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Risk Attitudes and Migration Decisions

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Zusammenfassung

Das Risiko in Bezug auf künftige Einnahmen und die Unsicherheit, die durch unvollständige Informationen über die Rendite und die Kosten des Umzugs entsteht, machen Migration zu einer von Natur aus riskanten Handlung. Falls sich die Risikobereitschaft von Individuum zu Individuum unterscheidet, bestimmt die individuelle Risikoeinstellung, die als stabiles Persönlichkeitsmerkmal angesehen werden kann, ob tatsächlich Migration stattfindet. Individuen, die eine höhere Risikobereitschaft als andere aufweisen, neigen eher zu Migration. Dieser Zusammenhang besteht fort, wenn explizit risikoreiche Bedingungen am Wohnort in Form einer hohen Variabilität der Beschäftigungsmöglichkeiten berücksichtigt werden. Bei einem genaueren Blick wird das Bild jedoch mehrdeutig. Einerseits führt das vorhandene Risiko am gegenwärtigen Wohnort dazu, dass risikoaverse, potenzielle Migranten an einen Ort, der mehr Stabilität aufweist, ziehen. Andererseits werden Individuen, die äußerst risikobereit sind, möglicherweise zu riskanteren Standorten hingezogen, um ihre Chance auf überdurchschnittliche Einnahmen zu erhöhen, oder anders formuliert, sie werden von Migration hin zu stabileren Orten abgehalten.

Migration ist jedoch für viele kein einmaliges Ereignis. Migrationserfahrungen können die mit zukünftigen Migrationsentscheidungen verbundenen Kosten durch einen “Learning-by-Doing" Effekt senken. Entscheidend hierfür sind die Anpassung an unbekannte Umgebungen und die Verarbeitung von für den Migrationsprozess relevanten Informationen sowie zugleich der Erwerb von standortspezifischem Kapital an mehreren Orten. Aus diesem Grund migrieren Personen, die bereits umgezogen sind, mit höherer Wahrscheinlichkeit erneut. Diese Argumentation ist für alle Mitglieder des Haushalts, in dem bereits Migrationserfahrung besteht, gleichermaßen relevant, unabhängig davon, ob sie als Entscheidungsträger der Migration fungierten. So gilt dies bspw. auch für Kinder. Hierbei kommt auch die Frage auf, ob ein “trade-off" zwischen der Rolle der individuellen Einstellung zu Risiko und der Migrationserfahrung als entscheidender Faktor bei einer Migrationsentscheidung existiert.

Die vorliegende Dissertation analysiert den Zusammenhang zwischen der individuellen Risikoeinstellung, früheren Migrationserfahrungen und Migrationsentscheidungen. Dazu wird Migration in den Vereinigten Staaten zwischen Metropolitan Statistical Areas (MSAs) basierend auf einem Panel-Datensatz aus der „Panel Study of Income Dynamics“ (PSID) für den Zeitraum 1997-2015 betrachtet. Dieser Datensatz enthält eine Reihe von hypothetischen Glücksspielfragen, um individuelle Risikoeinstellungen zu ermitteln. Die Dissertation ist publikationsbasiert (kumulativ) und besteht aus drei Aufsätzen.

Im ersten Aufsatz wird der Zusammenhang zwischen der Risikobereitschaft von Individuen und ihrer Migrationsentscheidung analysiert. Der Schwerpunkt liegt hierbei auf dem

Argument der unvollkommenen und unvollständigen Informationen über die potenziellen Orte. Unter Verwendung von Zufallseffektspezifikationen und unter Berücksichtigung der herkömmlichen sozioökonomischen und arbeitsmarktbezogenen Merkmale als Kontrollvariablen kann festgestellt werden, dass ein positiver und statistisch signifikanter Zusammenhang zwischen Risikobereitschaft und MSA-übergreifenden Migration besteht. Die Risikoeinstellung ist für die Bundesstaaten übergreifende Migration und die Migration über größere Entfernungen noch deutlich wichtiger. Bei der Betrachtung der Selbstselektion wird mittels einer Heckman-Spezifikation festgestellt, dass die Risikobereitschaft eine Rolle dabei spielt, ob sich Individuen für Migration entscheiden. Jedoch spielt sie keine Rolle für die Gesamtzahl der Umzüge oder die Gesamtstrecke, die Individuen aufgrund von Umzügen zurücklegen.

Der zweite Aufsatz analysiert den Zusammenhang zwischen der Risikobereitschaft des Einzelnen und seiner Migrationsentscheidung unter expliziter Berücksichtigung der "Origin-Push" - und "OriginPull"-Effekte für risikoaverse bzw. risikobereite Personen, die sich aus dem Beschäftigungsrisiko am Herkunftsort ergeben. Mit Hilfe von Probit-Spezifikationen wird festgestellt, dass für Individuen, die sich in der Gruppe der äußerst Risikobereiten befinden, ein negativer und statistisch signifikanter Zusammenhang mit der Wahrscheinlichkeit einer Migration zwischen MSAs besteht (im Vergleich zu denjenigen, die eine höhere Risikoaversion aufweisen). Der Zusammenhang ist umso stärker, je höher das Beschäftigungsrisiko in der Herkunfts-MSA ist. Dies bestätigt die "Origin-Pull" -Hypothese für diejenigen, die sich an der oberen Grenze der Risikopräferenzverteilung befinden. Für die „OriginPush"- Hypothese wurden jedoch keine Beweise gefunden.

Im dritten und abschließenden Aufsatz liegt der Fokus auf einer bestimmten Art von Migrationserfahrung, der Migrationserfahrung während der Kindheit. Hierbei wird der Zusammenhang zwischen Migrationserfahrungen von Kindern und ihrer Entscheidung, als Erwachsene zu migrieren, analysiert. Um die endogene Natur der Migration in der Kindheit und deren gemeinsame Bestimmung mit der Migration im Erwachsenenalter zu berücksichtigen, wird ein rekursives bivariates Probit-Modell simultaner Gleichungen verwendet. Es lässt sich feststellen, dass es einen positiven und statistisch signifikanten Zusammenhang zwischen Migration in der Kindheit und der Wahrscheinlichkeit einer MSA-übergreifenden Migration als Erwachsener gibt. Die konventionellen Determinanten der Migration sowie die Merkmale der Kindheit und der Eltern werden als Kontrollvariablen einbezogen. Ergebnisse, die die Distanz zwischen MSAs als Kontrollvariable berücksichtigen, zeigen keine signifikanten Unterschiede zwischen Umzügen in der Kindheit über eine geringere oder größere Distanz. Unter Berücksichtigung der individuellen Risikoeinstellung spielt die Migrationserfahrung in der Kindheit bei äußerst risikoaversen Individuen eine wichtigere Rolle als bei weniger risikoaversen.

