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Risk attitudes and migration decisions

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Abstract

This paper analyzes the relationship between individuals' attitudes towards risk and their decision to migrate. We consider migration in the United States across metropolitan statistical areas (MSAs) between 1997 and 2015, based on data from the Panel Study of Income Dynamics (PSID). Using random-effects specifications, we find that being relatively more willing to take risks is positively and significantly related to cross-MSA migration. For cross-state migration and migration across larger distances, risk attitudes are slightly more important. A recursive bivariate probit model of simultaneous equations addresses the potential endogenous nature of attitudes towards risk and allows ruling out reverse causality.

KEYWORDS

interregional migration, metropolitan statistical areas (MSAs), Panel Study of Income Dynamics (PSID), risk attitudes, self-selection

JEL CLASSIFICATION

D81, J61, J62, R23

1 | INTRODUCTION

Migration is an inherently risky activity. While the idea that individuals' risk attitudes play a determinant role in migration propensities is by no means novel, empirical evidence remains scarce. The goal of this paper is to analyze the relationship between individuals' attitudes towards risk and their decision to migrate within the United States.

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Understanding the determinants of geographic mobility is important given the effects it may have on the efficient functioning of labor markets. As Borjas (2001, p. 69) points out, migration helps to “grease the wheels of the labor market,” meaning that labor resources are reallocated to places where they can be used in a more productive manner. From a policy perspective, a greater insight into the underlying reasons behind individual migration decisions allows for the design of more effective labor market and migration policies.

In economics, the traditional approach to the study of migration is the standard human capital model, which considers migration as a human capital investment decision (Sjaastad, 1962). Potential migrants calculate the value of labor market opportunities in both the current and the prospective location, and—taking into account the costs related to moving—choose the location which maximizes the net present value of lifetime earnings (Bodvarsson & Van den Berg, 2013). This approach implicitly assumes that there is no risk related to the value of labor market opportunities in different locations and that only monetary benefits are relevant for the migration decision. Both points have been addressed in the literature.

First, a more realistic assumption is that migration decisions are guided by the value of opportunities at the destination and the current location, with the former being based on expectations while the latter is known as it represents the status quo (Todaro, 1969). To say it differently, potential migrants are assumed to have complete information about the labor market opportunities in the current location, and are able to know the expected payoffs and the different probabilities of occurrence in the prospective location. This allows them to accurately weight the advantages and disadvantages of the migration and nonmigration options (DaVanzo, 1983). Risk, as defined by Knight (1921),¹ thus becomes part of the picture, however, without allowing for heterogeneity in risk aversion.

Second, the choice of the destination may also depend on market and nonmarket amenities (Rosen, 1974), including consumption and leisure goods (Shields & Shields, 1989). So, unlike in the standard human capital model, individuals may choose to migrate for reasons other than better income opportunities (Bodvarsson & Van den Berg, 2013), namely for the nonmonetary benefits of regional amenities. If the search for information about these amenity goods is costly, and assuming that potential migrants have less information about leisure and consumption opportunities in locations with which they are not familiar, uncertainty is generated.² It is the risk regarding future income and the uncertainty generated through incomplete information about both material and nonmaterial returns (and costs) of moving what makes migration an inherently risky activity (Jaeger et al., 2010; Williams & Baláž, 2012).³

In a seminal paper, Jaeger et al. (2010) show a positive relation between risk tolerance and internal migration in Germany. After controlling for conventional determinants of migration, those who are relatively more willing to take risks are found to be more likely to move across German districts. In line with these results, Guiso and Paiella (2004) find that individuals who are more risk-tolerant are more likely to have moved to a region different from their region of birth in Italy. Focusing on international migration, Williams and Baláž (2014) come to similar conclusions using data from the UK. There is also scarce evidence on how risk attitudes relate to migration in less developed countries. Akgüç et al. (2016) and Dustmann et al. (2017) consider rural–urban migration in China and find that less risk-averse individuals are more likely to migrate.⁴ In a study on high-skilled migrants from three south pacific countries, Gibson and McKenzie (2012) find that risk-seeking individuals are more likely to have ever

¹Risk is a type of uncertainty that is susceptible of measurement, that is, probabilities of occurrence can be attached to it.

²True uncertainty is of a nonquantitative nature and no probabilities can be assigned to it (Knight, 1921).

³The way in which risk attitudes affect migration may be ambiguous. The argument regarding imperfect and incomplete information may be equally relevant for risky conditions in the current location—in the form of income risk due to high-income variability (Conroy, 2009). The presence of risk in the current location would encourage risk-averse potential migrants, making them more likely to move to a location with a lower variability of income. This hypothesis is beyond the scope of this paper.

⁴On the other hand, Conroy (2009) arrives at opposite results when measuring rural-to-urban migration propensities of Mexican youth.

engaged in international migration. In these papers, an explicit analysis of the individual migration-risk relation over a longer time period is not addressed.⁵

This study is based on a panel data set for the period 1997–2015 from the Panel Study of Income Dynamics (PSID), a representative longitudinal survey of households in the United States. The data set includes a series of hypothetical-gamble questions to elicit individuals' risk attitudes, detailed geographical information, and a rich set of socioeconomic and labor-market controls. The paper contributes to the empirical literature on risk attitudes and migration in several ways: First, we are able to account for unobserved heterogeneity, migrant selection, and the potential endogenous nature of attitudes towards risk, something that has not been addressed so far. Second, due to the panel structure of the data set, the relationship between risk attitudes and migration propensities can be analyzed in a comprehensive way, allowing us to account for the role played by previous migration experience. Focusing on the intensive margin of migration is important given the reduced uncertainty faced by potential repeat migrants, which lowers the costs of subsequent migration (see e.g., DaVanzo, 1981, 1983). To say it differently, the role played by risk attitudes on migration may be substituted away by migration experience.⁶ Third, and related to the United States, the PSID data set allows for the use of metropolitan statistical areas (MSAs) as geographical units (besides states) enabling us to compare migration decisions within and across regions, which are likely to involve different degrees of uncertainty. To our knowledge, the literature in the United States has focused so far on international migration and has neglected internal migration. For example, using the Health and Retirement Study (HRS), Barsky et al. (1997) find statistically significant correlations between risk tolerance and previous international migration, while Halek and Eisenhauer (2001) show that individuals who have engaged in international migration are more likely to be less risk-averse than the host population. Although Greenwood and Sweetland (1972) and Chen and Rosenthal (2008) study the determinants of individual migration decisions across MSAs in the United States, they do not take into account attitudes towards risk. This also holds for the literature on internal migration to areas with warm weather (especially when housing prices are cheap, see Glaeser & Tobio, 2007; Rappoport, 2007). Finally, Molloy et al. (2011) study internal migration trends in the United States at many levels of disaggregation, including cross-MSA migration, and Kaplan and Schulhofer-Wohl (2017) partly attribute a secular decline in gross cross-state migration in the United States to a reduction in information costs, but their analyses do not focus on migrant behavior at the individual level. Fourth, and more generally, the study allows for first conclusions about whether the United States is different from other countries in terms of the migration-risk relation, that is, whether the underlying relation is linear or affected by country specifics in a nonlinear way.

Using random-effects specifications, we find that being relatively more willing to take risks is positively and statistically significantly related to cross-MSA migration, after controlling for conventional socioeconomic and labor-market characteristics. These results are robust to the selection of varying sets of covariates, a series of subsample analyses, and alternative definitions of migration. For migration across states and across larger distances—which normally involve larger uncertainty—risk attitudes play a slightly more important role. Furthermore, we find that risk attitudes play a role in determining whether individuals self-select into migration, with a significant positive effect on the distance moved, conditional on moving. The results remain robust to accounting for the potential endogenous nature of individual attitudes towards risk. The seminal work of Jaeger et al. (2010) presenting evidence on the relationship between risk attitudes and migration in the German context is used as a benchmark to compare our results. It seems that in Germany, a country with lower geographic mobility rates than the United States (Molloy et al., 2011) and a more risk-averse population (Fehr et al., 2006), the migration-risk

⁵Dustmann et al. (2017) use a panel of six waves to analyze the relationship between risk attitudes and the length of migration of rural–urban migrants in China, but they do not use the panel to measure migration propensities. Akgüç et al. (2016), Gibson and McKenzie (2012), and Conroy (2009) all rely on cross-sectional data with retrospective information on migration.

⁶Gibson and McKenzie (2012) find no significant effect of risk attitudes on return migration, and Jaeger et al. (2010) show that repeat migrants have a higher average willingness to take risks, but do not provide further empirical evidence.

relation is not very different. If at all, risk attitudes play a slightly larger role in the decision to migrate in Germany than in the United States.

The remainder of the paper is structured as follows. The next section presents a simple reformulation of the human capital model of migration that accounts for risk-aversion. Section 3 introduces the empirical strategy, while Section 4 describes the data. Random-effects and cross-section empirical results are presented in Sections 5 and 6, respectively. Section 7 concludes.

2 | THEORETICAL FRAMEWORK

To illustrate the individual migration decision, this section presents a reformulation of the human capital model of migration in which expected income at the prospective location guides the potential migrant's decision.

Assume, for simplicity, that there are only two locations, $m = k, j$. An individual residing in home location, k , has the possibility to move to a prospective location, j . Furthermore, assume that there are two states of the world, $s = 1, 2$, with 1 representing a good state, and 2 a bad state. If locations are characterized by payoffs w_s^m , the decision to migrate can be modeled as the purchase of a lottery ticket with two possible outcomes: w_1^j or "successful" migration, and w_2^j or "unsuccessful" migration (Heitmueller, 2005). Let p^j be the probability that the payoff of migrating to the prospective location is w_1^j , and let $1 - p^j$ represent the probability of obtaining payoff w_2^j , where $w_1^j > w_2^j$. An individual's expected income from migrating to location j can be expressed as follows:

$$E\left(Y^j(w_s^j, p^j)\right) = p^j(w_1^j) + (1 - p^j)(w_2^j) \quad (1)$$

The state s in the home location k is known. Hence, the expected income from staying is equal to the actual income, expressed by

$$Y^k(w_s^k) = w_s^k \quad (2)$$

Assuming that the purchase of the migration lottery ticket is not free, individuals have to pay a fee, C_{kj} , to cover the costs of migration.⁷ Individuals can then calculate the sum of discounted income flows by comparing Equations (1) and (2) in each period, t . Define Υ^{kj} as the net discounted income flow from migration from k to j

$$\Upsilon^{kj} = \sum_{t=0}^T \frac{E\left(Y_t^j(w_s^j, p^j)\right) - Y_t^k(w_s^k)}{(1 + r)^t} - C_{kj} \quad (3)$$

where r is the discount rate and T the length of life. Individuals maximize the returns from migration by choosing the location with the highest gain, that is, migration will occur only if $\Upsilon^{kj} > 0$.⁸

Two important implications can be drawn from this framework. First, an increase in the expected payoffs at the prospective location increases the net gains from migration, raising the likelihood of relocation. Analogously, an improvement in the payoffs at the current location increases the net gains from staying, lowering the likelihood of migration. Second, an increase in migration costs lowers the net gains from moving, reducing the likelihood of migration. The costs of migration in the standard human capital model are monetary costs stemming from transportation expenses, and are assumed to be related to distance. Accordingly, Sjaastad (1962) uses distance as a proxy for migration costs.⁹ For Bodvarsson and Van den Berg (2013), however, these costs may also include costs related to the loss of job seniority or foregone assets, which are both associated with age given that it is more likely

⁷We assume that migration costs do not exceed payoffs w_s^m . This could be rationalized by adding a state independent income e as an additional parameter to (1) and (2), where it is assumed that $e > 0$.

