a drought in the previous year in its construction, indicating the importance of climate drivers in the decision to migrate internally (in line with the broader migration literature).

Importantly, both MPI indices perform similarly across rural and urban/peri-urban subgroups (despite the fact that they were calibrated on a mostly rural dataset), with a slightly stronger point estimate in urban/peri-urban areas. Both indices also retain their predictive power when applied to departments not included in the original calibration data, suggesting their applicability to the rest of Honduras. Nevertheless, the MPI shows lower predictive power when aggregated at the community level, with community-level average MPI scores holding a weak relationship with community-level migration rates.

Push factors turn out to be important components in the MPI calibration (see Almanzar et al., 2022, and Ceballos et al., 2023), illustrated by the contribution to the MPI score of components such as the rate of recent migration in the community and whether a household currently receives any remittances. In this sense, 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 explanatory power even after controlling for local migration rates (proxied by the 2022/23 rate of returnees) or after including municipality or aldea fixed effects. 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, indicates that the MPI is not simply a proxy for the strength of localized migration outflows, but that it is rather capturing specific features of the household and its members that makes them more prone to migrating and allowing policymakers to distinguish between neighboring households' propensity to migrate.

Finally, it could be argued that internal and external migration arise from a similar decision process at the household level, and that separately analyzing their drivers would thus be unnecessary, removing the need to have both an i-MPI and an e-MPI. To assess such claims, we conduct so-called placebo tests by jointly including both MPI indices when modelling, respectively, domestic and cross-border migration instances. We find that, when doing so, the i-MPI (e-MPI) retains its predictive ability when attempting to explain instances of domestic (cross-border) migration, with the placebo MPI not providing additional explanatory power beyond that of the main index. This finding supports the conclusion that both indices seem to indeed capture distinct aspects around households' cross-border and domestic migration decisions.

Overall, our results strongly support the idea that tracking 10-12 indirect questions can successfully inform the probability of migration ex-ante. Even with imperfect training data, both the i-MPI and the e-MPI for Honduras at a given point in time are significant predictors of migration instances one year later. Of course, it is important to note that the MPI is a proxy that performs well on average. In other words, the MPI cannot predict the migration of individual households, but it is rather useful for identifying groups of households with a higher propensity to migrate. How best to use such indices for targeting development programs and for monitoring the migration sentiment among local communities remain important avenues for future work.

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ACKNOWLEDGMENTS

We thank Raíces Colectivo for outstanding data collection efforts over the two survey rounds. The study was funded by the Honduras Mission of the United States Agency for International Development (USAID) and One CGIAR's Fragility, Conflict, and Migration Initiative. The funding sources had no role in data collection, data analysis, or report writing, the conclusions of the study are solely the responsibility of the authors and do not necessarily reflect the views of the International Food Policy Research Institute (IFPRI), One CGIAR, USAID, or the United States Government. Jessica Heckert and Florencia Paz provided useful comments on an earlier version of the manuscript.