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1 Chapter 1
General Introduction

1.1 Introduction

The idea that individuals' risk attitudes play a determinant role in migration propensities is by no means novel, however, empirical evidence remains scarce. Understanding the determinants of geographic mobility is important given the effects it may have on the efficient functioning of labour markets. As Borjas (2001, p. 69) points out, migration helps to "grease the wheels of the labour market", meaning that labour 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 labour market and migration policies.

In economics, migration is often viewed as a human capital investment decision (Sjaastad 1962). Potential migrants calculate the value of labour 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 and Van den Berg 2013). To say it differently, individuals tend to base their decision to migrate on their expected income (Todaro 1969). As migrants are not necessarily guaranteed a job upon relocation and, according to Jaeger et al. (2010), are assumed to have less information about other non-monetary potential benefits of moving (e.g. leisure opportunities at the destination), migration is an inherently risky activity. Given that a central feature of the theory of choice under risk and uncertainty is that individuals differ in their tolerance towards risk (Arrow 1965; Pratt 1964), individuals' attitudes towards risk are likely to play a determinant role in their migration decisions. The latter argument still holds when explicitly accounting for risky conditions in the location of origin—in the form of high variability in employment opportunities or income. However, the picture becomes ambiguous. According to Conroy (2009), the presence of risk in the location of origin would push risk-averse potential migrants into relocating to a more stable location. On the other hand, those who are among the most willing to take risks may either be more able to cope with high levels of risk or be attracted to more risky locations as a way to increase their chance of receiving above-average earnings (Jaeger et al. 2010), i.e. they are pulled from migrating to more stable locations.

Migration, however, is not a once in a lifetime occurrence. A potential repeat migrant may be inclined to either move back to the location of origin (return migration) or may instead decide to move to a third location (onward migration). Similarly to their initial move, these potential repeat migrants would need to form expectations on the net benefits of the repeat migration act (Dierx 1988; Grant and Vanderkamp 1986), with two key fundamental differences, however. First, potential migrants with previous migration experience would arguably be better at gathering and processing information that is relevant for the migration process compared to individuals who have never moved before (DaVanzo 1981, 1983). This is due to a "Learning- by-doing" effect that reduces the costs of subsequent migration (Bowman and Myers 1967; Morrison 1971). The implication is that potential repeat migrants would exhibit higher propensities of migration than those who never moved (DaVanzo and Morrison 1981; Eldridge 1965). Second, and specific to potential return migrants, knowledge about income, leisure, and consumption opportunities in the location of origin is likely to persist, facilitating the recuperation of foregone location-specific capital like local reputation, social networks, and close friendships (DaVanzo 1981, 1983). If location-specific capital in a particular location reduces the costs of migrating to it, individuals with location-specific capital in more than one location would be more likely to migrate than those whose location-specific capital is limited to one particular location. The above-mentioned reasoning is similarly relevant for all members of the household who are exposed to the migration experience, regardless of whether they acted as the decision-makers. Childhood migrants are also likely to develop ties to more than one location and to benefit from a "Learning- by-doing" effect related to adapting to unfamiliar environments and processing information that is relevant for the migration process. This would imply a reduction in the costs associated with migration, increasing the probability of future migration.

This dissertation analyzes the relationship between individuals' attitudes towards risk, migration experience and migration decisions. In a first step, Chapter 2 analyzes the relationship between individuals' attitudes towards risk and their decision to migrate focusing on the argument regarding imperfect and incomplete information about prospective locations. Chapter 3 builds up on the insights from the second chapter and expands the analysis by explicitly accounting for the "origin-push" and "origin-pull" effects for risk-averse and risk-seeking individuals, respectively, that arise from employment risk at the location of origin. Chapter 4 turns the focus onto a particular type of migration experience, namely, migration experience during childhood. The relationship between individuals' childhood migration experience and their decision to migrate as adults is analyzed, accounting for the potential endogenous nature of childhood migration and a likely joint determination with adult migration propensities.

1.2 Data sources

The main data source used throughout this dissertation is the Panel Study of Income Dynamics (PSID) of the University of Michigan, a representative longitudinal panel survey of households in the United States (U.S.). From 1997 to 2015, 10 biennial waves of the PSID with information on socio-economic and labour market characteristics are merged with a Geospatial dataset that includes disaggregated geographical information of individuals participating in the survey. In Chapter 3, additional data from the U.S. Bureau of Economic Analysis, U.S. Bureau of Labor Statistics, U.S. Department of Justice, and the U.S. Department of Agriculture are used to capture regional characteristics of individuals' locations of origin. On the other hand, Chapter 4 utilizes retrospective information on childhood and parental characteristics of PSID respondents to analyze the relationship between individuals' childhood migration experience and their decision to migrate as adults. In addition, all chapters make use of the 1996 wave of the PSID, which contains a comprehensive set of hypothetical-gamble questions related to lifetime income used to elicit the attitudes towards risk of all employed heads of household (see section 1.4 for a detailed explanation of the elicitation of risk attitudes used in this dissertation).

1.3 Contributions to the literature and summary of results

1.3.1 Chapter 2

The goal of chapter 2 is to analyze the relationship between individuals' attitudes towards risk and their decision to migrate within the U.S., focusing on the argument regarding imperfect and incomplete information about prospective locations. This chapter contributes to the empirical literature on risk attitudes and migration in several ways. First, in that, it takes full advantage of the panel structure of the dataset by studying the relationship between risk attitudes and migration propensities in a comprehensive way by means of random-effects specifications that assist in controlling for unobserved heterogeneity. Second, the chapter analyses whether risk attitudes play a role in the intensive margin of migration, i.e. the distance moved or the number of moves. This is studied accounting for migrants' self-selection, something that has not been addressed so far. Third, and related to the U.S., to our knowledge, the literature so far has focused on international migration and has neglected internal migration (cf. section 2.1). The PSID dataset 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. Fourth, and more generally, the analysis allows first conclusions about whether the U.S. is different from other countries in terms of the migration-risk relation, i.e. whether the underlying relation is linear or affected by country specifics in a non-linear way.

The results show that being relatively more willing to take risks is positively and statistically significantly related to cross-MSA migration, after controlling for conventional socio-economic and labour market characteristics. For migration across states and across larger distances—which normally involve larger uncertainty—risk attitudes seem to be even more important. When considering self-selection, we find with a Heckman specification that risk attitudes play a role in determining whether individuals self-select into migration, but not for the total number of moves or the total distance moved, conditional on moving. Finally, comparing the results with those of Jaeger et al. (2010)—a seminal paper on the relationship between risk attitudes and migration that use data from Germany—it seems that the migration-risk relationship is not very different in the U.S., if at all, risk attitudes play a slightly larger role in the decision to migrate in Germany.