⁸The generalization of this setting to many alternative locations is straightforward. This can be done by simply computing the discounted income flows for existing location alternatives, M , and choosing the option which yields the highest value of Υ^M .

⁹Psychic costs from leaving family and friends behind have been shown to increase with distance as well (Schwartz, 1973).



that older individuals have acquired higher seniority throughout their career and accumulated more assets. Therefore, older age can be expected to increase the costs of migration.

Following Heitmueller (2005), we further assume that individuals differ in their degree of risk-aversion. With constant relative-risk aversion (CRRA), that is, absolute risk-aversion that declines with wealth,¹⁰ Equation (1) becomes

$$E\left(Y_{i,t}^j(w_s^j, p^j, \gamma)\right) = p^j \frac{(w_1^j)^{1-\gamma}}{1-\gamma} + (1-p^j) \frac{(w_2^j)^{1-\gamma}}{1-\gamma} \quad (4)$$

where γ represents the coefficient of relative risk-aversion, and where we assume that $\gamma \in \mathbb{N}$, $\gamma \neq 1$, and $w_s^j > 1$, while Equation (2) is unaffected by the level of risk-aversion. Note that the model above collapses to the standard expected income approach when $\gamma = 0$, allowing comparability to earlier studies while enabling the analysis of the effect of risk-aversion. The net return to migration, Y_i^{kj} , now varies across individuals due to the risk-aversion parameter, γ . It can be shown (see Appendix A for the proof) that

$$\frac{\partial E\left(Y_i^j(w_s^j, p^j, \gamma)\right)}{\partial \gamma} < 0, \quad \frac{\partial Y_i^k(w_s^k)}{\partial \gamma} = 0 \quad (5)$$

and, hence

$$\frac{\partial Y_i^{kj}}{\partial \gamma} < 0 \quad (6)$$

meaning that an increase in the parameter of risk-aversion, γ , lowers the net gains from migration, decreasing the likelihood that individual i migrates to location j .

3 | ESTIMATION STRATEGY

This section introduces the empirical strategy to analyze the relationship between individuals' attitudes towards risk and the decision to migrate across MSAs in the United States. The probability estimations of migration decisions are based on panel data, which allows for taking individual unobserved heterogeneity into account and controlling for self-selection into migration. We first apply a random-effects probit specification for the binary migration choice, we then run a Heckman selection model and additionally consider the distance moved. Finally, the potential endogenous nature of attitudes towards risk is accounted for by estimating a recursive bivariate probit model of simultaneous equations.

3.1 | Random-effects probit specification

Individuals may have a "specific preference" for staying in (or migrating to) a given location due to, among other things, an intrinsic predilection for certain types of regional amenities that cannot be captured by observable factors. If individual unobserved effects are assumed to be uncorrelated with the willingness to take risks,¹¹ a random-effects probit specification for the binary migration choice yields consistent estimates of the coefficient β . Following Wooldridge (2010, 2013), the decision of individual i to migrate in period t is modeled by a continuous latent variable, Y_{it}^* ,

¹⁰The coefficient of relative risk-aversion is given by $\gamma = -(w)u''(w)/u'(w)$. Brunnermeier and Nagel (2008), and Chiappori and Paiella (2011) show that CRRA is an empirically relevant measure to explain microeconomic behavior.

¹¹A relaxation of this assumption is addressed in Section 3.3.

$$y_{it}^* = \beta x_{it} + \epsilon_{it}, \quad i = 1, \dots, N; t = 1, \dots, T$$

$$\text{with } y_{it} = 1 \text{ if } y_{it}^* > 0, \text{ and } 0 \text{ otherwise} \quad (7)$$

where x_{it} is a vector of independent variables, and $\epsilon_{it} = c_i + \mu_{it}$ is the sum of the random effect, c_i , and an idiosyncratic error, μ_{it} . Assuming c_i to be an independent random draw from a normal distribution, $c_i \sim N(0, \sigma_c^2)$, and c_i and x_{it} to be independent from each other, the panel-level likelihood l_i is given by¹²

$$l_i = \int_{-\infty}^{\infty} \frac{e^{-c_i^2/2\sigma_c^2}}{(2\pi)^{1/2}\sigma_c} \prod_{t=1}^T F(y_{it}, x_{it}\beta + c_i) dc_i \quad (8)$$

with $F(y, x_{it}\beta + c_i) = \Phi(x_{it}\beta + c_i)$ if $y \neq 0$ and $F(y, x_{it}\beta + c_i) = 1 - \Phi(x_{it}\beta + c_i)$ otherwise, where Φ is the cumulative distribution function (cdf). The log-likelihood, L , is the sum of the logs of the panel-level likelihoods, l_i . Note that the specification above assumes that the correlation between successive disturbances for the same individual is constant

$$\text{Corr}[\epsilon_{it}, \epsilon_{is}] = \frac{\sigma_c^2}{(\sigma_c^2 + \sigma_\mu^2)}, \quad t \neq s \quad (9)$$

which is a rather strong assumption. According to Ritsilä and Tervo (2002), the assumption could be relaxed by specifying c_{it} and c_{is} to be freely correlated within groups (here individuals), but not across groups. Nonetheless, they argue that such a procedure becomes increasingly difficult and that the restricted formulation laid out before is widely accepted as a preferred option. An alternative would be to follow a fixed-effects approach; however, there is no consistent estimator for a conditional fixed-effects probit model (Greene, 2003), and even if it were, the measure of risk attitudes—the main explanatory variable in our model—would not be included given that it is assumed to be time-invariant.

3.2 | Heckman specification

To analyze the role played by risk attitudes in the self-selection of migrants over the intensive margin of migration, the two-stage nature of the process will be considered, with the first stage being the probability that an individual ever migrates and the second stage being the total distance moved, conditional on migrating. To account for the potential econometric problem of sample selection—which occurs when individuals self-select into a group, a two-stage Heckman selection model presents the standard solution (Heckman, 1979). In the first stage, the decision of individual i to migrate across MSAs is modeled by the latent variable y_i^* . The selection equation¹³

$$y_i^* = \beta x_i + \epsilon_i, \quad i = 1, \dots, N$$

$$\text{with } y_i = 1 \text{ if } y_i^* > 0, \text{ and } 0 \text{ otherwise} \quad (10)$$

defines the individuals who migrate at least once during the sample period. In the outcome equation

$$s_i^* = \theta z_i + v_i, \quad i = 1, \dots, N \quad (11)$$

s_i indicates, for each individual, the total distance moved in kilometers, and is unobserved if $y_i = 0$. Both equations include vectors of explanatory variables, x_i and z_i , and error terms, ϵ_i and v_i , that are assumed to be standard normally distributed and normally distributed, respectively. Furthermore, in Equation (10), ϵ_i is assumed to be uncorrelated with the explanatory variables. To correct for a potential selection bias,¹⁴ the inverse Mills ratio (IMR)

¹²Given that, in general, there is no analytical solution, numerical methods have to be used. The most common approach is to use a Gauss-Hermite quadrature method (Butler & Moffitt, 1982).

¹³For consistency, given that the selection model is estimated via a probit specification, the same notation as in the random-effects probit is used.

¹⁴Selection bias is indicated by a correlation between the errors ($\text{corr}(\epsilon_i, v_i) = \rho_i \neq 0$).

$$\lambda(x\beta) = \phi(x\beta) / \Phi(x\beta) \quad (12)$$

is computed from Equation (10), with ϕ and Φ denoting the standard normal probability density function (pdf) and the cumulative distribution function (cdf), respectively. Finally, including the IMR as an additional regressor in the outcome equation, we get

$$s_i^* = \theta z_i + \rho_i \sigma_v \lambda(x\beta) + v_i \quad (13)$$

which can be consistently estimated by ordinary least squares (OLS) with standard errors bootstrapped based on 500 replications (Wooldridge, 1995). According to Wooldridge (2013), to avoid a collinearity problem, Equation (10) should include at least one additional variable that is not present in Equation (13). This variable is assumed to determine the selection of the dependent variable—whether the individual migrates—but not to determine the final outcome—the distance moved.

Potential migrants from MSAs with better economic conditions can be expected to (already) receive relatively high wages or face a lower likelihood of unemployment. This translates into increased net gains from staying, lowering the likelihood of migration. Thus, the variable selected is the MSA personal income per capita in 1997, as economic conditions in the first observed MSA of residence are likely to play a role in whether migration is observed within our sample period. Specifically, higher MSA personal income per capita is expected to be a determinant of nonselection into migration, while a relationship with the total distance moved seems less likely or less easy to hypothesize. Nonetheless, one could argue that possible spillover effects to neighboring areas following worsening economic conditions in a given MSA may induce migrants from that MSA to move as far away as possible. To account for this potential problem, the exclusion variable is tested across different subgroups of migrants with increasingly greater migration distances.

3.3 | Recursive bivariate probit specification

A violation of the assumption that ϵ_i is independent of the explanatory variables in Equation (10) would lead to biased estimates. There may be some factors not usually considered among the conventional determinants of migration that are correlated with both individual attitudes towards risk and migration propensities. For example, parental educational attainment plays a significant role in shaping an individual's willingness to take risks (Dohmen et al., 2011) but also has been shown to have an effect on offsprings' future educational attainment (Chevalier et al., 2013), which increases the expected payoffs of migration, making the individual more likely to move (cf. Section 2). Therefore, it is possible that individuals' willingness to take risks is of an endogenous nature.

