IS THERE A PATIENCE PREMIUM ON MIGRATION?

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Abstract: The very few studies on the empirical link between time preference and migration involve small samples or do not control for cognitive skills. This study uses data from a large, nationally representative survey with information on time preferences and cognitive skills to investigate whether cross-region migrants in Spain are less impatient than individuals who choose to remain in their birth region. The empirical model incorporates predicted probabilities of misclassifying lifetime migrant status. The results suggest that the effect of impatience on the likelihood of migrating internally is negative but decreasing, and that it is smaller than the effect on the likelihood of migrating abroad.

Keywords: Internal migration, time preference, misclassification, binary choice, Spain.

JEL codes: C35, D91, J60.

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1. INTRODUCTION

Standard models of migration recognize that changing locations is costly. The costs of migrating (e.g. out-of-pocket expenses, psychological costs of changing one's environment) tend to occur in the short term whereas the benefits of migrating are reaped in the future, so more patient individuals might be expected to be more likely to migrate (Gibson and McKenzie 2011). Nowotny (2014), however, shows that if potentially mobile persons expect benefits in their home region to exceed benefits in the destination region in the future, then the more patient among them are less likely to migrate. The extent to which migrants have above- or below-average levels of patience therefore needs to be determined empirically.

The time preference composition of migration flows may have important consequences for both sending and receiving regions. Individuals' levels of patience have been found to be correlated with behaviors involving intertemporal tradeoffs such as savings rates, educational attainment, and medical adherence; with personality traits such as cognitive ability and agreeableness; and with economic outcomes such as income level and personal unemployment (Cohen et al. 2020). The time preference composition of migration flows is also relevant from a purely scientific point of view. Given the positive role of patience in human capital formation (see, for instance, Golsteyn et al. 2014, Cadena and Keys 2015), a positive effect of patience on migration would help to explain the college "migration premium" (Malamud and Wozniak 2012).

The lack of questions on time preferences in the main data sources used to construct migration rates has prevented research in this area from being conducted. The very few studies that have been produced on the empirical link between time preference and migration have developed their own specialized surveys (e.g. Gibson and McKenzie 2011, Arcand and Mbaye 2013, Nowotny 2014, Goldbach and Schlüter 2018). These studies have found that more patient individuals are more likely to migrate internationally and internally, and less likely to migrate illegally. In general, though, these patterns have been observed in small samples, which limits their generalizability to the larger population, or have not controlled for individuals' cognitive skills.[1] As to the latter issue, previous research suggests that patience and cognitive ability are positively correlated (e.g. Frederick 2005, Burks et al. 2009, Dohmen et al. 2010, Benjamin et al. 2013). Thus, if individuals dislike what they do not perceive precisely and cognitive ability reduces the noise in perceiving the utility of complex options (Burks et al. 2009), the most able may be more likely to perceive the benefits of migrating and hence more likely to migrate. In that case, previous estimates of the link between patience and migration would be biased upward.

Newly available data from the Survey of Financial Competences (referred to here by its Spanish abbreviation ECF) make it possible to investigate further the existence of a patience migration premium. The ECF is intended to collect nationally representative information about financial knowledge and practices in Spain via a questionnaire proposed by the International Financial Education Network, but that questionnaire is supplemented by a question about birth place and items designed to measure time preferences and cognitive skills. As is common in the empirical literature on time preference, time preferences are assessed experimentally using a Money Earlier or Later (MEL) task (Cohen et al. 2020). Cognitive skills are measured with validated questions answered by the respondent in private, so that no other household member can help them.

[1] The samples analyzed by Nowotny (2014) are large, but the migration information refers to migration willingness. The samples analyzed by Gibson and McKenzie (2011) consist entirely of highly skilled individuals.

Thus, the ECF enables the empirical link between time preference and migration to be investigated on the basis of a large sample and purged of the influence of cognitive skills.

MEL tasks are probably a good choice for assessing time preference if alternative income streams determine individuals' migration decisions, but less so if the decision is motivated by alternative streams of utility. However, even if the output of MEL tasks cannot be directly translated into discount rates, it still may serve to predict behavior by classifying individuals as relatively patient or impatient (Cohen et al. 2020). In this respect, Rieger et al. (2021) document that the measurements yielded by the different methodologies for inferring time preferences share a common factor in high external validity: This factor is related to a wide spectrum of variables which it has been suggested may be influenced by time preferences.

The residential information provided by the ECF is limited to the region of birth and the region of residence at the time of the survey. Comparing residence at birth and at survey yields a "reduced-form" measure of lifetime migration (Carlson 2007) that may contain errors of omission (false nonmigrants) and errors of commission (false migrants). As argued by Molloy et al. (2011), some true migrants will have returned to their birth region after having spent time elsewhere, whereas individuals who moved when they were still a member of their parents' household are indistinguishable in the data from individuals who moved during their adult lives. As a result, binary choice models of migrant status that do not take classification errors into account can be very misleading: Even a slight misclassification can produce substantially biased estimates (Hausman et al. 1998, Ramalho 2002, Meyer and Mittag 2017).

This paper employs Bollinger and David's (1997) predicted probabilities estimator to fit a probit model accounting for misclassification of migrant status. Models of classification errors are estimated on the basis of a representative sample of the Spanish population drawn from the 2011 Census. In addition to information on residence at birth and at the Census date, the Census indicates the year of arrival in the region of residence, which reveals interim moves between birth and the census date and (as argued below) provides a basis for inferring the autonomy of migration decisions. The estimated individual probabilities of classification errors are then incorporated into a modified probit likelihood function which is maximized on the ECF sample, as only that sample contains the information on migration determinants needed for this research.

The paper is organized as follows. Section 2 reviews the data and the construction of the samples. Section 3 defines the main measures and presents descriptive evidence of the link between time preference and migration. The econometric specification is discussed in Section 4. Section 5 presents the regression results and analyzes their robustness. Section 6 lists the main conclusions and points out some avenues for future research.

2. DATA AND SAMPLE SELECTION

The data for this study are taken from two publicly available data sets: The ECF and the 2011 Spain Population Census. The ECF provides the primary sample for analysis. The Census provides a validation sample for migrant status. Note that since the early 1980s Spain has been organized into 17 regions (known as autonomous communities and corresponding to EU NUTS 2 territories) and two autonomous towns (the enclaves of Ceuta and Melilla, on the north coast of Africa). These 17 regions are divided into a total of 50 provinces (EU NUTS 3 territories), with boundaries which were set in 1927. Hence, for individuals born before the 1980s the birth region shown is the region to which the birth province currently belongs.

2.1. ECF[2]

The ECF (Banco de España and National Securities Market Commission 2018) is an individual survey that seeks to assess knowledge and understanding of financial concepts in Spain. Sampling is intended to be representative of the population aged 18–79 living in private households in all 17 Spanish regions. The sample is drawn from the 2011 Census updated with information from the continuous population register of each municipality ("*padrón municipal*"). 16,025 individuals out of the original sample of 21,250 were contacted during the fieldwork (interviewers were obliged by contract to make at least five contact attempts). Non-contacts include individuals no longer residing at the address specified in the register and individuals who were absent. Of the individuals contacted, 6,708 declined to answer and 763 were unable to give any type of information. This leaves 8,554 individuals, interviewed face-to-face at home between end-September 2016 and end-May 2017.

The ECF indicates the region (or country) of birth plus the region of residence at the time of the interview.[3] Since it is not possible to know whether immigrants have migrated since arriving in Spain, immigrants (986 individuals) are excluded from the analysis. So are a further 859 persons on whom there is data missing for one of more of the variables used in the analysis. Military personnel (13 persons) are also removed as their migration decisions might be non-autonomous. Thus, the ECF sample comprises 6,696 individuals, none of whom was born in Ceuta or Melilla.