1.3.2 Chapter 3

The goal of chapter 3 is to analyze the relationship between individuals' attitudes towards risk and their decision to migrate within the U.S., when explicitly accounting for what we have denominated the "origin-push" and "origin-pull" effects for risk-averse and risk-seeking individuals, respectively (see section 3.2). The literature considering risky conditions in the origin usually focuses on migration as a risk diversification mechanism for risk-averse families in developing countries (see e.g. Stark 1981; Stark and Levhari 1982). The few studies conducted in developed countries implicitly assume a population of risk-averse individuals, and thus, do not explicitly take into account differences in risk-taking propensities (see e.g. Arzaghi and Rupasingha 2013; Daveri and Faini 1999). In a developing country setting and assuming the household to be an indivisible unit, Conroy (2009) is, to the best of our knowledge, the only empirical work studying the "origin-push" hypothesis for risk-averse individuals that uses a direct measure of individual attitudes towards risk. Chapter 3 complements Conroy (2009) in two fundamental ways. First, it introduces and tests the "origin-pull" hypothesis for risk-seeking individuals, together with the "origin-push" hypothesis for the risk-averse. Second, it presents the first evidence of a developed country. Using probit specifications that include an interaction between risk attitudes and our measure of risk at the location of origin, the results show that those who are among the most willing to take risks are significantly less likely to migrate (compared to those with higher risk aversion), the higher the risk at the origin, supporting the 'origin-pull" hypothesis. No evidence is found in favour of the "origin-push" hypothesis for risk-averse individuals, however.

1.3.3 Chapter 4

The goal of chapter 4 is to analyze the relationship between individuals' childhood migration experience and their decision to migrate as adults within the U.S. To the best of our knowledge, no study has analyzed the relationship between childhood migration experience and migration propensities during adulthood. Childhood mobility has been shown to have an effect on future educational attainment (Hango 2006), social integration during adulthood (Myers 1999), and health outcomes through the life-cycle (Jelleyman and Spencer 2008), to name a few. However, its long-term effects on adult migration patterns have not been addressed. On the other hand, the migration literature has extensively analyzed the relationship between migration experience and repeat migration (DaVanzo 1981, 1983; DaVanzo and Morrison 1981; Grant and Vanderkamp 1986), but no focus has been put on the role of childhood migration experience. Chapter 4 seeks to fill the gaps in both streams of literature by arguing that the conceptual framework of repeat migration, with its emphasis on information costs and location-specific capital, is also applicable for migration experience during childhood.

Using a recursive bivariate probit model of simultaneous equations to account for the endogenous nature of childhood migration and its joint determination with migration during adulthood, the results show that being a childhood migrant is positively and statistically significantly related to the likelihood of cross-MSA adult migration. Childhood migration is even more important when removing from the sample those who moved during childhood and return to their MSA of birth as adults, i.e. return childhood migrants. Accounting for the distance between MSAs of residence during childhood leads to no substantial differences between nearer and farther childhood moves. When considering individual attitudes towards risk, childhood migration experience seems to be more important for the most risk-averse.

A final concern addressed in this chapter relates to the formation of risk preferences and the possibility that risk attitudes may not be exogenous to adult migration decisions. Leaving childhood migration aside and focusing on the relationship between individual attitudes towards risk and adult migration, the results from probit specifications and recursive bivariate probit models of simultaneous equations are compared. Given that not only the direction of the effects of risk attitudes on adult migration and their strong statistical significance remain identical, but also that removing the endogeneity bias leaves the size of the effects virtually unchanged, we interpret our results as robust to accounting for unobservable cofounders. The latter complements the findings of chapter 2 in particular, and serves to nicely round off this dissertation.

1.4 Elicitation of individual attitudes towards risk

Risk attitudes are underlying attributes that cannot be directly observed. They need to be elicited from experiments or survey responses.[1] When studying the behavioural consequences of risk attitudes, self-assessment survey responses are commonly used. For example, Jaeger et al. (2010) use a self-assessment measure in which the respondents must rate themselves on an eleven-point scale on their own perception about their general

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

willingness to take risks. This method thus provides a general elicitation of risk attitudes, namely, one that is applicable across different contexts. The authors, however, recognize that the use of scales by survey respondents may carry potential problems (e.g. central tendency bias). Nonetheless, self-assessment risk elicitation methods have been used widely to link risk attitudes to various types of economic behaviour (see e.g. Budria et al. 2013; Caliendo et al. 2009). Hypothetical-gamble questions in surveys present a more comprehensive way to elicit risk attitudes (see Kimball et al. 2009). Even though seemingly domain-specific to financial risk, it has been established that risk attitudes elicited with this method are also able to explain non-financial behaviour (see e.g. Cramer et al. 2002; Guiso and Paiella 2004; Schmidt 2008).

In the 1996 wave of the PSID, all employed heads of household are asked the first question (M1), which reads as follows:[2]

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?[3]

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):

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

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

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

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?