In case of a binary outcome, conventional two-stage instrumental variable methods assume that the endogenous regressors are continuous (Wooldridge, 2010). Therefore, its use with a discrete endogenous regressor, particularly a binary one, may not be appropriate (Freedman & Sekhon, 2010), and simultaneous likelihood estimation procedures are preferred to account for the endogeneity derived from the presence of unobservables (Marra & Radice, 2011). Consider thus the following bivariate probit model, in which a dichotomous measure of the attitudes towards risk of individual i is modeled by the latent variable, r_i^* ,

$$\begin{aligned} r_i^* &= \alpha w_i + u_i, \quad i = 1, \dots, N \\ \text{with } r_i &= 1 \quad \text{if } r_i^* > 0 \quad \text{and } r_i = 0 \quad \text{otherwise,} \end{aligned} \quad (14)$$

and the decision of i to migrate across MSAs is modeled by

$$\begin{aligned} y_i^* &= \beta x_i + \delta r_i + \epsilon_i, \quad i = 1, \dots, N \\ \text{with } y_i &= 1 \quad \text{if } y_i^* > 0 \quad \text{and } y_i = 0 \quad \text{otherwise,} \end{aligned} \quad (15)$$

which is a reformulation of Equation (10) that includes the endogenous regressor r_i . Following Greene (2003), the latter takes the form of a recursive bivariate probit model of simultaneous equations, given that the endogenous

variable r_i appears on the right-hand side of Equation (15) and the outcome variable y_i is not a regressor in any equation (Kassouf & Hoffmann, 2006). Both equations include vectors of exogenous explanatory variables, x_i and w_i , and error terms, ϵ_i and u_i , that are assumed to have a bivariate normal distribution and not to be independent of each other. The correlation between the unobservables in both equations is determined by the correlation coefficient ρ ,

$$\rho = \text{Cov}[u_i, \epsilon_i | w_i, x_i] \quad (16)$$

whose statistical significance determines if the binary measure of individual attitudes towards risk and the binary migration decision are indeed simultaneously determined. According to Marra and Radice (2011), to induce variation in the treatment, Equation (14) should contain at least one additional regressor that is not present in Equation (15) and that is not directly related to the outcome. Given that a higher willingness to take risks is associated with a higher propensity to smoke (Dohmen et al., 2011; Jenks, 1992) and that risk attitudes have been found to be shaped by parental attitudes towards risk (Hryshko et al., 2011), an exclusion restriction is selected, namely a dummy variable that takes the value of 1 if at least one parent of the individual was a smoker, and zero otherwise. According to Greene (2003), the covariates included in the vector, x_i , directly influence the probability that y_i equals one. Variables that appear as regressors in both equations (14) and (15) influence the probability that r_i equals one, an effect that is transmitted back to y_i due to the inclusion of r_i in the right-hand side of Equation (15). The total marginal effects of these variables are calculated as the sum of these direct and indirect effects. The marginal effects of variables that appear only in Equation (15) consist only of direct effects, whereas the exclusion restriction appearing only in Equation (14) is assumed to consist only of an indirect effect on y_i . Finally, the marginal effect of attitudes towards risk in the outcome equation can be evaluated by the difference between the conditional probabilities of migrating when the binary risk measure equals 1, and when the risk measure is zero, that is,

$$\text{Prob}(y_i = 1 | w_i, x_i, r_i = 1) - \text{Prob}(y_i = 1 | w_i, x_i, r_i = 0) \quad (17)$$

setting $r_i = 1$ and $r_i = 0$ in turn for each observation, and then averaging over observations.

4 | DATA, VARIABLES AND SUMMARY STATISTICS

The data source for this study is the PSID of the University of Michigan, a representative longitudinal panel survey of households in the United States. From 1997 to 2015, 10 biennial waves of the PSID with information on socioeconomic and labor-market characteristics are merged with a Geospatial data set that includes disaggregated geographical information for individuals participating in the survey. In addition, we use the 1996 wave of the PSID, which contains a comprehensive set of hypothetical-gamble questions related to lifetime income used to elicit attitudes towards risk of all employed heads of household.

4.1 | Independent variable: Individual risk attitudes

Risk attitudes are underlying attributes that cannot be directly observed. They need to be elicited from experiments or survey responses.¹⁵ When studying the behavioral consequences of risk attitudes, self-assessment survey responses are commonly used. However, risk attitudes elicited in a more comprehensive way through hypothetical-gamble questions are also often used to explain economic behavior (see e.g., Cramer et al., 2002;

¹⁵For a comprehensive review of risk elicitation methods, see Charness et al. (2013).



Guiso & Paiella, 2004; Schmidt, 2008). Regardless of the elicitation method, a critical concern related to risk attitudes has to do with their stability.

According to Josef et al. (2016), individual risk-taking propensities can be considered as a personality trait, much similar to the Big Five personality traits studied in psychology. In this sense, these propensities can be regarded as particular, individual-specific risk attitudes for which some degree of temporal stability across the lifespan of the individual is expected. This depends, however, on how stability is conceptualized. Following the literature on personality research, Josef et al. (2016) identify two conceptualizations of stability that are relevant for this study. First, differential stability focuses on temporal between-variations, that is, it refers to the degree to which relative differences across individuals are maintained over time. They find that those who are relatively more (less) willing to take risks than others remained relatively more (less) likely to take risks as compared to others over time. The second dimension, individual-level stability, deals with within-variations, meaning that the focus lies on how consistent risk attitudes are at the level of the individual. They find no correlation of individual-level changes in risk-taking propensities with within-person changes in income. These results suggest that propensities in risk-taking can be understood as an individual personality trait with moderate stability across the life-cycle.

Additionally, a relative temporal stability has been found for risk attitudes elicited through different elicitation methods,¹⁶ including hypothetical-gamble questions about lifetime income (Sahm, 2012). Furthermore, the temporal stability of risk attitudes has been assumed in the empirical literature that studies its relation with economic behavior, including migration;¹⁷ and in studies using risk attitudes elicited through the questions posed in the 1996 wave of the PSID.¹⁸ Based on the literature reviewed above we treat our risk-aversion variable as time-invariant, but include some robustness checks.

In the 1996 wave of the PSID, all employed heads of household are asked the first question (M1), which reads as follows:¹⁹

Now I have another kind of question. Suppose you had a job that guaranteed you income for life equal to your current, total income. And that job was [your/your family's] only source of income. Then you are given the opportunity to take a new, and equally good job, with a 50-50 chance that it will double your income and spending power. But there is a 50-50 chance that it will cut your income and spending power by a third. Would you take the new job?²⁰

Depending on the answer given to the first question, respondents were then asked a follow-up question. Those who answered "yes" were asked (M2):

Now, suppose [that] the chances were 50-50 that the new job would double [your/your family's] income, and 50-50 that it would cut it in half. Would you still take the job?

If the individual answered "no" to question (M2), then the questionnaire was over. However, those who answered "yes" were asked question (M5):

¹⁶Using self-assessment survey measures, Dohmen et al. (2007) find stability over 2 years; and Andersen et al. (2008) find no general tendency of variation of risk attitudes elicited by experiments over 17 months.

¹⁷For example, observed migration in Jaeger et al. (2010) occurs between 2000 and 2006, and their risk information is collected in 2004.

¹⁸Kan (2003) explains decisions about job changes between 1991 and 1993 (5 years); while Charles and Hurst (2003) explain the likelihood to invest in stocks between 1984 and 1989 (12 years).

¹⁹The questions are textual citations of the Public Release Family File Codebook (see Panel Study of Income Dynamics, 1996).

²⁰Notice that the question states that the new job will be an equally good job, meaning that there is no difference in its nonmonetary characteristics. According to Barsky et al. (1997), individuals may be less willing to accept the new job if they have some type of nonmonetary attachments to their current job.

TABLE 1 Construction of the risk-index

Risk index	Decision rule					
0	if	M1 = "No"	&	M3 = "No"	&	M4 = "No"
1	if	M1 = "No"	&	M3 = "No"	&	M4 = "Yes"
2	if	M1 = "No"	&	M3 = "Yes"		
3	if	M1 = "Yes"	&	M2 = "No"		
4	if	M1 = "Yes"	&	M2 = "Yes"	&	M5 = "No"
5	if	M1 = "Yes"	&	M2 = "Yes"	&	M5 = "Yes"

Note: Constructed based on S. Brown et al. (2012).

Now, suppose that the chances were 50-50 that the new job would double [your/your family's] income, and 50-50 that it would cut it by 75 percent. Would you still take the new job?

On the other hand, individuals who gave a negative answer to question (M1), were then asked question (M3):

Now, suppose [that] the chances were 50-50 that the new job would double [your/your family's] income, and 50-50 that it would cut it by 20 percent. Then would you take the job?

If the individual answered "yes" to question (M3), then the questionnaire was over. However, those who answered "no" were asked question (M4):

Now, suppose that the chances were 50-50 that the new job would double [your/your family's] income, and 50-50 that it would cut it by 10 percent. Then would you take the new job?

A decision tree illustrating the respondents' decision making process can be found in Appendix B (see Figure B1). Following the methodology used by S. Brown et al. (2012), the responses are used to build a six-point index of the risk preferences of the heads of household. Table 1 illustrates the construction of the risk-index based on the answers provided by respondents to the sequence of the hypothetical gambles. The resulting index is decreasing in risk-aversion given that those who are willing to accept all the hypothetical gambles obtain a five—the highest value in the index. On the other hand, those who reject all the hypothetical gambles offered get a zero.²¹ Furthermore, as stated by Barsky et al. (1997, p. 540) "the categories can be ranked by risk aversion without having to assume a particular form for the utility function."

4.2 | Dependent variable: Migration

The geographic units selected for this study are MSAs. Each MSA consists of one or more counties with an urban area with a population of at least 50,000 and a high degree of social and economic integration—as measured by commutes to work (U.S. Office of Management and Budget, 2018). The U.S. Office of Management and Budget (OMB) has defined 383 MSAs (for a map, see Figure B2 in Appendix B). Given the size of the panel, not all MSAs are observed and, moreover, missing observations are likely to appear. There was missing information related to

²¹Following Jaeger et al. (2010), a binary risk-indicator is also constructed, which takes the value of 1 if a respondent obtains a value of 3 or higher in the scale.



MSAs in 14 observations, which were corrected by matching the county and the state of residence of respondents, leaving our sample with 256 of the MSAs defined by the OMB (for a list, see Table B1 in Appendix B).

By definition, MSAs do not cover rural areas. However, the PSID data set allows us to identify non-MSA regions in each state in the United States and enables us to also consider rural-to-urban and urban-to-rural migration. Therefore, our sample further includes 44 “artificial MSAs,” each one representing each state’s non-MSA region.²² MSAs are well suited for the purpose of this study as each geographical unit in the analysis should represent a distinct labor market capturing an agglomeration of economic activity, in order for the assumption of risk (and uncertainty) related to different regions to hold. The act of migration is thus defined as a move from one MSA to another. Migration is a dummy variable that takes the value of 1 if in period t an individual (head of household) resides in a different MSA as in $t - 1$.²³ All individuals who answered the risk questions in 1996 and remained in the sample in 2015 were included in the analysis. As a result, we are left with a balanced panel data set that allows us to track the migration history of 2005 heads of household across 256 MSAs, over 10 biennial waves of the PSID for a period of 18 years.

4.3 | Control variables

The literature on the determinants of migration reviewed above serves to guide the selection of control variables. These variables are categorized into socioeconomic, labor-market characteristics, and other control variables. Given the way the dependent variable is constructed, all the control variables are lagged by one period, when arguably, the migration decision was made

(a) Socioeconomic characteristics

We control for individual characteristics of the heads of household like gender, age, marital status, years of education, as well as for household level characteristics like the number of children in the household (if any) and family income. A total of 226 missing values across 49 individuals were identified for the variable years of education, which were replaced by the last nonmissing observation available for the respective individual. Remaining missing values were dealt with by using the next nonmissing observation available if the individual was 25 years old or older, under the assumption that people of this (or older) age are likely to have finished their educational path.²⁴ On the other hand, 69 observations across 61 individuals reported negative or zero income. These were recoded to 1 to avoid undefined values of the logarithms of the family income.

(b) Labor-market characteristics

Given that there are economic activities that require more location-specific capital (human and otherwise) than others (Shields & Shields, 1989), which in turn plays a role in migration propensities (DaVanzo, 1981), we control for nine types of industry. Also, a factor variable indicating the employment status of the heads of the household is added as an additional covariate.