The birth regions of 433 of the individuals on whom information was missing, were not disclosed by the ECF to preserve confidentiality. This feature suggests that these

[2] A complete description of the ECF and its methods is provided in Bover et al. (2019).

[3] For natives the ECF asks for the province of birth, but only the birth region is disclosed.

individuals may have been born in a region other than the one where they reside. Individuals with undisclosed birth regions are significantly different from individuals included in the sample in some observables: They tend, for example, to be more highly educated and cognitively skilled, and to reside in less populated regions. If individuals included in the sample were also selected in terms of unobservables affecting their (true) migrant status, the results would be contaminated by sample selection bias. This possibility is shown not to be a cause for concern when the robustness of the results is assessed.

2.2. 2011 Population Census

The 2011 Spain Population Census is the latest of its kind conducted by the National Statistics Institute (www.ine.es). It uses a register-based census (obtained mainly from the *padrón*) supplemented by a household survey for about 12% of the population living in private households. The province (or country) of birth plus the province of residence are drawn from the register. The survey asks for the year of arrival of each household member in the region of residence. When this year differs from the year of birth, it reveals interim moves between birth and the census date. When immigrants, natives residing/born outside the 17 regions,[4] and military personnel are disregarded, the resulting sample encompasses 2.9 million persons aged 18–79.

3. MEASURES AND DESCRIPTIVE EVIDENCE

3.1. Lifetime Migration

The following measure of lifetime migration can be constructed in both the ECF and the Census. A migrant is an individual who resides in a region other than that in which he/she

[4] Individuals born in Ceuta or Melilla are excluded because their birth place perfectly predicts successes/failures in the models of classification errors estimated below.

was born, and a nonmigrant is an individual who resides in the same region where he/she was born. As explained above, this reduced-form measure may contain errors of omission (false nonmigrants) and errors of commission (false migrants).

The year of arrival in the region of residence available in the Census makes it possible to reveal and model both types of errors. Firstly, however, it must be considered that migration during childhood may not reflect the child's preferences. We rely on whether individuals were legally able to work in the year of arrival in their region of residence to distinguish between autonomous (i.e. decided by the individual) and non-autonomous migration.[5] Migrations by individuals legally able to work are considered as autonomous, and migrations by individuals legally unable to work as non-autonomous. The results in Iversen (2002) support the use of children's ages as a driver for autonomy in migration decisions.

Individuals who were legally able to work in their year of arrival in their region of residence are therefore classified as true migrants. True nonmigrants are individuals who have resided since birth in the same region and individuals who were legally unable to work in their year of arrival. An issue with this more proper measure of lifetime migration is that the year of arrival might be reported wrongly by respondents. However, analyses of migration histories provided 12 years apart reveal underreporting of the number of moves by only 5% and a median date error of less than 1 year (Smith and Thomas 2003).

[5] The statutory minimum working age in Spain was set at 14 years in 1944 (although younger children were permitted to work in agriculture and family shops), and was raised to 16 in March 1980.

Columns (1) and (2) of Table 1 compare the proportions of reduced-form migrants in the ECF and the Census for the total population and for various strata. The figures for the proportion of the whole population are 14.5% in the ECF and 19.3% in the Census. Observed differences across strata in the Census are also detectable in the ECF, but rates are smaller in the latter. The lower ECF rates do not seem to result from a trend towards lower mobility: The reduced-form migration rate calculated for 2016 with the Continuous Sample of Work Histories (an administrative dataset compiled by Spain's Social Security authorities) is 18.7%. If individuals with undisclosed birth region were all migrants, the proportion of migrants in the ECF would be just 17.6%. Given that the ECF is an individual survey, its lower migration rates might be the consequence of a greater probability of survey non-contact among movers reducing the proportion of migrants in the sample. However, results in Imbens (1992) suggest that small amounts of endogenous sampling are unlikely to substantially alter estimated parameters.[6] In addition, to guard against possible misspecification our inference is based on robust estimators of variance.

Column (3) of Table 1 lists the proportion of true migrants in the Census, so columns (3) and (2) show the discrepancy between true and reduced-form estimates of lifetime migration. The proportion of individuals who have migrated at some time is 17.4%, suggesting that the reduced-form estimate for the total population is biased upward by 11%. Across strata, the bias ranges from 188% for individuals aged 18–24 to -9% for individuals aged 65 or older.

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[6] Ramalho (2002) develops an estimator for misclassified choice-based samples assuming misclassification probabilities independent from individual characteristics. This assumption does not hold in this study.

For true migrants, column (4) shows the percentage of reduced-form migrants. 100 minus the figure in this column thus gives the percentage of omission errors (false nonmigrants). That percentage is 27.1% on average, but rises to 29.1% for the 18–24-year-old group. Column (5) shows the percentage of commission errors (false migrants). For true nonmigrants, it gives the percentage of reduced-form migrants. This percentage is 8.0% on average, but it is substantially higher for the 45–64-year-old group, 11.2% of whom migrated non-autonomously. This group's higher rate of non-autonomous migration coincides with the "rural exodus", a period of intense internal migration in Spain in the 1960s and early 1970s, when people moved away from rural areas towards major industrial hubs (e.g. Bover and Velilla 2005).

3.2. Time Preference

The ECF includes an MEL task to measure time preferences. Respondents are presented sequentially with two hypothetical binary choices between immediate and delayed monetary rewards. In the first, they must choose between €2,000 today or €2,200 in a year's time. If they opt for the payment today, in the second choice the payment in a year's time is increased to €3,000, whereas if they opt first for the payment in a year's time, this is decreased to €2,100 in the second choice. Such a "staircase" structure is used for example by Goldbach and Schlüter (2018) and the Global Preference Survey (Falk et al. 2018), although the series of choices is longer in these studies.

0.9% of respondents answered "don't know" in the first binary choice, while of those who did choose a payment, 0.6% answered "don't know" in the second choice. "Don't know" responses may indicate either that respondents are unable to choose (as confounding factors may complicate the choice: See Frederick et al. 2002), or that they are indifferent between the two payments. We stick to the latter interpretation due to the presence of "don't knows" in the second choice, but we assess the robustness of the results to the exclusion of "don't knows."

The answers to the MEL task enable respondents to be sorted into four groups, which are described in Table 2 in terms of required rates of return (*RRR*s):[7] below 4.9%, between 4.9% and 9.8%, between 9.8% and 44.9%, and above 44.9%. For example, 10.6% of the sample has an *RRR* between 4.9% and 9.8%, as either they prefer €2,200 in a year's time to €2,000 today (but €2,000 today to €2,100 in a year's time) or they answer "don't know" in the first binary choice. Higher levels of *RRR* reflect greater impatience.

Fitting a lognormal curve to the *RRR* data, the interval regression estimates of the mean and variance are -1.47 and 4.14. The appropriateness of the lognormal model is tested with a chi-square test. The predicted number of individuals in each *RRR* group is listed in column (1) of Table 3. The test statistic is 2.64. The critical value at the 10% level with 1 df is 2.71. Therefore, the *RRR* distribution appears to be lognormal. Under lognormality, the overall mean *RRR* is 183%. Group means calculated using the formula developed in Wang et al. (2012) are listed in column (2) of Table 3.

Some caveats must be given before proceeding. First, for the discount rate to equal the *RRR*, financial rewards must be used on the date of receipt and the utility function must be locally linear (Cohen et al. 2020). If individuals smooth consumption over the

[7] When a respondent is indifferent between €d_1 today and €d_2 in a year's time, the *RRR* needed to induce her/him to forgo d_1 Euros immediately is $2\left(\left(d_2/d_1\right)^{1/2}-1\right)$. This definition assumes semiannual compounding of the annual interest rate as a natural compromise between the types of compounding that Spaniards are most familiar with (monthly/quarterly compounding on typical bank accounts, and annual reports on the rate of return from savings accounts, pension funds, or stock holdings).

life cycle, financial rewards at date t would be only loosely related to utility at date t. Fortunately, the ECF asks how much of an unexpected windfall gain[8] respondents would spend and how willing they are to take risks in financial matters, which may help to control for the type of consumer (on-receipt or optimizer) and the degree of concavity of the utility function, respectively.