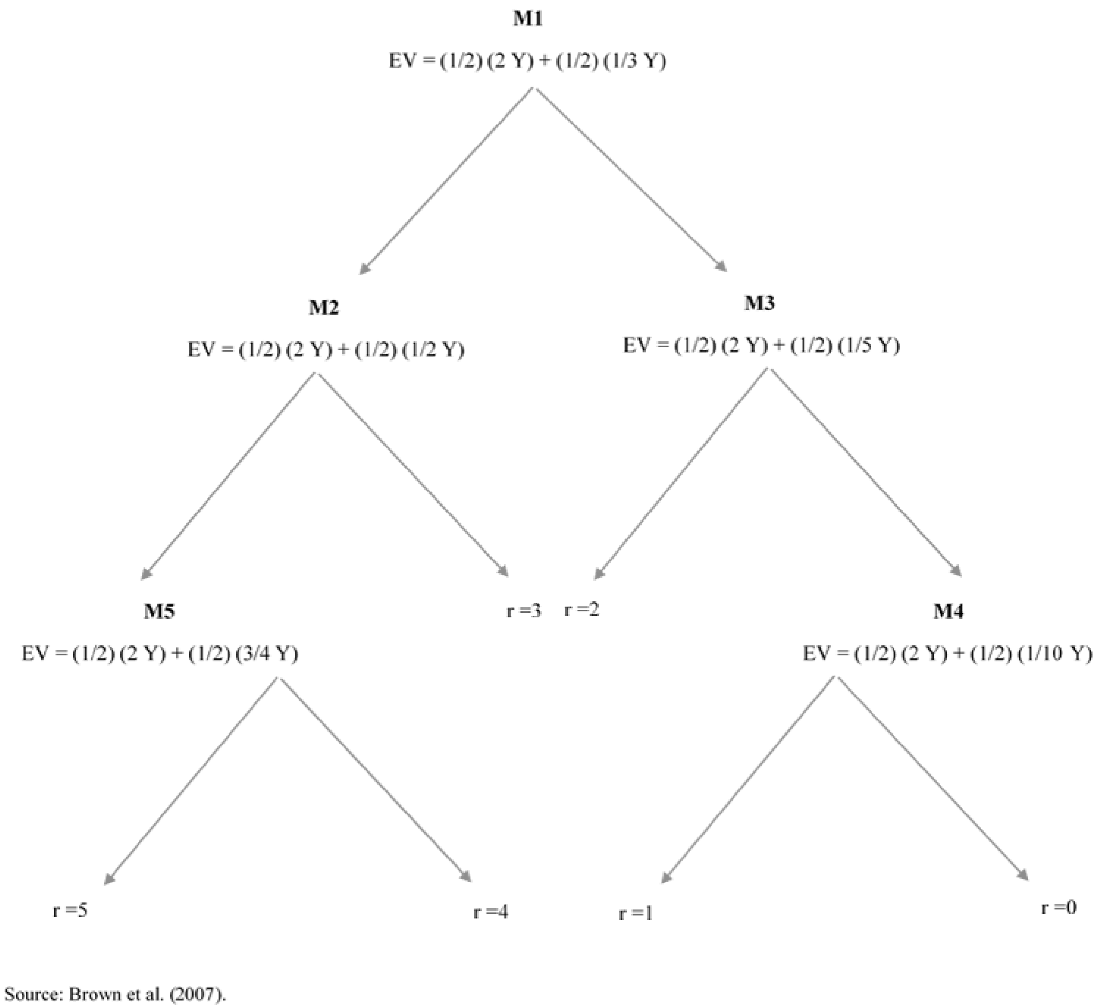

Figure 1.1: PSID risk decision tree

Notes: Constructed based on Brown et al. (2012).

Figure 1.1 shows a decision tree illustrating the respondents' decision making process. An individual is assumed to accept a risky job only if its expected utility exceeds that of the safe job. Hence, those who exhibit a higher tolerance towards risk are willing to accept jobs with worse potential negative outcomes (Kimball et al. 2009). According to the authors, with constant relative risk aversion (CRRA), i.e. absolute risk aversion that declines with wealth, gamble responses imply an upper and lower bound on an individual's willingness to take risks, under the assumption of no response error. Following the methodology used by Brown et al. (2012), the responses are used to build a six-point *risk-index* of the risk preferences of the heads of household.

Table 1.1: 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"

Notes: Constructed based on Brown et al. (2012).

Table 1.1 illustrates the construction of the risk-index based on the answers provided by respondents to the sequence of hypothetical-gamble questions. 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. 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." Following Jaeger et al. (2010), a binary *risk-indicator* is also constructed, which takes the value of 1 if a respondent obtains a score of 3 or higher in the scale. All specifications from chapter 2 are estimated using both the binary risk-index and the risk-indicator.[4] Finally, the risk-indicator is also used in parts of chapter 4 when addressing the potential endogenous nature of risk attitudes with respect to adult migration (cf. section 4.6.3).

[4]The results using the risk-indicator are not reported to ease readability. Both the direction and the statistical significance of the effects remain unchanged.

2 Chapter 2
Risk Attitudes and Migration Decisions

2.1 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 chapter is to analyze the relationship between individuals' attitudes towards risk and their decision to migrate within the United States (U.S.). Understanding the determinants of geographic mobility is important given the effects it may have on the efficient functioning of labour markets. As Borjas (2001, p. 69) points out, migration helps to "grease the wheels of the labour market", meaning that labour 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 would allow for the design of more effective labour 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 labour 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 and Van den Berg 2013). This approach implicitly assumes that there is no risk related to the value of labour 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 labour 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 non-migration 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 non-market amenities (Rosen 1974), including consumption and leisure goods (Shields and Shields 1989). So,

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

unlike in the standard human capital model, individuals may choose to migrate for reasons other than better income opportunities (Bodvarsson and Van den Berg 2013), for example, for the non-monetary 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 non-material returns (and costs) of moving what makes migration an inherently risky activity (Jaeger et al. 2010; Williams and Baláž 2012).

A central feature of the theory of choice under risk and uncertainty is that individuals differ in their tolerance towards risk (Arrow 1965; Pratt 1964), and individuals' attitudes towards risk have been shown to have an impact on economic behaviour in different contexts like occupational choice (Cramer et al. 2002; Dohmen et al. 2011b), financial investment (Charles and Hurst 2003; Guiso and Paiella 2004), and marriage and fertility (Schmidt 2008). In the specific case of migration, the attitudes towards risk of potential migrants determine whether they indeed act on their intention to migrate (Bodvarsson and Van den Berg 2013). Thus, it is reasonable to hypothesize that individuals who are relatively more willing to take risks have a higher propensity for migrating.[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. Williams and Baláž (2014) come to similar conclusions using data from the U.K. and focusing on international migration.

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-to-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 engaged in international

[2]True uncertainty is of a non-quantitative nature and no probabilities can be assigned to it (Knight 1921).

[3]The 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 high variability in employment opportunities (Conroy 2009). The presence of risk in the current location may differently affect individuals with varying degrees of risk-aversion. This concern is addresed in chapter 3.

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

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 dataset for the period 1997-2015 from the Panel Study of Income Dynamics (PSID), a representative longitudinal survey of households in the U.S. The dataset includes a series of hypothetical-gamble questions to elicit individuals' risk attitudes, detailed geographical information, and a rich set of socio-economic and labour market controls. The chapter contributes to the empirical literature on risk attitudes and migration in several ways. First, due to the panel structure of the dataset, the relationship between risk attitudes and migration propensities can be analyzed in a comprehensive way, including whether conditional on having migrated, risk attitudes play a role in the number of moves.[6] In particular, we are able to account for unobserved heterogeneity and selection, something that has not been addressed so far. Second, and related to the U.S., to our knowledge, the literature so far has focused on international migration, and has neglected internal migration.[7] The PSID dataset allows for the use of Metropolitan Statistical Areas (MSAs) as geographical units (besides states)[8] enabling us to compare migration decisions within and across regions, which are likely to involve different degrees of uncertainty. Third, and more generally, the analysis allows first conclusions about whether the U.S. is different from other countries in terms of the migration-risk relation, i.e. whether the underlying relation is linear or affected by country specifics in a non-linear 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 socio-economic and labour market characteristics. For migration across states and across larger distances—which normally involve larger uncertainty—risk attitudes seem to be even more important. Furthermore, we find that risk attitudes play a role in determining whether individuals self-select into migration, but not for the number of

[5]Dustmann et al. (2017) use a panel of six waves to analyze the relationship between risk attitudes and the length of migration of rural-to-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.

[6]Gibson 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.