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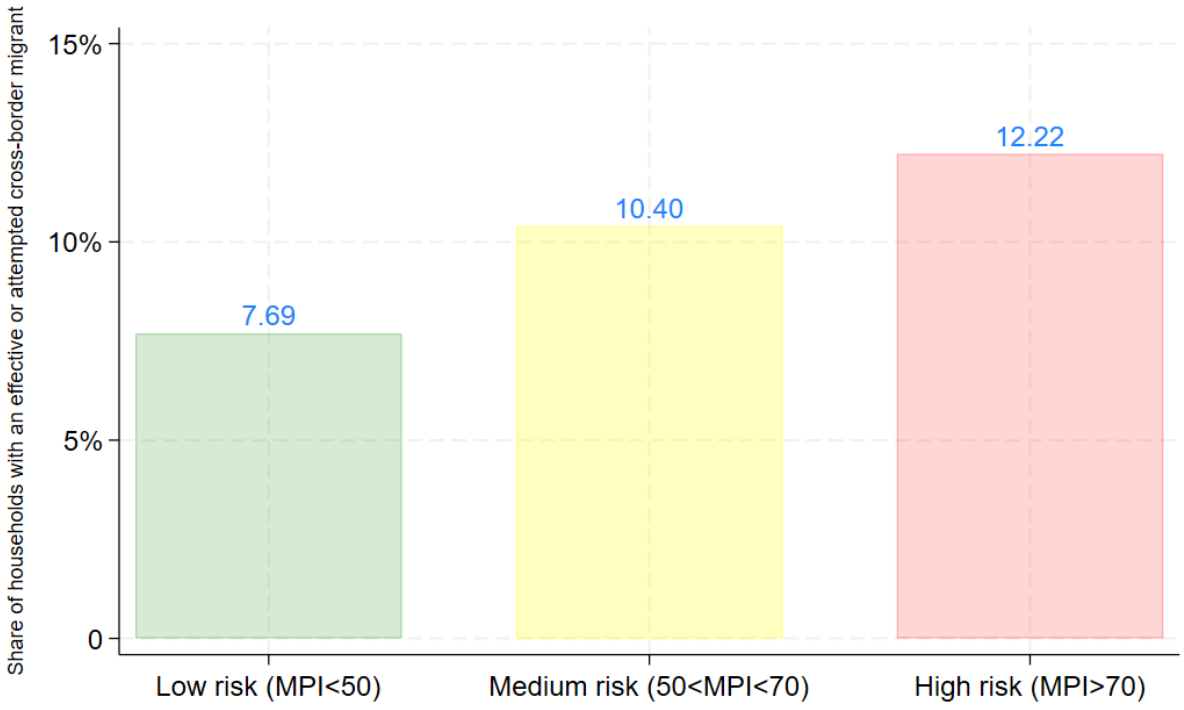
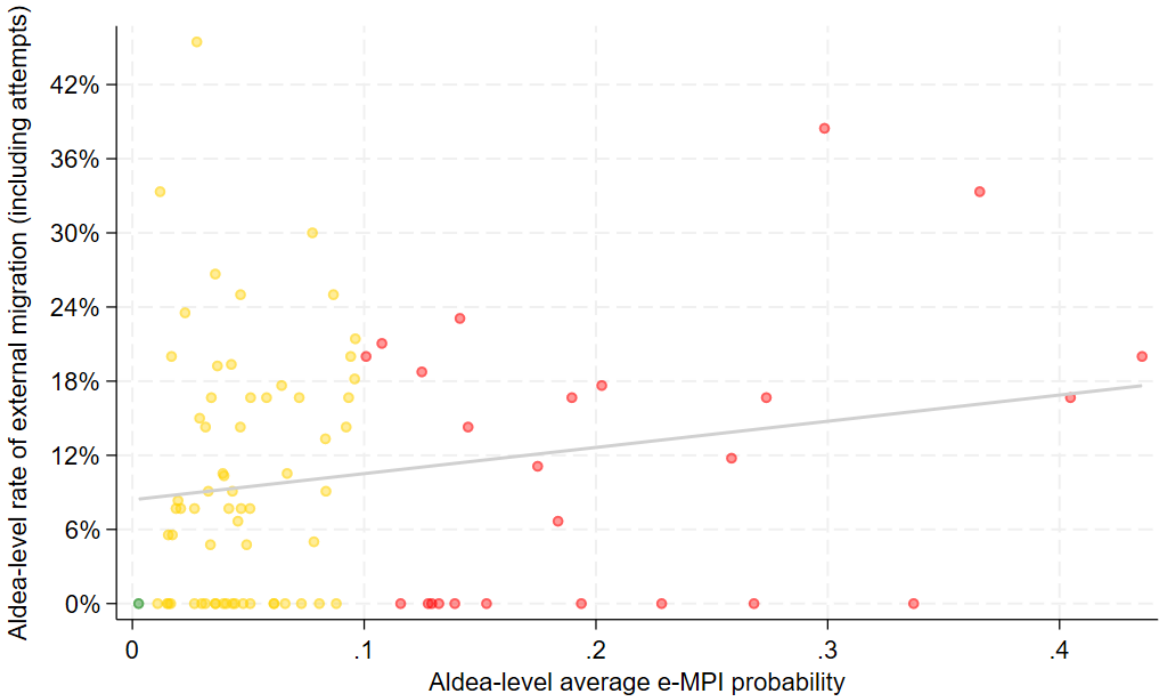
APPENDIX