²²Chen and Rosenthal (2008) follow a similar approach. Delaware, the District of Columbia, New Jersey, and Rhode Island do not have non-MSA regions. Furthermore, in our sample, we do not have individuals in rural areas in Connecticut, Maine, and Maryland.

²³Even though the human capital model focuses on the individual as the decision maker, migration is often a family decision. Here, the family is assumed to be a unit in which either all stay or all migrate (Mincer, 1978), and the head of household acts as a decision-maker who bases his/her decision on the family’s expected net gains from migration.

²⁴After applying these corrections, four missing observations across three individuals remained.

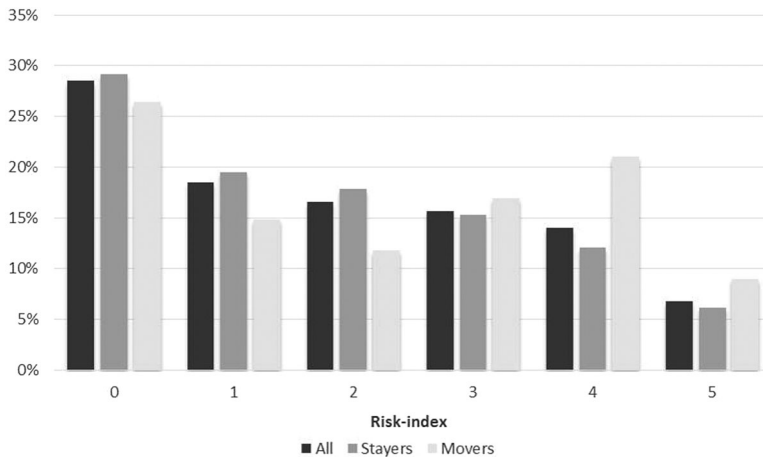


FIGURE 1 Distribution of the risk-index among stayers and movers

(c) Other control variables

To capture economic conditions in the MSAs, which may influence individuals' migration decisions, we use the MSA personal income per capita (in thousands of US dollars). In parts of the estimations, we also include 51 state dummies to capture other regional effects. The state controls are selected because—following the Tiebout (1956) hypothesis—state effects may play a role in determining migration propensities, given that it is at this administrative level that usually tax, property, and criminal legislation are enacted. Furthermore, the state of Louisiana is selected as the reference category, given that the city of New Orleans and its surrounding areas were the most affected by hurricane Katrina, an external shock that may have caused some forced relocations in its aftermath. Additionally, to control for another external shock, we include a dummy variable that takes the value of 1 for observations from waves coming after the global financial crisis of 2008. Overall, the sample consists of 18,028 period-individual observations.²⁵

4.4 | Summary statistics

Figure 1 shows the distribution of the risk-index differentiating among “Stayers” (those who never moved) and “Movers” (those who moved at least once).²⁶ Forty-nine percent of stayers exhibit the two lowest scores of the risk-index, while only 41% of movers fall in the same category of risk-aversion. On the other hand, the proportion of movers that are less risk averse is greater than the share of stayers with a similar predisposition to take risks. The two highest scores in the index correspond to 18% of stayers, whereas 30% of movers are in that group.

Table 2 presents a summary statistics at the individual level, for the 2005 heads of household in our sample. This is constructed using the arithmetic mean of the individual means of the variables over time. A total of 432 individuals (22%) are movers. The mean of the risk index of the heads of household is 1.89 and the SD is 1.62.

²⁵Thirteen observations are dropped by the statistical software due to the dummy = 1 for the state of Vermont predicting failure perfectly. Overall, with the four missings in education, there are 17 observations less than the 18,045 we should have for the 2005 individuals in our sample, given that we observe migration (with respect to 1997) starting in 1999.

²⁶See also Table B2 in Appendix B for a tabulation of the 6-point scale of the risk-index and the binary risk-indicator in the regression sample of 2005 individuals.

**TABLE 2** Summary statistics at the individual level

Variable	Individuals (<i>n</i>)	Mean	SD	Min.	Max.
Dependent variable					
Mover	2005	0.2154	0.4112	0	1
Key explanatory variable					
Risk-index	2005	1.8842	1.6252	0	5
Socioeconomic characteristics					
Female	2005	0.1790	0.3834	0	1
Age	2005	50.5392	10.3180	28	85
Married	2005	0.6707	0.4307	0	1
Number of children	2005	0.6885	0.7896	0	5.4
Years of education	2005	13.6948	2.1759	5.8	17
Home ownership	2005	0.7753	0.3413	0	1
Log of total family income	2005	10.9806	0.8057	6.7	14.1

Note: Migration is a dummy variable that takes the value of 1 if the individual moved across MSAs at least once between 1997 and 2015. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse/5 = least risk-averse. Factor variables like employment status and type of industry are not included.

Eighteen percent of households have female heads. On average, the heads of households are 51 years old and have 14 years of schooling.

The averages of the risk-index separated for both stayers and movers in the regression sample are presented in Table 3. These averages are larger for movers than for stayers across all characteristics, (almost) all being statistically significantly different from 0 at least at the 10% level of significance. Furthermore, those who moved more often are more risk-friendly than those who moved only once. Not only are the results from these comparisons a first indication in favor of the hypothesis that movers are likely to be more risk-tolerant than stayers, but also they conform well with what is expected based on the risk-related empirical literature. The average risk-index is larger for males than for females for both stayers and movers (both at the 1% significance level), which goes in line with Barsky et al. (1997), and Jaeger et al. (2010). Younger heads of household are consistently more risk-tolerant than older ones at the 5% level (Dohmen et al., 2011; Jaeger et al., 2010), and more educated individuals tend to be less risk-averse at the 1% level (Halek & Eisenhauer, 2001; Jaeger et al., 2010).²⁷

5 | RISK ATTITUDES AND MIGRATION, RANDOM-EFFECTS ESTIMATIONS

In a first step, we focus on migration as a binary choice at any point in time. We study the relationship between risk attitudes and the probability to migrate across MSAs, test alternative specifications with different sets of covariates and conduct a series of subsample analyses. Furthermore, to rule out the possibility of the results being driven by our particular geographic characterization, we explore different definitions of moves. In the next section, we will consider cross-section estimations as the second step of our analysis.

²⁷The significance levels of the within-stayer/mover-group comparisons are not mentioned in Table 3.

TABLE 3 Average measures of risk attitudes for stayers and movers

Variable	Average risk-index for	
	Stayers	Movers
All	1.80	2.18***
One move ^a		2.08***
Two moves ^a		2.21***
Three or more moves ^a		2.44***
Gender		
Female	1.62	1.75
Male	1.84	2.24***
Age		
<35	1.96	2.38***
35–65	1.85	2.18***
>65	1.17	1.93***
Marital status		
Married	1.80	2.09***
Nonmarried	1.68	2.23***
Children		
Yes	1.99	2.20***
No	1.71	2.15***
Years of education		
<12	1.65	1.90***
12–14	1.71	1.96***
>14	1.96	2.45***
Home ownership		
Yes	1.72	2.05***
No	1.93	2.13*
Log of total family income		
≤11	1.66	1.98***
>11	1.91	2.33***

Note: “Stayers” refers to individuals who never moved in the sample period 1997–2015. “Movers” indicates those who moved at least once. The values presented are the arithmetic mean of the individual means of the variables over time. For all Stayers-Movers comparisons: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse/5 = least risk-averse.

^at-tests on the equality of means with the sample with one less move. For the sample with only one move, the comparison is done with the mean of the Stayers. Factor variables like employment status and type of industry are not included.

5.1 | Cross-MSA migration baseline results

To analyze the relation of individuals' risk attitudes and migration propensities, we present the average marginal effects (AMEs) of a random-effects probit model (Table 4).²⁸ Given the way the dependent variable is constructed

²⁸Table B3 in Appendix B presents the summary statistics of the regression sample, with a mean of migration of 0.0417. Table B4 presents summary statistics of additional control variables used throughout the paper.



TABLE 4 Risk attitudes and the probability of migrating across MSAs between 1997 and 2015

Dependent variable: Cross-MSA migration since t-1	(1)		(2)		(3)		(4)	
	AME	SE	AME	SE	AME	SE	AME	SE
Key explanatory variable								
Risk-index ^a	0.0056***	(0.0013)	0.0043***	(0.0012)	0.0028**	(0.0012)	0.0027**	(0.0011)
Control variables (t-1)								
Socioeconomic characteristics								
Female ^a			-0.0189***	(0.0045)	-0.0262***	(0.0043)	-0.0252***	(0.0043)
Age			-0.0011***	(0.0001)	-0.0011***	(0.0001)	-0.0012***	(0.0002)
Married					-0.0095*	(0.0050)	-0.0094*	(0.0050)
Number of children					-0.0058***	(0.0017)	-0.0055***	(0.0017)
Years of education					0.0056***	(0.0009)	0.0054***	(0.0009)
Home ownership					-0.0436***	(0.0057)	-0.0451***	(0.0058)
Log of total family income					0.0020	(0.0016)	0.0032*	(0.0017)
Labor-market characteristics								
Employed (R.)								
Unemployed							0.0209**	(0.0091)
Retired							0.0231**	(0.0095)
Other employment status							0.0082	(0.0104)
Type of industry								
Construction/manufacturing (R.)								
Finance/real state							0.0087	(0.0085)
Mining/agriculture/ forestry/fisheries							-0.0103	(0.0096)
Transport/utilities/ communications							0.0026	(0.0064)
Wholesale/retail trade							-0.0053	(0.0054)
Professional/ business serv.							-0.0013	(0.0047)
Personal/ entertainment serv.							-0.0026	(0.0087)
Public administration							0.0112	(0.0074)
Other							-0.0004	(0.0073)
Financial crisis dummy							-0.0055	(0.0039)
MSA personal income per capita							-3 × 10 ⁻⁵	(0.0002)
State dummies							Yes	
Observations	18,028		18,028		18,028		18,028	
Individuals	2005		2005		2005		2005	

(Continues)

TABLE 4 (Continued)

Dependent variable: Cross-MSA migration since $t-1$	(1)		(2)		(3)		(4)	
	AME	SE	AME	SE	AME	SE	AME	SE
Baseline migration probability	0.0417		0.0417		0.0417		0.0417	
Rho	0.4290		0.4184		0.3711		0.3339	

Note: Average marginal effects (AMEs) of random-effects probit models are reported. Standard errors (SEs) are shown in parentheses. Migration is a dummy variable that takes the value of 1 if the individual moved across MSAs since $t - 1$. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse/5 = least risk-averse. Financial crisis is a dummy variable that takes the value of 1 if $t \geq 2009$. Probit coefficients are reported in Table B5 in Appendix B.

(R.) Reference category.

^aTime invariant variable.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

(migration = 1 if the individual changed MSAs since $t - 1$, and zero otherwise), all the control variables are lagged by one period, when arguably, the migration decision was made. Column 1 uses only the risk-index variable, while Column 2 additionally considers gender and age, factors that are likely exogenous to an individual's decision to migrate. In Column 3, other socioeconomic characteristics are added as additional regressors. Finally, Column 4 shows the results when also controlling for labor-market characteristics, the global financial crisis, MSA economic conditions, and state effects. All four specifications show that being relatively more willing to take risks is positively and statistically significantly related to the likelihood of engaging in migration across MSAs. The estimated AMEs reduce in magnitude as additional control variables are included (from 0.0056 in Column 1 to 0.0027 in Column 4), nonetheless the effect of risk attitudes on the probability of migrating remains strongly significant at the 5% level. This decline is consistent with variables like age and gender being strong predictors of risk attitudes (see Barsky et al., 1997; Dohmen et al., 2007; Dustmann et al., 2017), and marital status and years of schooling being in part jointly determined with migration (Jaeger et al., 2010).