[7]Using the Health and Retirement Study (HRS), Barsky et al. (1997) find statistically significant correlations between risk tolerance and previous international migration. Using the same dataset, 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.

[8]Greenwood and Sweetland (1972) and Chen and Rosenthal (2008) study the determinants of individual migration decisions across MSAs in the U.S., but they do not take into account attitudes towards risk. Molloy et al. (2011) study internal migration trends in the U.S. at many levels of disaggregation—including cross-MSA migration—but their analysis does not focus on migrant behaviour at the individual level.

moves or the distance moved, conditional on moving. 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 U.S. (Molloy et al. 2011) and a more risk-averse population (Fehr et al. 2006), the migration-risk relationship is not very different. If at all, risk attitudes play a slightly larger role in the decision to migrate in Germany than in the U.S.

The remainder of the chapter is structured as follows. The next section presents a simple reformulation of the human capital model of migration that accounts for risk-aversion. The empirical strategy is presented in section 2.3. Section 2.4 describes the data and includes summary statistics. Section 2.5 comprises the empirical results and section 2.6 concludes.

2.2 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

$$E(Y^j(w_s^j, p^j)) = p^j(w_1^j) + (1-p^j)(w_2^j) \tag{2.1}$$

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

$$Y^k(w_s^k) = w_s^k \tag{2.2}$$

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.[9] Individuals can then calculate the sum of discounted income flows by comparing (2.1) and (2.2) in each period, t. Define Υ^{kj}, as the

[9] We 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 (2.1) and (2.2), where it is assumed that $e > 0$.

net discounted income flow from migration from k to j

$$\Upsilon^{kj} = \sum_{t=0}^{T} \frac{E(Y_t^j(w_s^j, p^j)) - Y_t^k(w_s^k)}{(1+r)^t} - C_{kj} \tag{2.3}$$

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, i.e., migration will occur only if $\Upsilon^{kj} > 0$.[10]

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.[11] 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 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), i.e. absolute risk-aversion that declines with wealth,[12] equation (2.1) becomes

$$E(Y_{i,t}^j(w_s^j, p^j, \gamma)) = p^j \frac{(w_1^j)^{1-\gamma}}{1-\gamma} + (1-p^j)\frac{(w_2^j)^{1-\gamma}}{1-\gamma} \tag{2.4}$$

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 (2.2) 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 whilst enabling the analysis of the effect of risk-aversion.

[10] The 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.

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

[12] The 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.

The net return to migration, Υ_i^{kj}, now varies across individuals due to the risk-aversion parameter, γ. It can be shown (see Appendix A for the proof) that

$$\frac{\partial E(Y_i^j(w_s^j, p^j, \gamma))}{\partial \gamma} < 0, \quad \frac{\partial Y_i^k(w_s^k)}{\partial \gamma} = 0 \tag{2.5}$$

and, hence

$$\frac{\partial \Upsilon_i^{kj}}{\partial \gamma} < 0 \tag{2.6}$$

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.

2.3 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 U.S. 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 number of moves and the distance moved.

2.3.1 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,[13] 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 modelled by a continuous latent variable, y_{it}^*,

$$y_{it}^* = \beta x_{it} + \epsilon_{it}, \quad i = 1, ..., N; t = 1, ..., T \tag{2.7}$$
$$\text{with} \quad y_{it} = 1 \quad \text{if} \quad y_{it}^* > 0, \quad \text{and} \quad 0 \quad \text{otherwise}$$

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 by[14]

[13] A relaxation of this assumption is addressed in section 4.6.3 in chapter 4.

[14] Given 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 and Moffitt 1982).

$$l_i = \int_{-\infty}^{\infty} \frac{e^{-c_i^2/2\sigma_c^2}}{(2\pi)^{1/2}\sigma_c} \prod_{t=1}^{T} F(y_{it}, x_{it}\beta + c_i) dc_i \tag{2.8}$$

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

$$Corr[\epsilon_{it}, \epsilon_{is}] = \frac{\sigma_c^2}{(\sigma_c^2 + \sigma_\mu^2)}, \quad t \neq s \tag{2.9}$$

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.

2.3.2 Heckman specification

To analyze the role played by risk attitudes in the self-selection of migrants over the intensive margin of migration, namely the likelihood of repeat migration and the distance moved, 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 number of moves and the total distance moved, respectively. 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 modelled by the latent variable y_i^*. The selection equation[15]

$$y_i^* = \beta x_i + \epsilon_i, \quad i = 1, ..., N \tag{2.10}$$
$$\text{with} \quad y_i = 1 \quad \text{if} \quad y_i^* > 0, \quad \text{and} \quad 0 \quad \text{otherwise}$$

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

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

equation

$$s_i^* = \theta z_i + v_i, \quad i = 1, ..., N \tag{2.11}$$

s_i indicates, for each individual, either the total number of migration acts or 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 (2.10), ϵ_i is assumed to be uncorrelated with the explanatory variables.[16] To correct for a potential selection bias, the inverse Mills ratio (IMR)

$$\lambda(x\beta) = \phi(x\beta)/\Phi(x\beta) \tag{2.12}$$

is computed from equation (2.10), with ϕ and Φ denoting the standard normal probability function (pdf) and the cumulative distribution function (cdf), respectively. Finally, including the IMR as an additional regressor in the outcome equation we get

$$s_i^* = \theta z_i + \rho_i \sigma_v \lambda(x\beta) + v_i \tag{2.13}$$

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 (2.10) should include at least one additional variable that is not present in equation (2.13). This variable is assumed to determine the selection of the dependent variable—whether the individual migrates—but not to determine the final outcome—the number of migration acts, or the distance moved. The variable selected is a dummy that takes the value 1 if the head of household claimed to own the inhabited dwelling in every single observed period in our sample.

Ownership of fixed assets in the initial location is likely to increase the costs of migration, making an individual less likely to move. Homeownership has been shown to have a negative relationship with migration propensities (see e.g. Helderman et al. 2006) due to the arguably high transaction costs associated with the ownership of one's dwelling (Oswald 1996). Being a homeowner in every observed period is expected to be an important determinant of non-selection into migration,[17] while relationships with either the total number of moves or the total distance moved seem less likely or less easy to hypothesize.

[16] There is correlation between the errors if $corr(\epsilon_i, v_i) = \rho_i \neq 0$.

[17] The fitness of the exclusion variable is supported by its strong significance in the first-stage probit regression (see Table 2.8 in subsection 2.5.2).

2.4 Data, variables and summary statistics

The data source for this study is the Panel Study of Income Dynamics (PSID) of the University of Michigan, a representative longitudinal panel survey of households in the U.S. From 1997 to 2015, 10 biennial waves of the PSID with information on socio-economic and labour market characteristics are merged with a Geospatial dataset 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.