Second, the use of a hypothetical MEL task might produce biased preferences because respondents have no incentives to express their true preferences. In their review of the MEL literature, Cohen et al. (2020) conclude that there is little evidence of systematic differences between *RRR*s obtained in incentivized and unincentivized experiments, although they recommend conducting more research on this issue.

3.3. Risk Attitude

The ECF contains the following agree-disagree statement assessing attitudes toward risk in financial matters: "I'm prepared to risk a little money on saving or investing if I can then obtain a better return in the future." Responses are coded on a scale from 1 to 5, with 1 indicating complete disagreement and 5 indicating complete agreement. This financial-specific measure of risk may be useful to predict migration as, at least since Sjaastad (1962), it is typically viewed as an investment. But Dohmen et al. (2011) find that even if respondents do not view migration as an investment, context-specific measures of risk-taking predict risky behaviors in multiple contexts. They view this finding as suggestive of the existence of a single underlying risk trait.

3.4. Cognitive Skills

[8] "Imagine you were to win (e.g. in the Christmas lottery) an amount of money equivalent to your household's monthly income. What percentage would you spend during the following 12 months, rather than saving it or using it to repay outstanding debts?"

The ECF includes three items that measure cognitive skills. The first item is a question from the Survey of Adult Skills assessing numeracy (OECD 2009). Respondents are given a card with a line plot showing the number of births in the U.S. every ten years from 1957 to 2007, and asked during which period(s) births fell. The second item is adapted from a task booklet of the International Adult Literacy Survey (OECD and Statistics Canada 2000). It consists of a 193-word news article followed by three questions assessing reading comprehension. Two of the questions test for content explicitly mentioned in the news while the other tests for a concept implied by the news. The third item is a question taken from Frederick's (2005) Cognitive Reflection Test (CRT): "Imagine that to produce five pieces of equipment you need five machines working for five minutes. How long would 100 machines take to produce 100 pieces of equipment?" As argued by Frederick (2005), the suppression of the incorrect intuitive answer (100 minutes) requires cognitive reflection, namely the ability or disposition to resist reporting the response that first comes to mind.

Performance in each item is measured with a variable counting the number of correct responses: 0 or 1 in the first and third items; 0, 1, 2 or 3 in the second item. Table 4 shows that the three scores correlate positively with one another. However, the strength of the correlations is not great as the items are measuring conceptually different traits.

3.5. Descriptive Evidence

This section provides some descriptive evidence on the link between time preference and migration from the information available in the ECF. Figure 1 compares the distribution of *RRR*s between reduced-form migrants and nonmigrants. The distribution for migrants has more weight for the second most patient group, but also for the least patient group. In any case, the differences look small and a chi-square test does not reject the hypothesis that both samples come from a common distribution (p-value 0.11).

Table 5 compares average *RRR*s (calculated using the group means listed in Table 3 as ordered scores) and the percentage with *RRR* > 9.8% for migrants and nonmigrants and for subsamples stratified by demographics, cognitive skills, and risk attitude. The average *RRR* is 188.3% for migrants and 182.1% for nonmigrants, indicating more patient behavior among the latter. However, the percentage with *RRR* > 9.8% is smaller among migrants (65.2 vs. 67.0), showing more patient behavior among them. Across strata, migrants are mostly more patient when *RRR* is measured with the indicator for *RRR* > 9.8%, but the pattern is mixed when average *RRR*s are compared.

Table 5 also shows that women are less patient on average, and that patience decreases almost monotonically with age and increases almost monotonically with education and cognitive skills. Patience also tends to increase in willingness to take risks in financial matters. The probability of migrating increases monotonically with age, is larger for women and the least and most educated, exhibits an inverted-U-shaped relation in the reading comprehension score, and declines in the risk score (except for the most risk-taking class).

The existence of common factors influencing time preference and migration means that regression analysis must be used to characterize the link between them. Furthermore, given the evidence presented in Table 1, it is necessary to incorporate outside information about classification errors of migrant status in order to obtain unbiased estimates of migrant determinants.

4. SPECIFICATION

Let y_i^* (an unobserved propensity of individual *i* to migrate over her/his lifetime) be given by

$$y_i^* = x_i'\beta + \varepsilon_i \tag{1}$$

where x_i is a vector of observed regressors including an intercept, β is an unknown vector of parameters, and ε_i is a standard normal error term. Without misclassification of migrant status, the true migrant indicator

$$\tilde{y}_i = 1\left(y_i^* > 0\right) \tag{2}$$

where $1(\cdot)$ is the indicator function, would be observed. When true migrant status may be misclassified, the observed migrant indicator, y_i, must be distinguished from $\tilde{y}_i$. Interest centers on the marginal effects on the true migrant probability

$$\frac{\delta P\left(\tilde{y}_i = 1\right)}{\delta x_i} = \frac{\delta \Phi\left(x_i'\beta\right)}{\delta x_i} \tag{3}$$

where $\Phi(\cdot)$ denotes the standard normal cdf and δ is either Δ or ∂.

The probabilities of errors of commission and omission for the *i*th individual are defined as

$$P\left(y_i = 1 \middle| \tilde{y}_i = 0\right) = \alpha_{0i} \tag{4}$$

$$P\left(y_i = 0 \middle| \tilde{y}_i = 1\right) = \alpha_{1i} \tag{5}$$

We also refer to them as the conditional probabilities of misclassification. The total probability theorem is used to derive the observed migrant probability

$$P\left(y_i = 1\right) = \alpha_{0i} + \left(1 - \alpha_{0i} - \alpha_{1i}\right)\Phi\left(x_i'\beta\right) \tag{6}$$

Equation (6) implies the following log likelihood function

$$\begin{aligned} \ln L\left(\alpha_0, \alpha_1, \beta\right) = \sum_{i=1}^{N} y_i \ln\left(\alpha_{0i} + \left(1 - \alpha_{0i} - \alpha_{1i}\right)\Phi\left(x_i'\beta\right)\right) \\ + \left(1 - y_i\right)\ln\left(1 - \alpha_{0i} - \left(1 - \alpha_{0i} - \alpha_{1i}\right)\Phi\left(x_i'\beta\right)\right) \end{aligned} \tag{7}$$

where α_0 and α_1 are stacked vectors of α_{0i} and α_{1i}.

The unknown parameters $(\alpha_0, \alpha_1, \beta)$ are unidentified as there are $2N + \dim(\beta)$ parameters. Following Bollinger and David (1997), we employ a two-step procedure to estimate β. First, probit models for errors of commission and omission

$$\alpha_{0i} = \Phi(x'_{0i}\beta_0) \tag{8}$$

$$\alpha_{1i} = \Phi(x'_{1i}\beta_1) \tag{9}$$

are estimated from the true nonmigrant and true migrant samples of the Census, respectively. Besides an intercept, x_0 and x_1 include variables measured both in the Census and the ECF, so after estimating β_0 and β_1, $\hat{\alpha}_{0i} = \Phi\left(x'_{0i}\hat{\beta}_0\right)$ and $\hat{\alpha}_{1i} = \Phi\left(x'_{1i}\hat{\beta}_1\right)$ can be calculated for the ECF sample. Second, after replacing α_{0i} and α_{1i} in (7) with $\hat{\alpha}_{0i}$ and $\hat{\alpha}_{1i}$, the resulting expression is maximized with respect to β on the ECF sample. Under the assumption that α_{0i} and α_{1i} are consistently estimated, this "predicted probabilities estimator" (PPE) of β (Meyer and Mittag 2017) is consistent and asymptotically efficient. Given the large size of Census samples, $\hat{\alpha}_{0i}$ and $\hat{\alpha}_{1i}$ are considered as known probabilities.