These results are economically significant, given that in our most restrictive specification, a one-unit change in the risk-index increases the probability that an individual migrates between MSAs by 0.27%. This implies that a one-SD increase (1.62 points) in the willingness to take risks is associated with a 0.44 percentage point increase in the migration probability, which represents around 9.5% of the baseline cross-MSA migration probability of 4.17%. This specification was also reestimated adding the squared value of age as a covariate to capture a potential nonlinear relationship with migration, and including the education variable categorically to differentiate between individuals with at most a high school degree and those with college experience, as their migration patterns may differ (Faggian & Franklin, 2014). Both the magnitude and the statistical significance of the effect of the risk-index remained unchanged. Additionally, a specification using the binary risk-indicator was also estimated. As expected, there is a strong, positive, and highly significant relationship between the years of education and the likelihood of migration across MSAs, while a negative and highly significant relationship can be established between age and the probability of migration. These results go in line with the findings of Jaeger et al. (2010) and Williams and Baláž (2014). The presence of children in the household reduces the probability of migration, which goes in line with the results of Haussen and Uebelmesser (2018). In accordance with the findings of Hao et al. (2014) and Akgüç et al. (2016), a negative relationship can be established between being a female head of household and the probability of migration. Compared to those who were employed in period $t - 1$, those who were unemployed or retired are positively and significantly more likely to migrate.

**TABLE 5** Risk attitudes and the probability of migrating across MSAs: Alternative controls (I)

Dependent variable	(1)		(2)		(3)	
	Previous migration experience		Family income per capita		Equivalised family income	
Cross-MSA migration since t-1	AME	SE	AME	SE	AME	SE
Key explanatory variable						
Risk-index ^b	0.0020**	(0.0009)	0.0027**	(0.0011)	0.0027**	(0.0011)
Previous migration experience						
Moved before in the sample period	0.0362***	(0.0067)				
Family income per capita						
Log of family income p.c.			0.0031***	(0.0008)		
Equivalised log of family income p.c.					0.0042***	(0.0011)
Control variables (t-1)						
Socioeconomic characteristics	Yes		Yes ^a		Yes ^a	
Labor-market characteristics	Yes		Yes		Yes	
Type of industry	Yes		Yes		Yes	
Financial crisis dummy	Yes		Yes		Yes	
MSA personal income per capita	Yes		Yes		Yes	
State dummies	Yes		Yes		Yes	
Observations	18,028		18,028		18,028	
Individuals	2005		2005		2005	
Baseline migration probability	0.0417		0.0417		0.0417	
Rho	0.1335		0.3328		0.3326	

Note: Average marginal effects (AMEs) of random-effects probit models are reported. Standard errors (SEs) are shown in parentheses. Migration is a dummy variable that takes the value of 1 if the individual moved across MSAs since $t-1$. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse/5 = least risk-averse. Financial crisis is a dummy variable that takes the value of 1 if $t \geq 2009$. Probit coefficients are reported in Table B6 in Appendix B. (R.) Reference category.

^aDoes not include total family income and number of children.

^bTime invariant variable.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

5.2 | Alternative controls and subsample analyses

To analyze the robustness of our results to the selection of alternative covariates, Column 1 of Table 5 controls for migration experience, given that repeat migration is likely to occur if an individual has moved before (DaVanzo, 1981, 1983). For this, we include a dummy variable that takes the value of 1 if, in $t-1$, migration was already

observed within our sample period. The effect of the willingness to take risks remains significant at the 5% level and is associated with an increase in the probability of moving that represents around 8% of the baseline migration probability, which is smaller than the effect observed in the base specification. Not only can we observe that having moved before plays an important role in the decision to migrate, but also that the effect of individual attitudes towards risk seems to be partially substituted away by migration experience. Column 2 combines the total family income and the number of children into one variable denoting the total family income per capita. Due to economies of scale, household expenses may not grow proportionally with the growth of the household's size. If that is the case, an equivalisation method is needed to adjust how resources are shared within households due to their composition. Following OECD (2008), in Column 3, the total family income is divided by the square root of the family size. Compared to the baseline specification, both the magnitudes and the statistical significance of the effects of the risk-index remain unchanged.

Column 1 of Table 6 includes the ethnicity of the respondents as an additional covariate. Even though ethnic characteristics tend to be included in the empirical literature of the determinants of migration, it is sensible to consider that it is not ethnicity alone that has an effect, but rather its correlation with education or income, particularly in the United States (see Greenwood, 1975). According to Shields and Shields (1989), there is no theoretical justification for considering that ethnicity may increase or reduce the costs of migration. Compared to those of white ethnicity, African-Americans and Asian-Americans are significantly less likely to migrate. Column 2 modifies the dummy variable denoting whether an individual was married, to see if specific changes in marital status since the last observed period are particularly relevant. Being more willing to take risks remains positively and statistically significantly related to the likelihood of cross-MSA migration, with the AME for the risk-index being practically of the same magnitude as in the baseline results. Compared to those who were married in period $t - 1$ and remained married in period t , those who changed their marital status and those who remained non-married across both periods are all more likely to migrate. Specification 3 modifies the employment status variable in a similar manner. Compared to the baseline specification, both the magnitudes and the statistical significance of the effects of the risk-index remain unchanged. Those who lost their jobs (changed their status from employed to unemployed), and those who found a new job (went from being unemployed to employed), are both more likely to have migrated, compared to those who remained employed. These results are not surprising, considering that changing one's employment status may increase the likelihood of migration, given that job turnover and migration decisions may be closely related (Haussen & Uebelmesser, 2018).

Table 7 explores how the relationship between individuals' risk-attitudes and migration propensities changes when excluding individuals from the sample who may affect the results in a given direction. The baseline specification of Table 4 is estimated, but focusing only on respondents who were 30 years of age or older in 1997 (Column 1). This is done to exclude younger individuals who may have overstated their willingness to take risks due to their young age. Analogously, Column 2 removes respondents who were older than 65 years of age in 2015, that is, those who were born before 1950 and may have been overly cautious when answering the risk questions in 1996. Furthermore, Column 3 excludes both younger and older individuals. By grouping respondents in subsamples of similar age, these specifications serve as a sort of robustness check for the assumption of risk attitudes being time invariant. When excluding younger individuals, being more willing to take risks is associated with an increase in the probability of moving that is slightly lower than 12% of the base migration probability for this subsample. For the subsamples in Columns 2 and 3, the effects of the risk-index represents around 14% and 16% of their base migration probability, respectively. Finally, Column 4 restricts the sample to only include male heads of household, leading to an effect of risk attitudes that is slightly larger than the one in the baseline specification.

To analyse if the observed effects of risk attitudes on migration propensities vary by educational attainment, Columns 5 and 6 in the bottom panel of Table 7 consider subsamples of individuals with more than 12 years of education (completed high school) and with 14 years of education or less (no more than college education), respectively. Restricting the sample to those with at least high school education leads to an effect of risk attitudes that is slightly larger than the one in the baseline specification. On the other hand, the size of the effect for those

TABLE 6 Risk attitudes and the probability of migrating across MSAs: Alternative controls (II)

Dependent variable:	(1)		(2)		(3)	
	Ethnicity		Change in marital status		Change in employment status	
Cross-MSA migration since $t-1$	AME	SE	AME	SE	AME	SE
Key explanatory variable						
Risk-index ^b	0.0020*	(0.0011)	0.0026**	(0.0011)	0.0027**	(0.0011)
Ethnicity ^b						
White (R.)						
African-American	-0.0302***	(0.0040)				
Native-American	-0.0141	(0.0178)				
Asian-American	-0.0346***	(0.0133)				
Other ethnicity	0.0005	(0.0195)				
Changes in marital status						
Married to married (R.)						
Married to nonmarried			0.0626***	(0.0157)		
Nonmarried to married			0.0214**	(0.0106)		
Nonmarried to nonmarried			0.0121**	(0.0054)		
Changes in employment status						
Employed to employed (R.)						
Employed to unemployed					0.0398***	(0.0120)
Unemployed to employed					0.0383***	(0.0108)
Unemployed to unemployed					0.0235	(0.0183)
Other changes					0.0452***	(0.0073)
Control variables ($t-1$)						
Socioeconomic characteristics	Yes		Yes ^a		Yes	
Labor-market characteristics	Yes		Yes		No	
Type of industry	Yes		Yes		Yes	
Financial crisis dummy	Yes		Yes		Yes	
MSA personal income per capita	Yes		Yes		Yes	
State dummies	Yes		Yes		Yes	
Observations	18,028		18,028		18,028	
Individuals	2005		2005		2005	
Baseline migration probability	0.0417		0.0417		0.0417	
Rho	0.3098		0.3340		0.3390	

Note: Average marginal effects (AMEs) of random-effects probit models are reported. Standard errors (SEs) are shown in parentheses. Migration is a dummy variable that takes the value of 1 if the individual moved across MSAs since $t-1$. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse/5 = least risk-averse. Financial crisis is a dummy variable that takes the value of 1 if $t \geq 2009$. Probit coefficients are reported in Table B7 in Appendix B. (R.) Reference category.

^aDoes not include marital status.

^bTime invariant variable.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

who at most completed 2 years of college education represents around 13% of the base migration probability for the respective subsample. The role played by migration experience in the decision to move may be particularly relevant when considering those who have migrated across international borders. Column 7 thus excludes those who have international migration experience, meaning that they either grew up or were born abroad. Related to the respective base migration probabilities, the effect of risk attitudes is slightly lower as compared to the baseline results (9%). Finally, Column 8 excludes individuals who work in public administration, as this industry category includes those working in the military, who may be more likely to be frequently relocated. Being relatively more willing to take risks is associated with an increase in the migration probability that represents around 10% of the migration probability for the subsample.

5.3 | Alternative definitions of migration

Even though MSAs are assumed to represent distinct labor markets, they do not cover the totality of the US territory. The addition of the 44 “artificial MSAs” for each state with rural regions allows us to go beyond urban-to-urban migration across MSAs as defined by the OMB. Thus, we are able to observe any occurrence of urban-to-rural and rural-to-urban migration, but rural-to-rural mobility is observed only when it occurs across state borders. Given that the US states vary largely in terms of area, this specification may not be proper if it fails to capture migration occurring between rural areas within larger states like Texas (676,587 km²) or California (403,466 km²). To address this problem, specification 1 in Table 8 modifies the migration dummy to also take the value of 1 if an individual moves across two rural counties within the same state. This allows us to observe 74 additional instances of migration which occurred across rural counties within 24 states, increasing the baseline migration probability to 4.58%. The associated effect between risk attitudes and the respective migration probability (10%) is slightly larger than the one in the baseline results.