2.4.1 Independent variable: individual attitudes towards risk

Risk attitudes are underlying attributes that cannot be directly observed. Section 1.4 in the introductory chapter describes in detail the method used to elicit the measure of risk preferences used in this dissertation. 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, which focuses on temporal between-variations, i.e. 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,[18] 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 behaviour, including migration;[19] and in studies using risk attitudes elicited through the questions

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

[19]For example, observed migration in Jaeger et al. (2010) occurs between 2000 and 2006, and their risk

posed in the 1996 wave of the PSID.[20] Based on the literature reviewed above we treat our risk-aversion variable as time-invariant, but include some robustness checks.

2.4.2 Dependent variable: migration

The geographic units selected for this study are Metropolitan Statistical Areas (MSAs). The U.S. Office of Management and Budget (OMB) defines each MSA as a region that consists of one or more counties in which an urban area with a population of at least 50,000 is found, having a high degree of social and economic integration as measured by commutes to work. The OMB has defined 383 MSAs (for a map, see Figure B1 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 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).[21]

By definition, MSAs do not cover rural areas. However, the PSID dataset allows us to identify non-MSA regions in each state in the U.S. and enables us to also consider rural-to-urban and urban-to-rural migration. Therefore, our sample further includes 44 "artificial MSAs",[22] each one representing each state's non-MSA region.[23] MSAs are well suited for the purpose of this study as each geographical unit in the analysis should represent a distinct labour 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 $t-1$.[24]

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 dataset

information is collected in 2004.

[20] Kan (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).

[21] Chapter 4 uses data on respondents' MSA of birth and the MSA in which they grew up. Appending this retrospective geographic information entails the inclusion of 49 further OMB MSAs. Therefore, Table B1 lists a total of 305 MSAs.

[22] For simplicity, these regions will be referred to as MSAs, regardless of their type.

[23] Chen 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.

[24] Even though the human capital model focuses on the individual as the decision maker, migration is often a household decision. Here, the household 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 household's expected net gains from migration. The terms "individual" and "head of household" are used indistinctly.

that allows us to track the migration history of 2,005 heads of household across 300 MSAs, over 10 biennial waves of the PSID for a period of 18 years.

2.4.3 Control variables

The literature on the determinants of migration reviewed above serves to guide the selection of control variables. These variables are categorized into socio-economic, labour market characteristics, and other control variables.

a) Socio-economic 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 presence of children in the household 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 non-missing observation available for the respective individual. Missing values across 13 individuals remained. These were corrected using the next non-missing 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.[25] On the other hand, 69 observations across 61 individuals reported negative or zero income. These were recorded to 1 to avoid undefined values of the logarithms of the family income.

b) Labour market characteristics

Given that there are economic activities that require more location-specific capital (human and otherwise) than others (Shields and 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 head of the household is added as an additional covariate.

c) Other control variables

In parts of the estimations, we include 51 state dummies to capture 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 tax, property, and criminal legislation are usually 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.

[25] After applying these corrections, 4 missing observations across 3 individuals remained.

Overall, the sample consists of 18,028 period-individual observations.[26]

2.4.4 Summary statistics

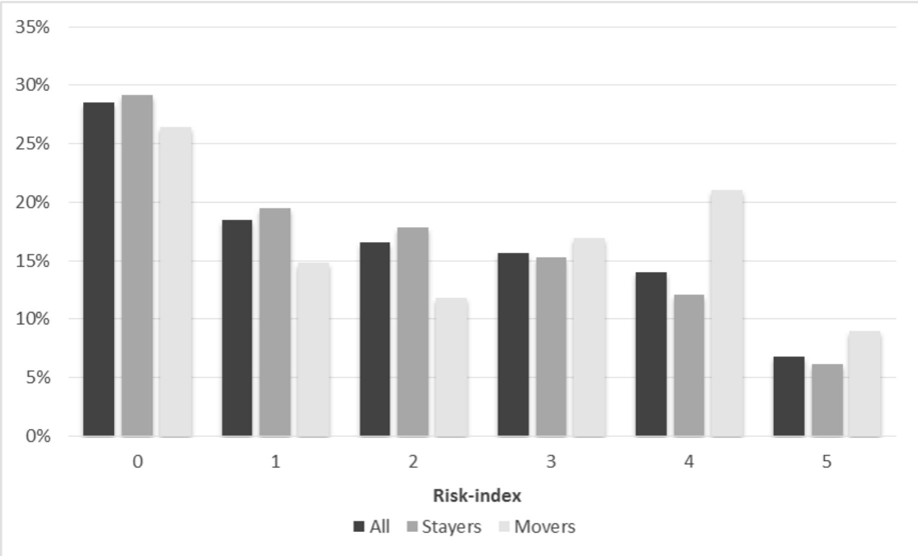

Figure 2.1: Distribution of the risk-index among stayers and movers

Notes: Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse / 5 = least risk-averse.

Figure 2.1 shows the distribution of the risk-index differentiating among "Stayers" (those who never moved) and "Movers" (those who moved at least once).[27] 49% 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 2.1 presents summary statistics at the individual level, for the 2,005 heads of household in our sample. This is constructed using the arithmetic mean of the variables of the individual means 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 standard deviation is 1.62. 18% 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

[26] 13 observations are dropped by the statistical software due to the dummy=1 for the state of Vermont predicting failure perfectly. Overall, with the 4 missings in education, there are 17 observations less than the 18,045 we should have for the 2,005 individuals in our sample, given that we observe migration (with respect to 1997) starting in 1999.

[27] See 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 2,005 individuals.

Table 2.1: Summary statistics at the individual level

Variable	Individuals (n)	Mean	Std. Dev.	Min.	Max.
Dependent variable					
Migration	2,005	0.2154	0.4112	0	1
Key explanatory variable					
Risk-index	2,005	1.8842	1.6252	0	5
Socio-economic characteristics					
Female	2,005	0.1790	0.3834	0	1
Age	2,005	50.5392	10.3180	28	85
Married	2,005	0.6707	0.4307	0	1
Children	2,005	0.6885	0.7896	0	5.4
Years of education	2,005	13.6948	2.1759	5.8	17
Log of total family income	2,005	10.9806	0.8057	6.6767	14.0999

Notes: 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 empoyment status and type of industry are not included.

sample are presented in Table 2.2. These averages are larger for movers than for stayers across all characteristics, (almost) all being statistically significantly different from 0 at the 1% 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 favour 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, 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 (Dohmen et al. 2011b; Jaeger et al. 2010), and more educated individuals tend to be less risk-averse (Halek and Eisenhauer 2001; Jaeger et al. 2010).[28]

2.5 Empirical results

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. Furthermore, to rule out the possibility of our results being driven by our particular geographic characterization, we explore different definitions of moves. In a second step, we pay special attention to migrants' self-selection focusing on the intensive margin of migration, namely the likelihood of repeat migration and the distance moved.