Function (7) is not globally concave in β, and since estimators corresponding to local maxima may have no useful properties a number of steps are taken to increase the chance that the maximum obtained is global.[9] Maximizations are conducted using the Newton–Raphson algorithm combined with steepest ascent, and convergence is accepted if the Hessian is negative definite and the scaled gradient is lower than 1^{-8}. Initial values

[9] See Train (2009) for a good treatment of numerical maximization.

for the maximization routine are linear probability estimates of β multiplied by 2.5.[10] The linear probability model (LPM) with misclassification, specified as

$$P(y_i = 1) = \alpha_{0i} + (1 - \alpha_{0i} - \alpha_{1i})(x_i'\beta) \tag{10}$$

is estimated after replacing α_{0i} and α_{1i} with $\hat{\alpha}_{0i}$ and $\hat{\alpha}_{1i}$ by ordinary least squares without an intercept and constraining the coefficient of α_{0i} to unity.

The focus of the specification of x_0 and x_1 is more on prediction than on isolating causal effects. However, saturating x_0 and x_1 can lead to large standard errors of elements of $\hat{\beta}$ if elements of x_0 or x_1 appear in x. x_0 includes personal attributes correlated with family migration propensity in Spain and outcomes of migrant children (Bover and Velilla 2005, Zuccotti et al. 2017): Birth-region-specific restricted cubic splines in the birth year with knots placed at 5-year intervals (1935, 1940,…,1990) (11 variables),[11] plus indicators for attained education and labor force status. Omission errors occur because of return moves to the birth region. Hence, x_1 includes personal attributes correlated with the propensity to return (DaVanzo 1983, Saenz and Davila 1992, Newbold

[10] Except for the coefficient on the intercept included in x, which is the linear probability estimate of the coefficient on $(1 - \alpha_{0i} - \alpha_{1i})$ in (10) minus 0.5 multiplied by 2.5 (Amemiya 1981).

[11] Estimating (8) with an interaction between birth region and single-year birth cohort reveals that the propensity to migrate non-autonomously grew in some regions during the Spanish Civil War and/or the "rural exodus", and that it is roughly constant for the younger cohorts. Placing knots at 10-year intervals oversmooths the effect of the Civil War. Fitting region-specific fifth order polynomials yields predictions for 1994–1998 that look inconsistent with reality.

and Bell 2001): Birth-region-specific third order polynomials in age plus indicators for sex, attained education, labor force status, and housing tenure.[12]

Baseline results for the migration model are presented for six specifications of x, corresponding to three functions of *RRR* and two sets of control variables. Time preferences are measured alternatively with indicators for *RRR* group, an indicator for *RRR* > 9.8%, and a quadratic function of *RRR*. The use of dummy variables to model the empirical link between time preference and migration is probably a good choice given the potential complexity of the link (Nowotny 2014). The grouping of time preferences into just two categories may reduce biases from classification errors in time preferences, increases efficiency, and facilitates comparison with Gibson and McKenzie (2011). The monetary rewards in the MEL task could have been different, which would have generated alternative categorizations of *RRR*. To deal with this arbitrariness, *RRR* is also treated as a continuous variable by replacing each individual's unobserved *RRR* with the corresponding conditional mean listed in Table 3 (Hsiao and Mountain 1985). The quadratic function allows for a simple type of nonlinearity.

The first set of controls comprises sex, single-year age group (accounting for possible age-dependent time preferences: Bishai 2004), and birth region. The second set adds attained education, the number of books at home at the age of 10, cognitive skills, the willingness to take risks in financial matters, and the marginal propensity to consume

[12] Estimating (9) with indicators for single-year age group interacted with birth region reveals cross-region convergence in the propensity to return up to the late 20s, followed by divergence from the late 30s onwards.

(MPC) from windfall income.[13] Education and the number of books read might simultaneously increase a person's ability to appreciate the future (Becker and Mulligan 1997) and to live in other places, confounding the relation of interest. Krupka and Stephens (2013) find that measured rates of time preference are responsive to individuals' immediate economic conditions. In this respect, the MPC may not control only for the type of consumer but also for individuals' economic resources at the interview date (Jappelli and Pistaferri 2014). Table 6 presents summary statistics for these variables and for those used in estimations conducted in Census samples.

5. REGRESSION RESULTS

5.1. Errors of Commission

The results in column (1) of Table 7 indicate that attained education plus being unemployed or an employee are positively related to the likelihood of being misclassified as a migrant (i.e. of migrating non-autonomously). This likelihood is lower for the self-employed. The left panel of Figure 2 shows $\hat{\alpha}_{0i}$ for cohorts of individuals born in the regions of Extremadura and Catalonia. For Extremadura, individuals born between 1945 and 1965 show a relatively high incidence of non-autonomous migration, which declines progressively thereafter. In contrast, the incidence in Catalonia is small for the oldest cohorts but increases for the youngest ones, as traditional industrial regions with net in-migration balanced migratory flows (Bover and Velilla 2005). Descriptive statistics for $\hat{\alpha}_{0i}$ calculated in the ECF sample are shown in Table 6.

[13] The lack of controls for marital status and the spouse's time preference at the time when the migration decision was taken may be inconsequential: Results in Leigh (1986) suggest that time preference and being married are unrelated, and the evidence in Gnagey et al. (2020) points to positive assortative mating on time preferences.

5.2. Errors of Omission

The results in column (2) of Table 7 indicate that migrants more likely to be misclassified as nonmigrants (i.e. to return to their birth region) tend to be male, less educated, nonparticipants in the labor force, and owners who have inherited their dwelling. The right panel of Figure 2 shows $\hat{\alpha}_{1i}$ for individuals born in Extremadura and Catalonia as a function of age. For Catalonia, the incidence of omissions starts growing steadily in the mid 30s, probably because older persons are exposed for longer to the risk of returning. This incidence, however, is mainly declining in age for people born in Extremadura, so older migrants from this region appear to be much less likely to return. Descriptive statistics for $\hat{\alpha}_{1i}$ calculated in the ECF sample are shown in Table 6.

5.3. Time Preference and Migrant Status: Baseline Results

Table 8 presents the estimated parameters given by probit and predicted probabilities regressions of y on x. In general, estimated probit parameters appear attenuated or positively biased. For those parameters representing time preference that are attenuated, the average degree of attenuation is 55%. The combined probability of misclassification in the data, $\hat{\alpha}_{0i} + \hat{\alpha}_{1i}$, is substantial but not overwhelming (it averages 0.41, ranging between 0.21 and 0.91), as reflected in the larger standard errors of the PPE (probit standard errors are biased downward because they do not take into account the inaccuracy of the data). For any specification of x, the PPE provides a better fit to data than probit.

Columns (11) and (12) of Table 8 show the results for the quadratic function of *RRR*. For any set of controls, *RRR* has a negative though decreasing effect on the likelihood of ever migrating for most of the *RRR* range (the function reaches a minimum at around *RRR* = 243% and then curves upward). According to Nowotny (2014), this profile suggests that expected wages in the region of origin do not eventually surpass expected wages at destination. Estimates, however, are imprecise, and a Wald test of joint significance of *RRR* and RRR^2 in both columns yields *p*-values of 0.17 and 0.20, respectively.