In the human capital model, the monetary costs of migration are related to distance (Sjaastad, 1962), and psychic costs from leaving family and friends behind are likely to increase with distance as well (Schwartz, 1973). In principle, a cross-state move should require traveling a larger distance than a move to a neighboring MSA. But more importantly, under the hypothesis that “people vote with their feet” (Tiebout, 1956), cross-state comparisons of amenities may play a role in migrant self-selection given that it is at this administrative level that tax, property, and criminal legislation are usually enacted. So, in general, moving across states could be considered to bear higher costs together with higher uncertainty than relocating to a different MSA within the same state. If the uncertainty associated with migration is increased, individual risk attitudes should play a larger role as determinants of migration, other things equal. Column 2 in Table 8 considers the baseline specification, but with a dependent dummy variable that takes the value of 1 if the individual moved across states since $t - 1$. The estimated effect of the risk-index on the cross-state migration probability is slightly larger as the effect observed for cross-MSA migration. A one-standard-deviation increase in the willingness to take risks is associated with an increase in the cross-state migration probability that represents a little more than 10% of the baseline cross-state migration probability of 2.80%.

Moving across states does not necessarily translate into moves of larger distance. It is possible that two adjacent MSAs may be separated by a state line (e.g., Cleveland, TN and Dalton, GA), or that the territory of an MSA goes across state lines (e.g., Kansas city, MO-KS).²⁹ To properly analyze the association between migration costs and further away moves, it is important to consider the actual distance traveled by those who migrate. Following Sinnot (1984), distance is measured using the straight-line of the “great circle” distance identified based

²⁹A total of 33 MSAs in our regression sample cover territory in more than one state.



TABLE 7 Risk attitudes and the probability of migrating across MSAs: Subsample analyses

	(1)		(2)		(3)		(4)	
	No younger than 30 y.o. in 1997		No older than 65 y.o. in 2015		Older than 30 (1997)/younger than 65 (2015)		No female heads of household	
Dependent variable: Cross-MSA migration since t-1	AME	SE	AME	SE	AME	SE	AME	SE
Key explanatory variable								
Risk-index ^a	0.0027**	(0.0012)	0.0039***	(0.0014)	0.0041***	(0.0015)	0.0030**	(0.0013)
Control variables (t-1)								
Socioeconomic characteristics	Yes		Yes		Yes		Yes	
Labor-market characteristics	Yes		Yes		Yes		Yes	
Type of industry	Yes		Yes		Yes		Yes	
Financial crisis dummy	Yes		Yes		Yes		Yes	
MSA personal income per capita	Yes		Yes		Yes		Yes	
State dummies	Yes		Yes		Yes		Yes	
Observations	15,414		12,931		10,326		14,778	
Individuals	1714		1438		1148		1644	
Baseline migration probability	0.0366		0.0458		0.0392		0.0459	
Rho	0.3467		0.3384		0.3571		0.3396	

Dependent variable: Cross-MSA migration since t-1	(5)		(6)		(7)		(8)	
	AME	SE	AME	SE	AME	SE	AME	SE
Key explanatory variable								
Risk-index ^a	0.0029**	(0.0012)	0.0029**	(0.0013)	0.0023*	(0.0012)	0.0025**	(0.0012)
Control variables (t-1)								
Socioeconomic characteristics	Yes		Yes		Yes		Yes	
Labor-market characteristics	Yes		Yes		Yes		Yes	
Type of industry	Yes		Yes		Yes		Yes	
Financial crisis dummy	Yes		Yes		Yes		Yes	
MSA personal income per capita	Yes		Yes		Yes		Yes	
State dummies	Yes		Yes		Yes		Yes	
Observations	15,994		11,430		16,913		16,573	
Individuals	1831		1345		1881		1953	
Baseline migration probability	0.0439		0.0356		0.0420		0.0406	
Rho	0.3400		0.3562		0.3441		0.3407	

Note: Average marginal effects (AMEs) of random-effects probit models are reported. Standard errors (SEs) are shown in parentheses. Migration is a dummy variable that takes the value of 1 if the individual moved across MSAs since t-1. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse/5 = least risk-averse. Financial crisis is a dummy variable that takes the value of 1 if t ≥ 2009. Probit coefficients are reported in Table B8 in Appendix B.

^aTime invariant variable.

***p < 0.01; **p < 0.05; *p < 0.1.



TABLE 8 Risk attitudes and the probability of migrating: Alternative definitions of migration

Dependent variable	(1)		(2)		(3)		(4)	
	AME	SE	AME	SE	AME	SE	AME	SE
All migration types								
Key explanatory variable	0.0029**	(0.0012)	0.0018*	(0.0009)	0.0025**	(0.0010)	0.0018*	(0.0009)
Risk-index ^a								
Control variables (t-1)								
Socioeconomic characteristics	Yes		Yes		Yes		Yes	
Labor-market characteristics	Yes		Yes		Yes		Yes	
Type of industry	Yes		Yes		Yes		Yes	
Financial crisis dummy	Yes		Yes		Yes		Yes	
MSA personal income per capita	Yes		Yes		Yes		Yes	
State dummies	Yes		Yes		Yes		Yes	
Observations	18,028		18,028		18,028		18,028	
Individuals	2005		2005		2005		2003	
Baseline migration probability	0.0458		0.0280		0.0361		0.0300	
Rho	0.3324		0.3451		0.3325		0.3481	

Note: Average marginal effects (AMEs) of random-effects probit models are reported. Standard errors (SEs) are shown in parentheses. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse/5 = least risk-averse. Financial crisis is a dummy variable that takes the value of 1 if t ≥ 2009. Probit coefficients are reported in Table B9 in Appendix B.

^aTime invariant variable.

***p < 0.01; **p < 0.05; *p < 0.1.

on the latitude and longitude of the internal central point of each MSA. Whenever a respondent lives in a rural area, the internal point coordinates of the county of residence are used.

The US Department of Transportation, Bureau of Transportation Statistics (2003) reports that the average one-way commute distance in the United States is approximately 15 miles (24 km). On the other hand, according to a poll conducted by Answer Financial, a US insurance agency, the state with the longest average commute distance is New Hampshire, with 46.9 miles or 75 km (see Leonard, 2018).³⁰ Accordingly, Column 3 redefines migration as moves of 75 km or more. The magnitude of the effect of risk attitudes (around 11% of the respective migration probability) is larger than in the baseline results. To test the robustness of this result, Column 4 doubles the cut-off distance, redefining migration as moves of 150 km or more. The effect of risk attitudes (10%) is a bit higher than the one in the baseline specification. It seems that for migration across larger distances—which normally involve larger uncertainty—risk attitudes play a slightly more important role.

6 | RISK ATTITUDES AND MIGRATION, CROSS-SECTION ESTIMATIONS

Our empirical findings show that higher tolerance towards risk is associated with a higher probability of being a migrant. In this section we pay special attention to the relationship between risk attitudes and the intensive margin of migration, that is, the total number of moves and the total distance moved. After estimating a cross-section baseline specification to use as a benchmark, the focus is turned to repeat migrants, as risk attitudes might play a different role in subsequent moves. Given that movers, that is, individuals who move at least once during the period of observation, might be inherently different from stayers, that is, those who do not move, not controlling for individual self-selection might bias the results. Therefore, we apply the Heckman selection model introduced in Section 3.2 to analyse whether risk attitudes play a role in the distance moved, conditional on being a mover. We then address the concern of individuals' attitudes towards risk being endogenous and simultaneously determined with migration propensities. Finally, the seminal work of Jaeger et al. (2010) is used as a benchmark to compare our results.

6.1 | Baseline cross-section results

Table 9 presents the AMEs of probit estimations where the dependent variable is a dummy that takes the value of 1 if the individual moved at least once during the period 1997–2015. The analysis consists now of a cross-section of the 2005 individuals in our sample. All the covariates used in the fourth specification of Table 4 are included, with the exception of the financial crisis dummy and state controls. For time-variant variables, we assign the value for the year 2005, arguably the mid-point between our latest year of available data (2015), and the year the risk attitudes were elicited (1996).³¹ Finally, MSA personal income per capita is set to the year 1997, as economic conditions in the first observed MSA of residence may play a role in determining whether an individual is a mover or a stayer.

In the most restrictive specification, a one-unit change in the risk-index increases the probability that an individual migrates between MSAs by 1.54%. This implies that a one-SD increase (1.62 points) in the willingness to take risks is associated with an increase in the probability of being a mover that represents a bit less than 12% of the baseline migration probability of 21.54%. Similar to the results found in the random-effects baseline specification, homeownership, older age, and being a female head of household reduce the probability of migrating across

³⁰The poll does not consider commuters that take public transport.

³¹Furthermore, given that the youngest individual in our sample had 21 years of age in 1997, it is likely that by 2005 all individuals would have completed their education path.



TABLE 9 Risk attitudes and the probability of migrating across MSAs between 1997 and 2015—cross-section estimations

Dependent variable: Cross-MSA migration at least once	(1)		(2)		(3)		(4)	
	AME	SE	AME	SE	AME	SE	AME	SE
Key explanatory variable								
Risk-index ^a	0.0237***	(0.0054)	0.0192***	(0.0055)	0.0143***	(0.0054)	0.0154***	(0.0054)
Control variables (in 2005)								
Socioeconomic characteristics								
Female ^a			-0.0743***	(0.0218)	-0.0968***	(0.0259)	-0.0913***	(0.0266)
Age			-0.0039***	(0.0008)	-0.0043***	(0.0010)	-0.0059***	(0.0011)
Married					-0.0048	(0.0282)	-0.0009	(0.0281)
Number of children					-0.0122	(0.0096)	-0.0143	(0.0095)
Years of education					0.0284**	(0.0043)	0.0297***	(0.0045)
Home ownership					-0.1375***	(0.0295)	-0.1481***	(0.0295)
Log of total family income					-0.0187*	(0.0101)	-0.0109	(0.0108)
Labor-market characteristics								
Employed (R.)								
Unemployed							0.0213	(0.0597)
Retired							0.2015***	(0.0636)
Other employment status							0.0661	(0.0672)
Type of industry								
Construction/manufacturing (R.)								
Finance/real state							0.0772*	(0.0461)
Mining/agriculture/ forestry/fisheries							-0.1409***	(0.0427)
Transport/utilities/ communications							0.0261	(0.0341)
Wholesale/retail trade							0.0272	(0.0323)
Professional/ business serv.							0.0039	(0.0255)
Personal/ entertainment serv.							0.0770	(0.0556)
Public administration							0.0545	(0.0393)
Other							-0.0085	(0.0512)
MSA personal income per capita (in 1997)							-0.0043**	(0.0019)
Financial crisis dummy							No	
State dummies							No	
Individuals	2005		2005		2005		2005	
Baseline migration probability	0.2154		0.2154		0.2154		0.2154	

(Continues)

TABLE 9 (Continued)

Dependent variable: Cross-MSA migration at least once	(1)		(2)		(3)		(4)	
	AME	SE	AME	SE	AME	SE	AME	SE
Pseudo R2	0.0088		0.0240		0.0581		0.0749	

Note: Average marginal effects (AMEs) of cross-section probit models are reported. Standard errors (SEs) are shown in parentheses. Migration is a dummy variable that takes the value of 1 if the individual moved across MSAs at least once between 1997 and 2015. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse/5 = least risk-averse. Financial crisis is a dummy variable that takes the value of 1 if $t \geq 2009$. Probit coefficients are reported in Table B10 in Appendix B. (R.) Reference category.