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)	0.142**	0.140**	0.142**	0.143**	0.056	0.140*	0.193	0.134*	0.138	0.135**
	(0.064)	(0.064)	(0.065)	(0.068)	(0.076)	(0.077)	(0.122)	(0.073)	(0.160)	(0.065)
Reported intention to migrate 12m ago		0.074***								
		(0.024)								
Rate of returnees 2021-22			-0.068							
			(1.652)							
i-MPI (probability)										0.216
										(0.230)
Income p.c. - Lowest tercile	0.023	0.018	0.023	0.027	0.033	0.035	0.011	0.037	0.015	0.021
	(0.025)	(0.025)	(0.025)	(0.025)	(0.027)	(0.029)	(0.048)	(0.029)	(0.050)	(0.025)
Income p.c. - Middle tercile	0.027	0.023	0.027	0.029	0.040	0.032	0.017	0.036	0.040	0.025
	(0.024)	(0.023)	(0.024)	(0.024)	(0.026)	(0.028)	(0.045)	(0.029)	(0.045)	(0.024)
Reports financial difficulties to reach the end of the month	-0.020	-0.022	-0.020	-0.023	-0.023	-0.004	-0.035	-0.006	-0.048	-0.021
	(0.028)	(0.027)	(0.027)	(0.027)	(0.030)	(0.033)	(0.047)	(0.030)	(0.063)	(0.028)
Engaged in agricultural production	0.013	0.014	0.013	0.020	-0.000	0.025	-0.019	0.036	-0.024	0.012
	(0.020)	(0.019)	(0.020)	(0.020)	(0.022)	(0.023)	(0.042)	(0.024)	(0.040)	(0.020)
Faced adverse climate event in last 12m	-0.023	-0.009	-0.023	-0.019	-0.032	-0.121	0.125**	-0.054	0.050	-0.023
	(0.080)	(0.081)	(0.080)	(0.079)	(0.084)	(0.113)	(0.055)	(0.129)	(0.099)	(0.081)
Faced mild food insecurity in last 12m	0.049*	0.048*	0.049*	0.057**	0.070**	0.067**	-0.004	0.023	0.120**	0.048*
	(0.026)	(0.026)	(0.026)	(0.027)	(0.029)	(0.031)	(0.051)	(0.032)	(0.047)	(0.026)
Faced moderate food insecurity in last 12m	-0.027	-0.033	-0.027	-0.030	-0.059**	-0.068**	0.088*	-0.026	-0.035	-0.028
	(0.024)	(0.024)	(0.024)	(0.025)	(0.028)	(0.028)	(0.046)	(0.030)	(0.046)	(0.024)
Faced severe food insecurity in last 12m	0.024	0.026	0.024	0.027	0.029	0.044	-0.017	0.036	0.001	0.024
	(0.035)	(0.034)	(0.034)	(0.035)	(0.036)	(0.041)	(0.065)	(0.042)	(0.059)	(0.035)
Suffered from crime in last 12m	0.034	0.032	0.034	0.018	0.015	0.049	-0.055	0.019	0.063	0.036
	(0.041)	(0.041)	(0.041)	(0.041)	(0.046)	(0.052)	(0.062)	(0.051)	(0.072)	(0.041)
Number of crime instances in last 12m	-0.018***	-0.019***	-0.018***	-0.017***	-0.011	-0.018**	-0.003	-0.013*	-0.030*	-0.018***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.008)	(0.008)	(0.010)	(0.007)	(0.017)	(0.006)
Perceives high level of insecurity in community	-0.002	-0.003	-0.002	0.005	0.001	-0.013	-0.010	-0.004	0.004	-0.001
	(0.026)	(0.026)	(0.027)	(0.029)	(0.034)	(0.033)	(0.042)	(0.030)	(0.059)	(0.026)
Aspirations: (Income goal - actual), in logs	0.010	0.008	0.010	0.009	0.011	0.021***	-0.009	0.015**	0.004	0.010
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.018)	(0.007)	(0.016)	(0.008)

Perceptions: ''In case of a problem I can go to local authorities for help''	-0.030	-0.032	-0.030	-0.029	-0.043*	-0.040	-0.002	-0.016	-0.049	-0.031
	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)	(0.028)	(0.047)	(0.027)	(0.057)	(0.024)
Perceptions: ''Police and the justice system protect honest citizens''	-0.012	-0.009	-0.012	-0.010	-0.010	0.007	-0.060	-0.014	-0.022	-0.013
	(0.023)	(0.022)	(0.022)	(0.023)	(0.024)	(0.027)	(0.041)	(0.026)	(0.049)	(0.023)
Perceptions: ''If I am victim of a crime I always denounce it to authorities''	-0.003	-0.002	-0.003	-0.001	-0.008	0.005	-0.032	-0.022	0.049	-0.004
	(0.024)	(0.024)	(0.024)	(0.024)	(0.027)	(0.027)	(0.052)	(0.024)	(0.065)	(0.024)
Perceptions: ''In my country there are plenty of opportunities to thrive''	0.009	0.011	0.009	0.009	0.027	0.023	-0.020	-0.011	0.059	0.010
	(0.023)	(0.022)	(0.023)	(0.023)	(0.025)	(0.027)	(0.043)	(0.026)	(0.048)	(0.023)
Perceptions: ''I feel included in my community's social activities''	0.044**	0.043**	0.044**	0.035	0.042*	0.029	0.081*	0.036	0.043	0.043**
	(0.021)	(0.021)	(0.021)	(0.022)	(0.024)	(0.026)	(0.043)	(0.025)	(0.045)	(0.021)
Perceptions: ''I usually trust other people''	0.034	0.042	0.034	0.042	0.030	0.005	0.074	0.022	0.059	0.034
	(0.029)	(0.029)	(0.029)	(0.029)	(0.032)	(0.032)	(0.062)	(0.034)	(0.054)	(0.029)
A member of the household is mentally or physically impaired	0.010	0.015	0.010	0.008	0.015	0.007	0.023	-0.016	0.074	0.011
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.035)	(0.060)	(0.033)	(0.064)	(0.030)
Constant	-0.029	-0.040	-0.028	-0.025	-0.005	-0.040	-0.002	-0.036	-0.079	-0.035
	(0.109)	(0.110)	(0.113)	(0.109)	(0.115)	(0.131)	(0.189)	(0.146)	(0.183)	(0.110)
Number of observations	1,003	1,003	1,003	1,003	1,003	723	280	678	325	1,003
R-squared	0.023	0.035	0.023	0.050	0.137	0.035	0.070	0.029	0.051	0.024