Table 9 presents the estimated average marginal effects (AMEs) given by the PPE.[14] In column (1), the incidence of migration is lowest in the two least patient groups. The largest effect is observed among individuals with *RRR* between 9.8% and 44.9%, who are 3.3 percentage points (pps) (*S.E.* 1.9) less likely to have ever migrated than individuals with an *RRR* below 4.9% (the base group). This effect, which is statistically different from zero at 10%, represents 19% of the average probability of ever migrating (17.4%). The impact for those with an *RRR* above 44.9% is smaller (-2.3 pps, *S.E.* 2.1), probably reflecting the decreasing effect of *RRR* pointed out above. For individuals with *RRR* between 4.9% and 9.8% the estimated effect is zero. In column (2) the addition of further controls reduces the size of these impacts. The effect for those with an *RRR* between 9.8% and 44.9% is still sizable at -2.9 pps (*S.E.* 1.8), representing 17% of the average probability of ever migrating, but it loses significance at standard levels.

In column (3), having an *RRR* of > 9.8% decreases the probability of ever migrating by 2.8 pps (*S.E.* 1.7). The addition of further controls leaves an effect of -2.3 pps (*S.E.* 1.5) (column 4), implying a decrease in the probability of ever migrating of 13%. This effect is somewhat smaller than previously reported estimates. In Gibson and McKenzie (2011), top students with *RRR* > 9.8% are found to be 12 to 13 pps less likely

[14] AMEs are obtained by averaging marginal effects across observations, with standard errors calculated using the delta method. For categorical variables represented by sets of indicators, AMEs are calculated by zeroing out all the indicators in the set and setting the corresponding indicator to unity for all observations.

to have ever migrated internationally, which amounts to around 20% of the average probability of ever migrating in their samples (64%).

In column (5), the estimated AME of *RRR* suggests that a 10-pp increase in *RRR* reduces the likelihood of ever migrating by approximately 0.38 pps (*S.E.* 0.22). Adding further controls in column (6) leaves an effect of -0.33 pps (*S.E.* 0.20). Larger responses are observed at low values of *RRR*. For example, when *RRR* = 9.8%, a 10-pp increase in *RRR* reduces the likelihood of ever migrating by approximately 1.56 pps (*S.E.* 0.89), an effect which attains significance at 10%.

Table 9 also lists estimated AMEs for some controls. Although measured imprecisely, the even columns show a college migration premium that is robust to the inclusion of a measure of impatience in x. College graduates are about 4.2 pps (*S.E.* 2.7) more likely to have ever migrated than people with primary education or less, which is equivalent to 24% of the average probability of ever migrating. Excluding *RRR* from the set of regressors yields a college premium of 4.3 pps (*S.E.* 2.7), suggesting that behavior in the MEL task does not account for the lifetime migration premium of college education. If education is excluded from x_0 and x_1, the impact of college rises to 7.1 pps (*S.E.* 2.9), so as far as lifetime migration is concerned, a significant part of the college premium works through its influence on the probabilities of migrating non-autonomously and returning to the birth region.

AMEs of cognitive skills appear small. For example, a one-standard-deviation increase in the reading comprehension score raises the probability of ever migrating by about 0.5 pps (*S.E.* 0.7). Excluding cognitive skills from the specification leaves the estimated link between time preference and migration almost unchanged. For example, the estimated AME of the indicator for *RRR* > 9.8% becomes -2.3 pps (*S.E.* 1.6). (The same conclusion holds if instead of being excluded cognitive skills are interacted with the function of *RRR*). This conclusion is reassuring for studies that identify the effect of patience on migration without controlling for cognitive skills.

The effect of the risk index is negative. A one-standard-deviation increase in this index reduces the probability of ever migrating by approximately 1.5 pps (*S.E.* 0.8). Most previous studies report a positive correlation between willingness to take risks in general and migration (Jaeger et al. 2010, Gibson and McKenzie 2011, Nowotny 2014, Akgüç et al. 2016, Dustmann et al. 2017, and Huber and Nowotny 2018), although Jaeger et al. (2007) find that willingness to take risks in financial matters is essentially unrelated to the probability of migrating. If the risk score is an imperfect proxy for willingness to take risks and that willingness is negatively correlated with *RRR*,[15] the estimated effect of *RRR* could be negatively biased. Interacting the risk score with the function of *RRR* changes the estimated effect of *RRR* only a little except when it is treated as a continuous variable: A 10-pp increase in *RRR* reduces the likelihood of ever migrating by 0.25 pps (*S.E.* 0.25).

Having more than 10 books at home at the age of 10 tends to reduce the likelihood of ever migrating. A one-standard-deviation increase in the MPC from windfall income reduces the likelihood of ever migrating by about 1.6 pps (*S.E.* 1.0), an effect which attains significance at 10%. If the MPC depends inversely on individuals' resources, this result suggests that migration and wealth may be positively correlated.

5.4. Time Preference and Migrant Status: Robustness to Sensitivity Analyses

Panel 1 of Table 10 shows that excluding respondents who answer "don't know" in the MEL task leaves the estimated effects of impatience almost unchanged (results for the quadratic specification cannot be obtained because lognormality of *RRR* is rejected when

[15] In a consume-on-receipt model with no background consumption, the less risk-averse the individual is, the lower *RRR* is (Cohen et al. 2020).

“don’t knows” are excluded). The same conclusion holds if the third order polynomials in age included in x_1 are replaced by (more flexible) restricted cubic splines with knots placed at 5-year intervals (20, 25,…,75); see Panel 2 of Table 10.

The sample selection bias introduced by excluding observations with undisclosed birth region is assessed using Heckman’s twostep method applied to the LPM with misclassification (10).[16] The sample selection equation contains x (save for the birth region) plus the population on January 1, 2017 for the region of residence. This is a very significant predictor of selection (i.e. of disclosing the birth region), with the probability of being disclosed increasing with population. Panel 3A of Table 10 presents AMEs yielded by (10). Panel 3B presents AMEs obtained after estimating (10) with the inverse Mills ratio included in x. The differences between the two panels are small, especially when the full set of controls is used, and the inverse Mills ratio term (shown in the bottom row of Panel 3B) is statistically insignificant in all specifications.

The finding of a negative effect of impatience on the likelihood of ever migrating could be an artifact of reverse causality. Through a process of positive feedback, successful migration could teach people to be more patient. Gibson et al. (2019) find no significant impact of moving on time preferences using a follow-up survey of permanent migrants from a poor to a rich country. We try to account for a potential reverse causality effect by controlling for annual household income as a measure of economic success

[16] Arezzo and Guagnano (2019) develop an estimator for misclassified binary choice models with sample selection assuming misclassification probabilities independent of individual characteristics.

(income might be endogenous to migrant status).[17] Panel 4 of Table 10 presents AMEs obtained with income included in x. The negative correlation between impatience and the probability of ever migrating becomes, if anything, a little larger.

6. CONCLUSIONS

The ECF conducted in Spain in 2016 offers a unique opportunity for assessing the link between time preference and migration on the basis of a large sample and controlling for individuals' cognitive skills. The residential history collected by this survey, however, is limited to a baseline comparison of region at birth and at survey, which introduces misclassification of lifetime cross-region migrant status. In a sample representative of the same population drawn from the 2011 Census, considering the year of arrival in the region of residence and whether the individual was legally able to work in that year reduces the proportion of migrants from 19.3% to 17.4%. This reduction is the result of approximately 27% of migrants returning to their birth region and 8% of nonmigrants migrating non-autonomously.

Modeling migrant status conditional on individual probabilities of misclassification produces parameter estimates that are significantly different from estimates that do not condition on those probabilities. Results suggest that *RRR*s for financial flows and the probability of ever migrating tend to be inversely related even after individuals' cognitive skills are accounted for. The nature of the link manifests most clearly when *RRR* is modeled as a quadratic function: The effect on the likelihood of ever migrating is negative but decreasing, consistent with expected wages in the region of

[17] Household income is recorded in six categories. About 10 percent of respondents provide no data for this variable. For each missing value, the ECF provides five imputed values. Following Little and Rubin (2002), we conduct multiple imputation estimations.

origin not eventually surpassing expected wages at destination. Being impatient decreases the probability of ever migrating by 13% when time preferences are modeled with an indicator for *RRR* > 9.8%, which is smaller than the effect estimated for international migrations of top students. Removing cognitive skills from the specification leaves the results almost unchanged. The inclusion of *RRR* hardly reduces the college migration premium.