^aTime invariant variable.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

MSAs. On the other hand, there is a strong, positive, and highly significant relationship between the years of education and the likelihood of being a mover. Finally, better economic conditions in the MSA of origin—which are assumed to increase the net gains from staying, seem to lower the likelihood of migration, as observed by the negative association between MSA personal income per capita and cross-MSA migration.

6.2 | Risk attitudes and the intensive margin of migration

6.2.1 | Risk attitudes and repeat migration

Assuming that repeated migration is likely to occur if the individual has migration experience (DaVanzo, 1981, 1983), a positive relationship between the willingness to take risks and the number of moves can be hypothesized.³² At the same time, the role of risk attitudes for subsequent moves can be expected to decrease as migration experience might gain importance. Supportive empirical evidence is almost inexistent, however. Gibson and McKenzie (2012) find no significant effect of risk attitudes on return migration. Jaeger et al. (2010) show that repeat migrants have a higher average willingness to take risks, but do not provide further empirical evidence. Table 10 repeats the cross-section analysis, differentiating among movers' total number of moves. The first column considers stayers along with those who moved only once during the sample period. A one-SD increase in the willingness to take risks is associated with an increase in the probability of being a one-time-mover that represents more than 12% of the base migration probability for this subsample. Column 2 further includes those who migrated twice and the third specification adds those who moved up to three times.³³ The associated effects of the risk-index represent less than 12% of the respective baseline probability for both specifications. Overall, the role played by risk attitudes in the probability of being a mover is slightly stronger in the model that considers one-time-movers only. This goes in line with the results from the first column in Table 5 (cf. Section 5.2), where we observed that the effect of individual attitudes towards risk seems to be partially substituted away by migration experience.

³²See Table 3 (cf. Section 4.4) where those who have moved more often have a higher average level of the risk-index.

³³Only 33 individuals moved four or more times. See Table B12 in Appendix B for a tabulation of the frequencies of cross-MSA moves among the 2005 respondents in our sample.

**TABLE 10** Risk attitudes and migration, by total number of moves

Dependent variable: Cross-MSA migration at least once	(1)		(2)		(3)	
	Max 1 move		Max 2 moves		Max 3 moves	
	AME	SE	AME	SE	AME	SE
Key explanatory variable						
Risk-index ^a	0.0099**	(0.0047)	0.0131**	(0.0053)	0.0148***	(0.0053)
Control variables (in 2005)						
Socioeconomic characteristics	Yes		Yes		Yes	
Labor-market characteristics	Yes		Yes		Yes	
Type of industry	Yes		Yes		Yes	
Individuals	1,804		1,933		1,972	
Baseline migration probability	0.1280		0.1862		0.2023	
Pseudo R ²	0.0449		0.0583		0.0702	

Note: Average marginal effects (AMEs) of probit models are reported. Standard errors (SEs) are shown in parentheses. Migration is a dummy variable that takes the value of 1 if the individual moved across MSAs at least once between 1997 and 2015. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse/5 = least risk-averse. Probit coefficients are reported in Table B11 in Appendix B.

^aTime invariant variable.

*** $p < 0.01$.; ** $p < 0.05$.; * $p < 0.1$.

6.2.2 | Risk attitudes, self-selection, and migration distance

Assuming that movers are indeed different from stayers, we analyze the determinants of individual decisions to self-select into migration, and how these determinants—especially the risk attitudes—relate to the distance moved. For this purpose, the two-stage Heckman selection model introduced in Section 3.2 is applied. The first stage deals with the probability that an individual migrates across MSAs at least once, and the second stage studies the total distance moved. Table 11 reports the AMEs of the first stage probit in Column 1, whereas Column 2 displays the OLS coefficients from the second stage, which further includes the total number of moves as a covariate, to account for the possibility of individuals moving repeatedly across shorter distances. Selection is identified, given that the IMR is significantly different from zero at the 5% level. Economic conditions in the first observed MSA of residence seem to be a determinant for nonselection into migration, as the MSA personal income per capita in 1997 is negatively associated with the probability of being a mover. Being relatively more willing to take risks is not only positively and statistically significantly related to the likelihood of self-selecting into migration (first-stage regression) but also plays a role in determining how far individuals move, conditional on moving. For movers, a one point increase in the risk-index is associated with an increase in the migration distance of around 166 km.

One could argue, however, that spillover effects to neighboring areas following worsening economic conditions in a given MSA may induce that MSA's migrants to move as far away as possible. If that is the case, the exclusion variable selected would no longer be appropriate as the assumption of it not being directly related to the final outcome would be violated (see Section 3.2). To account for this potential problem, Table 12 estimates the second stage of the Heckman selection model, differentiating among movers with increasingly larger total distance moved. The first column considers those who moved 75 km or more, while Columns 2, 3, and 4, consecutively double the cut-off distance. Not only does the positive and significant association between risk attitudes and the distance moved remain but, in addition, selection is observed in all specifications, signaling the robustness of our results and the fitness of the exclusion variable. Conditional of being a mover with a total migration distance of 600 km or

TABLE 11 Risk attitudes, self-selection, and migration distance

	(1)		(2)	
	First-stage probit Stayer and mover		Second-stage OLS Total Km moved	
	AME	SE	Coef.	SE
Key explanatory variables				
Risk-index ^a	0.0154***	(0.0053)	166.8159**	(83.4552)
MSA personal income per capita (in 1997) ^a	-0.0043**	(0.0020)	-	-
Inverse Mill's ratio	-	-	4753.9250**	(1972.7270)
Control variables (in 2005)				
Socioeconomic characteristics	Yes		Yes	
Labor-market characteristics	Yes		Yes	
Type of industry	Yes		Yes	
Total number of moves	No		Yes	
Individuals	2005			
Selected individuals			432	
Baseline migration probability	0.2154			
Pseudo R ²	0.0749			
R ²			0.4091	

Note: The average marginal effects (AMEs) of the first stage of a Heckman selection model are reported in Column 1, where the dependent variable is a dummy that takes the value of 1 if the individual moved across MSAs at least once between 1997 and 2015. The OLS coefficients of the second stage of a Heckman model are reported in Column 2, where the dependent variable is the total distance moved. Standard errors (SEs) are shown in parentheses in Column 1. Column 2 reports bootstrapped standard errors based on 500 replications. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse/5 = least risk-averse. Probit coefficients of the first stage are reported in Table B13 in Appendix B.

^aTime invariant variable.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

more, being relatively more willing to take risks is associated with an increase in the distance traveled of around 272 km.

6.3 | Endogenous and simultaneous determination of risk attitudes and migration

Studying the relationship between individuals' attitudes towards risk and their decision to migrate controlling only for the conventional determinants of migration may lead to an omitted-variable bias. As argued in Section 3.3, parental education may be one factor influencing both individual attitudes towards risk and migration propensities.³⁴ Some conventional determinants of migration may also prove to be problematic in our particular setting. For example, an individual's age—which is determined at birth and is likely exogenous to an individual's decision to

³⁴Another example is the number of siblings. Only children have been found to be less risk tolerant than those with siblings (J.M. Brown & Grable, 2015), whereas the mobility of young adults has been shown to depend on the presence of siblings (Rainer & Siedler, 2009).



TABLE 12 Risk attitudes, self-selection, and migration distance: Robustness checks based on total distance moved

Dependent variable: Total distance moved	(1)		(2)		(3)		(4)	
	75 km or more Coef.	SE	150 km or more Coef.	SE	300 km or more Coef.	SE	600 km or more Coef.	SE
Key explanatory variables								
Risk-index ^a	171.5921*	(87.8223)	163.2361*	(96.1690)	184.0233*	(150.3044)	272.8740**	(128.8052)
Inverse Mill's ratio	5140.5340***	(1998.25)	5042.1530**	(2358.07)	6074.2240**	(2815.65)	8290.2510***	(3100.60)
Control variables (in 2005)								
Socioeconomic characteristics	Yes		Yes		Yes		Yes	
Labor-market characteristics	Yes		Yes		Yes		Yes	
Type of industry	Yes		Yes		Yes		Yes	
Total number of moves	Yes		Yes		Yes		Yes	
Selected individuals	399		348		291		234	
R2	0.3955		0.3751		0.3857		0.4285	

Note: The OLS coefficients of the second stage of a Heckman model are reported, where the dependent variable is the total distance moved, if the individuals moved at least 75 km (Column 1), 150 km (Column 2), 300 km (Column 3), and 600 km (Column 4), respectively. Bootstrapped standard errors (SEs) based on 500 replications are shown in parentheses. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse/5 = least risk-averse.

^aTime invariant variable.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

migrate—may simultaneously raise the costs of migration decreasing the likelihood of moving (cf. Section 2), and have a significant impact on attitudes towards risk (Dohmen et al., 2011). It has been established that migration experience is an important determinant of subsequent migration (DaVanzo, 1981, 1983). If individuals consider migration to be risky, successful migration experience may lead them to overestimate their willingness to take risks. This is particularly relevant if a measure of risk aversion is built based on the self-assessment of respondents about their general willingness to take risks as in Jaeger et al. (2010). Regardless of the more comprehensive way in which our risk-index is built (cf. Section 4), the potential simultaneous determination of risk attitudes and migration cannot be rejected a priori. To capture migration experience before the elicitation of risk attitudes, we include a dummy variable that takes the value of 1 if, in 1996, an individual resides in an MSA that is either different to the MSA of birth or the MSA in which he/she grew up.

Considering that risk attitudes may be endogenous and simultaneously determined with migration, the recursive bivariate probit of simultaneous equations introduced in Section 3.3 is applied. In a first step (not stage), the endogenous binary risk-indicator is regressed on a series of covariates that can be grouped into those determined at birth, for example sex, age, and ethnicity; (childhood) characteristics determined before the elicitation of risk attitudes, for example, being an only child, and migration experience; and characteristics of the respondents' parents in the form of their educational attainment. Additionally, an exclusion restriction related to the smoking behavior of respondents' parents is included. The second step deals with the probability that an individual migrates across MSAs at least once and includes the conventional covariates from the fourth specification of Table 9, as well as the same group of regressors from the first step, except for the exclusion restriction. The value of ρ is -0.57 and statistically significant at the 10% level, signaling that our binary measure of attitudes towards risk and the dichotomous migration decision are indeed simultaneously determined. Column 1 of Table 13 shows the results for the endogenous binary risk-indicator. As expected, there is a negative and highly significant relationship between age and the willingness to take risks, which goes in line with the findings of Dohmen et al. (2011). Having a father with at least some tertiary education is associated with a higher willingness to take risks, compared to those whose father received less than 12 years of education. In accordance with Jenks (1992), there is a positive relationship between parental propensity to smoke and (the offspring's) attitudes towards risk. This is statistically significant at the 5% level, which shows the fitness of this covariate as an exclusion variable. Of particular importance is the fact that no statistically significant relationship between migration experience before the elicitation of risk attitudes and the willingness to take risks can be found, which allows us to rule out the possibility of our results being driven by reverse causality.