2.5.1 Risk attitudes and migration, random-effects estimations

a) Cross-MSA migration

To analyze the relation of individuals' risk attitudes and migration propensities, we present

[28]The significance levels of the within-stayer/mover-group comparisons are not reported in Table 2.2.

Table 2.2: Average measures of risk attitudes for stayers and movers

Variable	Average risk-index for:	
	Stayers	Movers
All	1.80	2.18***
One move^o		2.08***
Two moves^o		2.21***
Three or more moves^o		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***
Non-married	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***
Log of total family income		
<=11	1.66	1.98***
>11	1.91	2.33***

Notes: "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 variables of the individual means 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. ^{o} denotes t-tests on the equality of means with the sample with one move less. 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.

the average marginal effects (AMEs) of a random-effects probit model (Table 2.3).[29] Given the way the dependent variable is constructed (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 socio-economic characteristics are added as additional regressors. Finally, column 4 shows the results when also controlling for labour market characteristics, the global financial crisis, 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 0.0030 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 0.30%. This implies that a one-standard-deviation increase (1.62 points) in the willingness to take risks is associated with a 0.48 percentage point increase in the migration probability, which represents around 12% of the baseline cross-MSA migration probability of 4.17%.[30] Furthermore, it is important to notice that these results do not account for risky conditions in the location of origin. If we consider the "origin-pull" hypothesis for risk-seeking individuals presented in chapter 3, high-risk MSAs may be pulling from migrating those who are among the most willing to take risks. The underlying relationship between risk attitudes and migration could thus be even more strongly positive.

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. (ibid.) and Williams and Baláž (2014). The presence of children in the household reduces the probability of migration,

[29]Table B3 in Appendix B presents the summary statistics of the regression sample, with a mean of migration of 0.0417.

[30]This specification was also reestimated adding the squared value of age as a covariate to capture a potential non-linear relationship with migration. Both the magnitude and the statistical significance of the effect of the risk-index remained unchanged. Additionally, all specifications were also estimated using the binary risk-indicator.

Table 2.3: Risk attitudes and the probability of migrating across MSAs between 1997 and 2015

Dependent variable:	(1)		(2)		(3)		(4)	
cross-MSA migration since t-1	AME	SE	AME	SE	AME	SE	AME	SE
Key explanatory variable								
Risk-index°	0.0056***	(0.0013)	0.0043***	(0.0012)	0.0031**	(0.0012)	0.0030**	(0.0012)
Control variables (t-1)								
Socio-economic characteristics								
Female°			-0.0218***	(0.0061)	-0.0340***	(0.0068)	-0.0344***	(0.0068)
Age			-0.0011***	(0.0001)	-0.0017***	(0.0002)	-0.0016***	(0.0002)
Married					-0.0214***	(0.0046)	-0.0221***	(0.0046)
Children					-0.0071***	(0.0017)	-0.0066***	(0.0017)
Years of education					0.0053***	(0.0009)	0.0049***	(0.0009)
Log of total family income					0.0009	(0.0015)	0.0009	(0.0016)
Labour market characteristics								
Employed (R.)								
Unemployed							0.0250***	(0.0096)
Retired							0.0243**	(0.0096)
Other employment status							0.0121	(0.0111)
Type of industry								
Construction / manufacturing (R.)								
Finance / real state							0.0094	(0.0086)
Mining / agriculture / forestry / fisheries							-0.0082	(0.0100)
Transport / utilities / communications							0.0030	(0.0064)
Wholesale / retail trade							-0.0048	(0.0054)
Professional / business serv.							0.0004	(0.0048)
Personal / entertainment serv.							-0.0003	(0.0091)
Public administration							0.0120*	(0.0075)
Other							-0.0007	(0.0073)
Financial crisis dummy							-0.0037	(0.0033)
State dummies							Yes	
Observations	18,028		18,028		18,028		18,028	
Individuals	2,005		2,005		2,005		2,005	
Baseline migration probability	0.0417		0.0417		0.0417		0.0417	
Rho	0.4290		0.4184		0.3896		0.3612	

Notes: Average marginal effects (AMEs) of random-effects probit models are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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 B4 in Appendix B. (R.) Reference category. °Time invariant variable.

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. Working in public administration significantly increases the probability of migration as compared to those who work in construction or manufacturing. This may be due to the fact that the public administration category includes those working in the military, who may be more likely to be relocated more frequently.

Table 2.4: Risk attitudes and the probability of migrating across MSAs: Alternative controls

Dependent variable: cross-MSA migration since t-1	(1) Previous migration experience		(2) Ethnicity		(3) Change in employment status	
	AME	SE	AME	SE	AME	SE
Key explanatory variable						
Risk-index°	0.0022**	(0.0010)	0.0025**	(0.0012)	0.0031***	(0.0012)
Previous migration experience						
Moved before in the sample period	0.0362***	(0.0068)				
Ethnicity°						
White (R.)						
African-American			-0.0268***	(0.0042)		
Native-American			-0.0050	(0.0208)		
Asian-American			-0.0378***	(0.0107)		
Other ethnicity			0.0030	(0.0203)		
Changes in employment status						
Employed to employed (R.)						
Employed to unemployed					0.0452**	(0.0126)
Unemployed to employed					0.0409***	(0.0111)
Unemployed to unemployed					0.0285	(0.0195)
Other changes					0.0476***	(0.0075)
Control variables (t-1)						
Socio-economic characteristics	Yes		Yes		Yes	
Labour market characteristics	Yes		Yes		No	
Type of industry	Yes		Yes		Yes	
Financial crisis dummy	Yes		Yes		Yes	
State dummies	Yes		Yes		Yes	
Observations	18,028		18,028		18,028	
Individuals	2,005		2,005		2,005	
Baseline migration probability	0.0417		0.0417		0.0417	
Rho	0.1600		0.3429		0.3659	

Notes: Average marginal effects (AMEs) of random-effects probit models are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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 B5 in Appendix B. (R.) Reference category. °Time invariant variable.

To analyze the robustness of our results to the selection of alternative covariates, column

1 of Table 2.4 includes a dummy variable 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 in this specification remains significant at the 5% level and is associated with an increase in the probability of moving that represents around 9% of the baseline migration probability, which is smaller than the effect played by risk attitudes in the base specification. Therefore, 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 previous migration experience (see also section 4.6.3 in chapter 4).

Column 2 of Table 2.4 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, rather than this personal characteristic being correlated with education or income, particularly in the U.S. (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. Specification 3 modifies the employment control variable to see if specific changes in employment 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 employed in period $t-1$ and remain employed in period t, 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 migrate. 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 and Uebelmesser 2018).