Cadena and Keys (2015) provide compelling evidence that impatient individuals tend to exhibit preference reversals in educational investment. To investigate the role of time-inconsistent preferences in the decision whether to migrate, additional variables such as willingness to migrate and the level of regret for inappropriately deciding in the past would be needed. Time preferences may also have some influence on intraregional migrations, as the same type of comparison between short-term costs and expected long-term benefits would seem to apply.

DECLARATIONS

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Conflicts of interest

The author declares that he has no conflicts of interest.

Availability of data and material

The dataset analyzed in this study is constructed from publicly available data published by the Banco de España, Spain’s National Securities Market Commission, and Spain’s National Statistics Institute. Instructions for how other researchers can obtain these data are collected in the electronic supplementary material of this article.

Code availability

The Stata do files used to create dataset and results are collected in the electronic supplementary material of this article.

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TABLES AND FIGURES

Table 1. Lifetime cross-region migrants (%), by data source and definition of migrant.

	All			True migrants	True non-migrants	Observations			
	Reduced-form migrants		True migrants	Reduced-form migrants	Reduced-form migrants	All		True migrants	True non-migrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ECF	Census	Census	Census	Census	ECF	Census	Census	Census
Total population	14.5	19.3	17.4	72.9	8.0	6,696	2,903,397	487,870	2,415,527
Sex									
Female	15.7	20.1	18.2	73.5	8.2	3,331	1,471,038	259,092	1,211,946
Male	13.3	18.5	16.5	72.3	7.9	3,365	1,432,359	228,778	1,203,581
Age									
18–24	2.5	6.9	2.4	70.9	5.3	650	266,942	5,331	261,611
25–44	8.9	13.9	11.6	71.7	6.3	2,250	982,121	110,599	871,522
45–64	16.7	24.0	20.8	72.9	11.2	2,660	1,074,919	212,514	862,405
65+	28.3	28.7	31.6	74.0	7.7	1,136	579,415	159,426	419,989
Education									
Primary or less	20.6	23.8	23.3	73.7	8.6	1,051	749,933	159,557	590,376
Low secondary	13.6	18.3	15.4	71.9	8.6	1,835	893,122	133,456	759,666
Upper secondary	10.2	15.5	13.0	71.3	7.2	2,236	733,386	95,044	638,342
Higher education	17.6	20.6	19.4	74.3	7.7	1,574	526,956	99,813	427,143

Notes: Population estimates. Individuals aged 18–79 residing in the 17 regions of Spain. Reduced-form migrants are individuals who reside in a region other than that in which they were born. True migrants are individuals who were legally able to work in their year of arrival in their region of residence. True nonmigrants are individuals who have resided since birth in the same region and individuals who were legally unable to work in their year of arrival in their region of residence.

Table 2. Required rate of return (%) in the MEL task.

	First binary choice: €2,000 today	First binary choice: €2,200 in a year's time
Second binary choice:		
€2,000 today	*RRR* > 44.9 [37.1]	4.9 < *RRR* ≤ 9.8 [10.6]
Money in a year's time[a]	9.8 < *RRR* ≤ 44.9 [29.7]	*RRR* ≤ 4.9 [22.6]

Notes: [a]: €3,000 if the respondent first chose €2,000 today; €2,100 if the respondent first chose €2,200 in a year's time. 6,696 individuals aged 18–79 residing in the 17 regions of Spain. Sample percentages are in brackets.

Table 3. Comparison of fitted and actual distributions.

(1) Lognormal model			(2)
Logarithm of *RRR* range	Actual	Model[a]	Mean *RRR* (%)
$\ln RRR \leq \ln 4.9$	1,513	1,503	2.1
$\ln 4.9 < \ln RRR \leq \ln 9.8$	710	748	7.2
$\ln 9.8 < \ln RRR \leq \ln 44.9$	1,991	1,956	23.1
$\ln 44.9 < \ln RRR$	2,482	2,489	471.5

Notes: [a]: *RRR* ~ $LN\left(-1.47, 4.14\right)$. 6,696 individuals aged 18–79 residing in the 17 regions of Spain.

Table 4. Pearson correlation coefficient between cognitive measures.

	Numeracy	Reading comprehension
Reading comprehension	0.23	
Cognitive reflection	0.18	0.17

Notes: 6,696 individuals aged 18–79 residing in the 17 regions of Spain.

Table 5. Required rates of return (%) for reduced-form lifetime cross-region migrants and nonmigrants.

	Average *RRR*		% with *RRR* > 9.8		Observations		
	Non-migrants	Migrants	Non-migrants	Migrants	Non-migrants	Migrants	% migrants
All	182.1	188.3	67.0	65.2	5,838	858	12.8
Sex							
Female	194.4	205.5	68.5	66.9	2,884	447	13.4
Male	170.0	169.7	65.6	63.3	2,954	411	12.2
Age							
18–24	129.1	202.7	60.4	52.6	631	19	2.9
25–44	152.5	159.7	61.6	52.9	2,059	191	8.5
45–64	199.9	184.4	70.2	69.6	2,282	378	14.2
65+	243.9	213.1	76.4	68.5	866	270	23.8
Education							
Primary or less	266.7	228.6	80.5	73.7	872	179	17.0
Low secondary	223.6	244.8	74.6	76.1	1,613	222	12.1
Upper secondary	160.1	190.4	64.2	67.3	2,019	217	9.7
Higher education	109.7	104.2	53.4	46.7	1,334	240	15.2
Numeracy[a]							
0	213.4	217.2	72.5	70.6	3,349	521	13.5
1	139.9	143.7	59.7	56.7	2,489	337	11.9
Reading comprehension[a]							
0	256.0	160.3	75.7	58.8	255	34	11.8
1	231.7	227.1	74.6	70.5	668	122	15.4
2	199.6	203.2	69.7	68.6	1,864	306	14.1
3	154.3	167.4	63.0	61.4	3,051	396	11.5
CRT[a]							
0	197.3	199.4	69.3	68.0	4,393	671	13.3
1	135.7	148.7	60.2	55.1	1,445	187	11.5
Risk index							
1	239.0	264.1	75.7	74.0	1,437	288	16.7
2	183.3	156.5	67.8	61.7	1,129	188	14.3
3	154.5	132.5	62.8	55.3	1,271	152	10.7
4	152.0	160.8	62.5	65.1	1,343	149	10.0
5	170.2	148.3	64.3	60.5	658	81	11.0

Notes: Sample estimates. Individuals aged 18–79 residing in the 17 regions of Spain. Average *RRR* is calculated using the group means listed in Table 3 as ordered scores. [a]: Number of correct answers. The risk index is coded on a scale from 1 to 5, with 1 indicating unwilling to take financial risks and 5 indicating very willing to take financial risks.

Table 6. Descriptive statistics.