Being relatively more willing to take risks is positively and statistically significantly related to the likelihood of engaging in migration across MSAs (Column 2). The marginal effect of the binary risk-indicator, calculated following Equation (17) (cf. Section 3.3), is 0.0583. This means that being in the less risk averse category increases the probability of being a mover by 5.83%. This effect is just slightly larger than the AME of 0.0577 found when the outcome equation in Column 2 is estimated by a simple probit, that is, without taking into account the endogenous nature of attitudes towards risk (See Table B15 in Appendix B). Given that not only the direction of the effect of risk attitudes on migration and its strong statistical significance remain identical (at the 1% level), but also that removing the endogeneity bias barely changes the size of the effect, we interpret our results as robust to accounting for unobservable cofounders.

6.4 | Comparability of results

Individuals' attitudes towards risk are shown to be positively and statistically significantly related to migration propensities. However, we find it useful to compare our results with the ones obtained in similar studies. In particular, we are interested in a comparison with the results for Germany to see whether the migration-risk relation is linear or affected by country specifics in a nonlinear way. For this purpose, the study by Jaeger et al. (2010), who present evidence on the

**TABLE 13** Recursive bivariate probit model of simultaneous equations

Dependent variable	(1)		(2)			
	Binary risk-indicator		Cross-MSA migration at least once			
	Direct		Direct	Indirect	Total	
	AME	SE	AME	AME	AME	SE
Key explanatory variable ^a						
Binary risk-indicator	-	-	0.0583***	-	0.0583***	(0.0044)
Migration experience	0.0334	(0.0218)	0.0879***	0.0621***	0.1500***	(0.0377)
Socioeconomic characteristics (2005)						
Female ^a	0.0138	(0.0295)	-0.0749***	-0.0444**	-0.1194***	(0.0436)
Age	-0.0063***	(0.0010)	-0.0035**	-0.0035***	-0.0070***	(0.0024)
Ethnicity ^a						
White-American (R.)						
African-American	-0.0693***	(0.0267)	-0.0734***	-0.0581***	-0.1316***	(0.0415)
Native-American	-0.2608**	(0.1113)	-0.0499	-0.0822	-0.1321	(0.1881)
Asian-American	0.2753**	(0.1387)	-0.1578**	-0.0668	-0.2247*	(0.1209)
Other ethnicity	-0.1984**	(0.0910)	0.0770	-8 × 10 ⁻⁵	0.0769	(0.1479)
Married	-	-	-0.0163	-	-0.0270	(0.0408)
Children	-	-	-0.0052	-	-0.0086	(0.0138)
Years of education	-	-	0.0159***	-	0.0264***	(0.0080)
Home ownership	-	-	-0.1297***	-	-0.2196***	(0.0601)
Log of total family income	-	-	-0.0148	-	-0.0245	(0.0160)
Labor-market characteristics (2005)						
Employed (R.)						
Unemployed	-	-	0.0072	-	0.0119	(0.0830)
Retired	-	-	0.1547***	-	0.2667***	(0.1020)
Other employment status	-	-	0.0319	-	0.0529	(0.0905)
Type of industry (2005)						
Construction/manufacturing (R.)						
Finance/real state	-	-	0.0626*	-	0.1043	(0.0656)
Mining/agriculture/forestry/fisheries	-	-	-0.1310***	-	-0.2030***	(0.0745)
Transport/communications/utilities	-	-	0.0314	-	0.0518	(0.0501)
Wholesale/retail trade	-	-	0.0216	-	0.0355	(0.0453)
Professional/business services	-	-	0.0120	-	0.0196	(0.0364)
Personal/entertainment services	-	-	0.0718	-	0.1200	(0.0802)
Public administration	-	-	0.0582*	-	0.0969*	(0.0591)
Other	-	-	0.0022	-	0.0037	(0.0750)
MSA personal income per capita (in 1997)	-	-	-0.0019	-	-0.0032	(0.0029)
Childhood/parental characteristics ^a						
Born in a rural area	-0.0215	(0.0244)	0.0537***	0.0313**	0.0850**	(0.0347)
Only child	0.0847*	(0.0503)	-0.0525	-0.0194	-0.0720	(0.0544)
Parents smoked	0.0435**	(0.0208)	-	0.0084*	0.0084*	(0.0045)

(Continues)

TABLE 13 (Continued)

Dependent variable	(1)		(2)			
	Binary risk-indicator		Cross-MSA migration at least once			
	Direct		Direct	Indirect	Total	
	AME	SE	AME	AME	AME	SE
Education of the father						
Less than 12 years (R.)						
12 years	-0.0213	(0.0269)	-0.0244	-0.0198	-0.0443	(0.0353)
More than 12 years	0.0668*	(0.0359)	-0.0111	0.0054	-0.0056	(0.0438)
Education of the mother						
Less than 12 years (R.)						
12 years	0.0021	(0.0277)	0.0476**	0.0307**	0.0784**	(0.0353)
More than 12 years	0.0232	(0.0366)	0.0376	0.0283	0.0659	(0.0456)
Individuals	2005		2005			
Base migration probability			0.2154			
Errors terms correlation:	Coef.		SE			
Rho	-0.5791*		(0.2335)			
	χ^2		$P > \chi^2$			
Wald test of Rho = 0	3.5391		0.0599			

Note: Average marginal effects (AMEs) of a recursive bivariate probit model of simultaneous equations are reported. Standard errors (SEs) are shown in parentheses. Migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Binary risk-indicator is a dummy variable that takes the value of 1 if risk-index is equal to 3 or higher. Coefficients are reported in Table B14 in Appendix B. (R.) Reference category.

^aTime invariant variable.

*** $p < .01$; ** $p < .05$; * $p < .1$.

relationship between risk attitudes and migration for Germany, is used as a benchmark. Country differences, particularly in terms of risk endowment and migration propensities, need to be taken into account when interpreting cross-national comparisons. For instance, Fehr et al. (2006) find that Germans tend to be more risk-averse than US Americans; in addition, Germany has lower geographic mobility rates (Molloy et al., 2011). Exact empirical replications may be impeded by some inherent country characteristics. For example, Jaeger et al. (2010) include a covariate indicating whether the place of origin of respondents is West or East Germany, something relevant for their country of study, but arguably not applicable for the United States.

Columns 1–3 in Table 14 present AMEs from our baseline cross-section probit specification, but including only the covariates used by Jaeger et al. (2010), whose results are presented in Columns J1–J3. Given that they observe migration between 2000 and 2006, our sample period is restricted to 1999–2005.³⁵ Furthermore, the SDs of the measures of risk aversion are used to allow comparability between their self-assessed risk-index, and our six-point index derived from hypothetical-gamble questions. The bottom row in each column shows the effects of the risk-index related to each specification's baseline migration probability. It seems that in the United States, the

³⁵Due to the PSID waves being biennial, we could not consider the exact same years.

**TABLE 14** Comparison of results to Jaeger et al. (2010)

	Jaeger et al. (2010)			This paper		
	Cross-section 2000–2006			Cross-section 1999–2005		
	(J1)	(J2)	(J3)	(1)	(2)	(3)
Key explanatory variable						
Risk-index ^a	0.0064	0.0042	0.0026	0.0157	0.0110	0.0077
Control variables						
Gender and age	No	Yes	Yes	No	Yes	Yes
Marital status and years of education	No	No	Yes	No	No	Yes
SD of risk-index ^a	2.7	2.7	2.7	1.88	1.88	1.88
AME*SD of risk-index	0.0173	0.0113	0.0070	0.0295	0.02068	0.0144
BMP	0.0580	0.0580	0.0580	0.1387	0.1387	0.1387
Effect related to BMP	29.79%	19.55%	12.10%	21.28%	14.92%	10.43%

Note: Average marginal effects (AMEs) of probit models are reported.

Abbreviations: BMP, baseline migration probability.

^aTime invariant variable.

migration-risk relation is not very different—if at all, risk attitudes play a slightly larger role in the decision to migrate in Germany (cf. Models J3 and 3).

7 | CONCLUSIONS

The presence of risk related to future income and the uncertainty generated through incomplete information about the returns and costs of moving makes migration an inherently risky activity (Jaeger et al., 2010; Williams & Baláz, 2012). If individuals differ in their risk-taking propensities (Arrow, 1965; Pratt, 1964), individual attitudes towards risk—which can be considered to be a stable personality trait (Josef et al., 2016)—will eventually determine whether they act on their intention to migrate (Bodvarsson & Van den Berg, 2013).

This paper contributes to the still scarce literature on the relationship between risk attitudes and migration decisions. The data set from the PSID allows us to use US MSAs as geographical units to provide evidence on the positive and strongly significant association between individual willingness to take risks and migration propensities. We complement the analysis by studying migration across states and across larger distances, which potentially entail higher levels of risk and uncertainty, and find that risk attitudes play a slightly more important role. The panel structure of the data allows us to account for unobserved heterogeneity and to address the issue of selection, something that has not been considered in the literature. We find that risk attitudes not only play an important role in the decision whether to move at least once across MSAs but are also associated with a larger migration distance, conditional on moving. Furthermore, we are able to consider the potentially endogenous nature of risk attitudes and to rule out the possibility of our results being driven by reverse causality.

Understanding the role played by risk attitudes in the decision to migrate is important given its implications for the efficient functioning of labor markets. In the same sense that being relatively more willing to take risks makes an individual more likely to migrate, population-averaged tolerance towards risk may impact aggregated internal migration propensities in different economies. For example, Fehr et al. (2006) find that Germans tend to be more risk-averse than US Americans. According to Jaeger et al. (2010), the latter may explain the higher mobility rates observed in the United States, which in turn may contribute to the lower frictions in the US labor market (Molloy et al., 2011). Even if labor

demand and supply would concur, the allocation of human capital may not be optimal due to layoffs and job openings occurring in different geographic locations (Simon, 1988). If geographic mobility is assumed to reduce the frictions in the labor market (Borjas, 2001), and if risk preferences play a key role in the decision to migrate, public planners should consider an insurance-based policy aimed at reducing the costs of migration and, thus, tackle frictional unemployment. Furthermore, if individuals are assumed to search for a job that matches their abilities and preferences under imperfect information (Johnson, 1978), and with job opportunities available across different regions, individual decisions in job turnover and migration may be closely related (Haussen & Uebelmesser, 2018). Improving the quality and accessibility of the information on job availability may also serve to reduce the costs related to migration.

Future research may focus on cross-national comparisons of the role played by risk attitudes in migration decisions and expand the analysis to include migration across international borders. This paper may also be extended by introducing a new source of risk, namely one that is related to income volatility in the current location. Contrary to the presence of risk in the prospective location, the presence of risk in the current location may encourage risk-averse potential migrants making them more likely to move to a location with a lower variability of income. This is left for future research.

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CONFLICT OF INTERESTS

The authors declare that there are no conflict of interests.

COMPLIANCE WITH ETHICAL STANDARDS

Some of the data used in this analysis are derived from Restricted Data Files of the PSID, obtained under special contractual arrangements designed to protect the anonymity of respondents. These data are not available from the authors. Persons interested in obtaining PSID Restricted Data Files should contact PSIDHelp@umich.edu.

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