	ECF (N = 6,696)				2011 Census: True migrants (N = 487,870)				2011 Census: True nonmigrants (N = 2,415,527)			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Age	47.5	15.7	18	79	56.0	14.2	18	79				
Birth year	1968.5	15.7	1936	1998					1964.3	16.5	1931	1993
Male	0.503				0.469							
Education												
Primary or less	0.157				0.327				0.244			
Low secondary	0.274				0.273				0.315			
Upper secondary	0.334				0.195				0.264			
Higher education	0.235				0.205				0.177			
Books at home (age 10)												
0–10	0.296											
11–25	0.209											
26–100	0.269											
101–200	0.102											
>200	0.124											
Numeracy	0.422	0.494	0	1								
Reading comprehen.	2.310	0.842	0	3								
CRT	0.244	0.429	0	1								
Risk score	2.732	1.349	1	5								
MPC	39.6	32.0	0	100								
Labor force status												
Not in labor force	0.336				0.466				0.336			
Self employed	0.114				0.067				0.095			
Employee	0.420				0.328				0.386			
Unemployed	0.130				0.139				0.183			
Housing tenure												
Owner (purchase)	0.740				0.791							
Owner (inherit./gift)	0.113				0.054							
Tenant	0.106				0.085							
Other	0.041				0.070							
Birth region												
Andalusia	0.142				0.181				0.185			
Aragón	0.054				0.039				0.045			
Asturias	0.046				0.023				0.021			
Balearic Islands	0.022				0.005				0.013			
Canary Islands	0.036				0.011				0.031			
Cantabria	0.034				0.014				0.014			
Castile-León	0.086				0.179				0.113			
Castile-La Mancha	0.056				0.113				0.064			
Catalonia	0.084				0.062				0.136			
Valencia Region	0.068				0.038				0.086			
Extremadura	0.068				0.082				0.043			
Galicia	0.074				0.070				0.058			
Madrid Region	0.082				0.097				0.088			
Murcia Region	0.040				0.020				0.026			
Navarre	0.029				0.013				0.020			
Basque Country	0.056				0.044				0.048			
La Rioja	0.022				0.011				0.010			
$\hat{\alpha}_{0i}$	0.078	0.051	0.006	0.303								
$\hat{\alpha}_{1i}$	0.336	0.135	0.099	0.898								

Table 7. Probit models of classification errors.

	(1) Commission errors		(2) Omission errors	
Explanatory variables	Coef.	S.E.	Coef.	S.E.
Male			.062***	.004
Primary education or less	Ref.		Ref.	
Low secondary education	.095***	.004	-.062***	.005
Upper secondary education	.123***	.004	-.104***	.006
Higher education	.156***	.004	-.165***	.006
Not in labor force	Ref.		Ref.	
Self employed	-.103***	.005	-.055***	.009
Employee	.014***	.004	-.148***	.006
Unemployed	.027***	.004	-.024***	.007
Owner (purchase)			-.268***	.007
Owner (inheritance/gift)			.419***	.011
Tenant			-.373***	.010
Other housing tenure			Ref.	
Intercept	-89.859***	8.028	-2.303***	.206
Log-likelihood	-602,224.1		-286,487.8	
R-squared	0.058		0.049	

Notes: (1): Estimated from the true nonmigrant sample including among the regressors birth-region-specific restricted cubic splines in the birth year with knots placed at 5-year intervals. Dependent variable = 1 if false migrant. (2): Estimated from the true migrant sample including among the regressors birth-region-specific third order polynomials in age. Dependent variable = 1 if false nonmigrant. *R*-squared is the ratio of the log likelihood of the fitted function to the log likelihood of a function with only an intercept. ***: Significant at 1%.

Table 8. Estimated parameters of lifetime migration models.

	Probit						Predicted probabilities estimator					
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$1(4.9\% < RRR \leq 9.8\%)$	.087	.110					.015	.013				
	(.078)	(.078)					(.181)	(.192)				
$1(9.8\% < RRR \leq 44.9\%)$	-.113*	-.076					-.255*	-.248				
	(.059)	(.060)					(.150)	(.156)				
$1(44.9\% < RRR)$	-.098*	-.037					-.173	-.131				
	(.057)	(.059)					(.155)	(.166)				
$1(9.8\% < RRR)$			-.134***	-.094**					-.216*	-.192		
			(.045)	(.046)					(.126)	(.120)		
RRR					-.691**	-.524*					-1.371*	-1.325*
					(.284)	(.286)					(.738)	(.744)
RRR^2					.140**	.107*					.281*	.273*
					(.059)	(.059)					(.152)	(.153)
Male	-.063	-.050	-.066	-.053	-.066	-.053	-.040	.023	-.045	.018	-.044	.023
	(.042)	(.043)	(.042)	(.043)	(.042)	(.043)	(.109)	(.113)	(.117)	(.113)	(.111)	(.114)
Low secondary education		-.029		-.030		-.030		-.074		-.081		-.075
		(.068)		(.068)		(.068)		(.189)		(.189)		(.190)
Upper secondary		.033		.030		.031		.010		.004		.009
		(.075)		(.075)		(.075)		(.192)		(.190)		(.192)
Higher education		.233***		.224***		.228***		.328		.310		.325
		(.082)		(.082)		(.082)		(.216)		(.210)		(.214)
11–25 books at home		-.090		-.091		-.089		-.146		-.144		-.142
		(.065)		(.065)		(.065)		(.174)		(.173)		(.173)
26–100		-.043		-.041		-.040		.052		.054		.059
		(.066)		(.066)		(.066)		(.158)		(.158)		(.156)
101–200		.022		.023		.025		-.119		-.113		-.116
		(.089)		(.089)		(.089)		(.252)		(.255)		(.253)

>200		-.064		-.063		-.061		-.178		-.180		-.178
		(.088)		(.088)		(.088)		(.268)		(.262)		(.265)
Numeracy		.037		.035		.036		.096		.101		.097
		(.048)		(.048)		(.048)		(.148)		(.148)		(.148)
Reading comprehension		.037		.037		.037		.049		.047		.049
		(.027)		(.027)		(.027)		(.070)		(.070)		(.070)
CRT		-.032		-.034		-.033		-.070		-.080		-.071
		(.053)		(.053)		(.053)		(.136)		(.135)		(.136)
Risk score		-.020		-.021		-.020		-.090*		-.091*		-.091*
		(.016)		(.017)		(.016)		(.050)		(.050)		(.050)
MPC (÷ 10)		-.014**		-.014**		-.014**		-.042*		-.042*		-.043*
		(.007)		(.007)		(.007)		(.025)		(.025)		(.025)
Intercept	-.846***	-.898***	-.814***	-.847***	-.794***	-.841***	-.927***	-.767*	-.912***	-.724*	-.872***	-.717
	(.145)	(.169)	(.143)	(.168)	(.145)	(.170)	(.332)	(.448)	(.330)	(.428)	(.338)	(.451)
Log-likelihood	-2,225.84	-2,209.96	-2,226.52	-2,211.21	-2,227.13	-2,211.55	-2,189.85	-2,178.17	-2,190.05	-2,178.58	-2,189.96	-2,178.27

Notes: The number of observations is 6,696. Regressors include indicators for single-year age group and birth region. 1(·) is the indicator function. Standard errors are in parentheses. *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.

Table 9. Predicted probabilities estimates of lifetime migration. Average marginal effects.

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
$1(4.9\% < RRR \leq 9.8\%)$	.002	.002				
	(.026)	(.025)				
$1(9.8\% < RRR \leq 44.9\%)$	-.033*	-.029				
	(.019)	(.018)				
$1(44.9\% < RRR)$	-.023	-.016				
	(.021)	(.021)				
$1(9.8\% < RRR)$			-.028*	-.023		
			(.017)	(.015)		
RRR					-.038*	-.033
					(.022)	(.020)
Male	-.005	.003	-.006	.002	-.006	.003
	(.014)	(.013)	(.015)	(.013)	(.014)	(.013)
Low secondary education		-.008		-.009		-.008
		(.021)		(.021)		(.021)
Upper secondary		.001		.000		.001
		(.022)		(.022)		(.022)
Higher education		.042		.040		.042
		(.027)		(.026)		(.027)
11–25 books at home		-.017		-.017		-.017
		(.020)		(.020)		(.020)
26–100		.007		.007		.007
		(.020)		(.020)		(.020)
101–200		-.014		-.013		-.014
		(.029)		(.029)		(.029)
>200		-.020		-.021		-.020
		(.029)		(.029)		(.029)
Numeracy		.011		.012		.012
		(.018)		(.018)		(.018)
Reading comprehension		.006		.006		.006
		(.008)		(.008)		(.008)
CRT		-.008		-.009		-.008
		(.016)		(.016)		(.016)
Risk score		-.011*		-.011*		-.011**
		(.006)		(.006)		(.006)
MPC (÷ 10)		-.005*		-.005*		-.005*
		(.003)		(.003)		(.003)

Notes: The number of observations is 6,696. Regressors include an intercept plus indicators for single-year age group and birth region. $1(\cdot)$ is the indicator function. Standard errors are in parentheses. *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.

Table 10. Robustness of predicted probabilities estimates of lifetime migration to alternative specifications. Average marginal effects.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Excluding "don't know" answers in the MEL task (N = 6,595)						
$1(4.9\% < RRR \leq 9.8\%)$	.006	.004				
	(.033)	(.026)				
$1(9.8\% < RRR \leq 44.9\%)$	-.031	-.028				
	(.024)	(.019)				
$1(44.9\% < RRR)$	-.021	-.013				
	(.025)	(.022)				
$1(9.8\% < RRR)$			-.027*	-.022		
			(.016)	(.016)		
Panel 2: Omission errors modeled with region-specific restricted cubic splines in age.						
	(1)	(2)	(3)	(4)	(5)	(6)
$1(4.9\% < RRR \leq 9.8\%)$	.003	.003				
	(.026)	(.025)				
$1(9.8\% < RRR \leq 44.9\%)$	-.033*	-.029				
	(.019)	(.019)				
$1(44.9\% < RRR)$	-.022	-.015				
	(.021)	(.021)				
$1(9.8\% < RRR)$			-.028*	-.023		
			(.016)	(.015)		
RRR					-.037*	-.033
					(.022)	(.020)
Panel 3A: LPM with misclassification.						
	(1)	(2)	(3)	(4)	(5)	(6)
$1(4.9\% < RRR \leq 9.8\%)$	.029	.033				
	(.026)	(.026)				
$1(9.8\% < RRR \leq 44.9\%)$	-.031*	-.023				
	(.018)	(.018)				
$1(44.9\% < RRR)$	-.026	-.013				
	(.018)	(.018)				
$1(9.8\% < RRR)$			-.037***	-.029**		
			(.014)	(.014)		
RRR					-.031**	-.025*
					(.014)	(.014)
Panel 3B: Heckman-corrected LPM with misclassification.						
	(1)	(2)	(3)	(4)	(5)	(6)
$1(4.9\% < RRR \leq 9.8\%)$	.030	.035				
	(.026)	(.026)				
$1(9.8\% < RRR \leq 44.9\%)$	-.035*	-.025				
	(.018)	(.018)				
$1(44.9\% < RRR)$	-.029	-.011				
	(.018)	(.019)				
$1(9.8\% < RRR)$			-.041***	-.029**		
			(.015)	(.014)		
RRR					-.035**	-.026*
					(.014)	(.014)

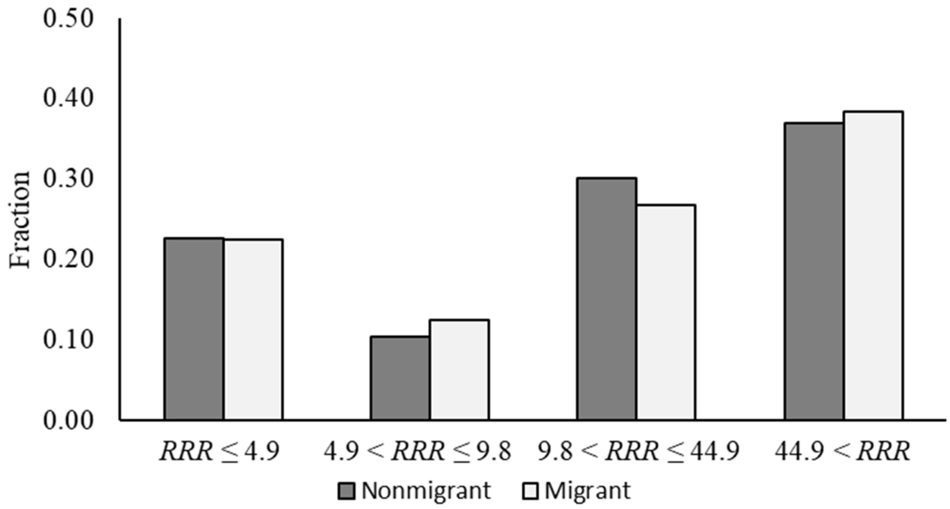
Inverse Mills ratio	-.348	-.284	-.354	-.292	-.358	-.290
	(.374)	(.295)	(.375)	(.296)	(.375)	(.296)

Panel 4: Household income included among the regressors.

	(1)	(2)	(3)	(4)	(5)	(6)
$1(4.9\% < RRR \leq 9.8\%)$	.000	.000				
	(.028)	(.026)				
$1(9.8\% < RRR \leq 44.9\%)$	-.034	-.034*				
	(.021)	(.019)				
$1(44.9\% < RRR)$	-.026	-.022				
	(.021)	(.021)				
$1(9.8\% < RRR)$			-.030*	-.028*		
			(.016)	(.015)		
RRR					-.040*	-.039*
					(.023)	(.021)

Notes: The number of observations is 6,696 except when noted. In all panels, the set of controls in columns (1), (3), and (5) comprises sex, single-year age group, and birth region; columns (2), (4), and (6) add education, the number of books at home at the age of 10, cognitive skills, the risk index, and MPC. $1(\cdot)$ is the indicator function. Standard errors are in parentheses. *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.

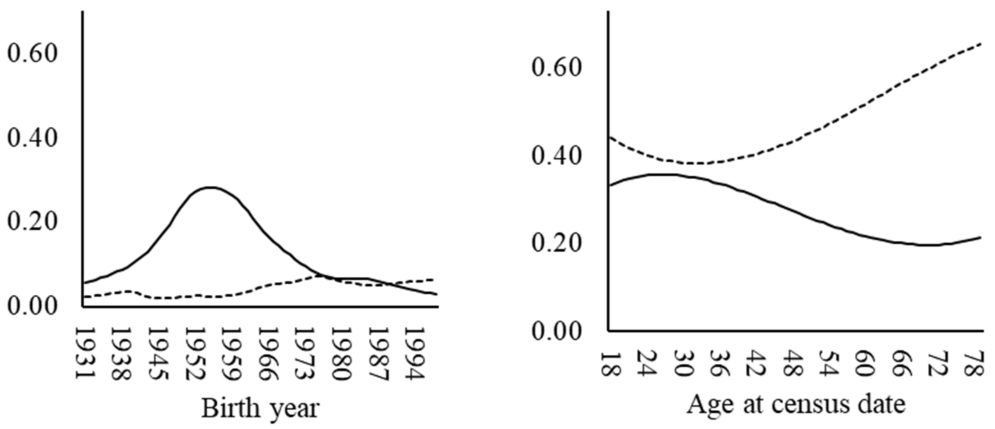
Figure 1. Required rates of return (%) for reduced-form lifetime cross-region migrants and nonmigrants.



Notes: Sample estimates. 5,838 nonmigrants and 858 migrants aged 18–79 residing in the 17 regions of Spain.

Figure 2. Misclassification probabilities estimates for people born in the regions of Extremadura (solid) and Catalonia (dotted).

$\hat{\alpha}_{0i}$	$\hat{\alpha}_{1i}$



Notes: The $\hat{\alpha}_{0i}$ and $\hat{\alpha}_{1i}$ depicted here are from estimations (1) and (2) in Table 7, respectively, and are obtained with controls set at modal values.