Table 2.5 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 2.3 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, i.e. those who were born before 1950 and may have been overly cautious when answering the risk questions in 1996. By grouping respondents in subsamples of similar age, these two 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 14% of the base migration probability for this subsample. A very similar result can be found for the subsample that does not consider older respondents, also amounting to a change in the likelihood of migration of around 14% of the respective base migration probability.

Table 2.5: Risk attitudes and the probability of migrating across MSAs: Subsample analyses

Dependent variable: cross-MSA migration since t-1	(1) No younger than 30 in 1997		(2) No older than 65 in 2015		(3) No international migration background		(4) No public administration type of industry	
	AME	SE	AME	SE	AME	SE	AME	SE
Key explanatory variable								
Risk-index°	0.0031**	(0.0012)	0.0041***	(0.0015)	0.0027**	(0.0012)	0.0027**	(0.0012)
Control variables (t-1)								
Socio-economic characteristics	Yes		Yes		Yes		Yes	
Labour market characteristics	Yes		Yes		Yes		Yes	
Type of industry	Yes		Yes		Yes		Yes	
Financial crisis dummy	Yes		Yes		Yes		Yes	
State dummies	Yes		Yes		Yes		Yes	
Observations	15,414		12,931		16,913		14,790	
Individuals	1,714		1,438		1,881		1,645	
Baseline migration probability	0.0366		0.0458		0.0420		0.0396	
Rho	0.3751		0.3733		0.3705		0.3576	

Notes: Average marginal effects (AMEs) of random-effects probit models are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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 B6 in Appendix B. °Time invariant variable.

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 3 thus excludes those who have international migration experience, meaning that they either grew up or were born abroad. On the other hand, column 4 excludes individuals who ever worked in public administration, as this category includes those working in the military, who may be more likely to be frequently relocated. Related to their respective base migration probabilities, these subsamples show slightly lower effects of risk attitudes as compared to those from the baseline results.

b) Alternative definitions of migration

Even though MSAs are assumed to represent distinct labour markets, they do not cover the totality of the U.S. territory. The addition of the 44 “artificial MSAs” for each state with rural regions allows us to go beyond urban-to-urban migration across the MSAs 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 U.S. 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 Km^2) or California (403,466 km^2). To address this problem, specification 1 in Table 2.6 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 is of similar magnitude as the one in the baseline results.

Table 2.6: Risk attitudes and the probability of migrating: Alternative definitions of migration

Dependent variable:	(1) All migration types		(2) Cross-state migration		(3) Migration distance larger than 75 Km	
	AME	SE	AME	SE	AME	SE
Key explanatory variable						
Risk-index°	0.0033***	(0.0012)	0.0021**	(0.0009)	0.0029***	(0.0011)
Control variables (t-1)						
Socio-economic characteristics	Yes		Yes		Yes	
Labour market characteristics	Yes		Yes		Yes	
Type of industry	Yes		Yes		Yes	
Financial crisis dummy	Yes		Yes		Yes	
State dummies	Yes		Yes		Yes	
Observations	18,028		18,028		18,028	
Individuals	2,005		2,005		2,005	
Baseline migration probability	0.0458		0.0280		0.0361	
Rho	0.3629		0.3775		0.3631	

Notes: Average marginal effects (AMEs) of random-effects probit models are reported. Standard errors (SEs) are shown in parentheses. ***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. Financial crisis is a dummy variable that takes the value of 1 if t>=2009. Probit coefficients are reported in Table B7 in Appendix B. °Time invariant variable.

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 travelling a larger distance than a move to a neighbouring 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 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 of migration is increased, individual risk attitudes should play a larger role as determinants of migration, other things equal. Column 2 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 (cf. Table 2.3). 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 12% of the baseline cross-state migration probability of 2.80%.

To properly analyze whether indeed the costs of migration are related to distance, it is important to consider that 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).[31] Accordingly, column 3 redefines migration as a move of 75 kilometres or more. Following Sinnot (1984), distance is measured using the straight-line of the "great circle" distance identified based 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 results show that the magnitude of the effect of risk attitudes (around 13% of the respective migration probability) is larger than in the baseline results.

2.5.2 Risk attitudes and migration, cross-section estimations

a) Risk attitudes, self-selection, and the intensive margin of migration

The empirical findings in section 2.5.1 show that higher tolerance towards risk is associated with a higher probability of being a migrant. Two aspects have however not yet been addressed: First, risk attitudes might play a different role in subsequent moves. Second, movers, i.e. individuals who move at least once during the period of observation, might be inherently different from stayers (those who do not move). Not controlling for individual self-selection might, therefore, bias the results.

If 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, as shown in Table 2.4. 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 2.7 presents the AMEs of probit estimations where the dependent variable is a

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

[32] See Table 2.2 where those who move more often have a higher average level of the risk-index.

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 2,005 individuals in our sample. All the covariates used in the fourth specification of Table 2.3 are included (cf. section 2.5.1), 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).[33]

Table 2.7: Risk attitudes and migration, by total number of moves

Dependent variable: Cross-MSA migration at least once	(1) Max 1 move		(2) Max 2 moves		(3) Max 3 moves		(4) All moves	
	AME	SE	AME	SE	AME	SE	AME	SE
Key explanatory variable								
Risk-index°	0.0096**	(0.0048)	0.0128**	(0.0053)	0.0144***	(0.0054)	0.0154***	(0.0054)
Control variables (in 2005)								
Socio-economic characteristics	Yes		Yes		Yes		Yes	
Labour market characteristics	Yes		Yes		Yes		Yes	
Type of industry	Yes		Yes		Yes		Yes	
Individuals	1,804		1,933		1,972		2,005	
Baseline migration probability	0.1280		0.1862		0.2023		0.2154	
Pseudo R2	0.0348		0.0474		0.0564		0.0597	

Notes: Average marginal effects (AMEs) of probit models are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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 B8 in Appendix B. °Time invariant variable.

The first column considers stayers along with those who moved only once during the sample period. A one-standard-deviation increase in the willingness to take risks is associated with an increase in the probability of being a one-time-mover that represents a little more than 12% of the base migration probability for this subsample. Column 2 further includes those who migrated twice, the third specification adds those who moved up to three times, and finally, column 4 includes all individuals regardless of their total number of moves.[34] The latter, which shows an effect of risk attitudes that represents a bit less than 12% of the baseline migration probability of 21.54%, could be considered as our baseline cross-section specification. Overall, the role played by risk attitudes in the probability of moving seems to be slightly stronger in the model that considers one-time-movers only.

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 risk attitudes—relate to repeat migration, or the distance moved. For this purpose, the two-stage Heckman selection model introduced in Section 2.3.2 is applied. The first stage

[33] Furthermore, 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.

[34] Only 33 individuals moved 4 or more times. See Table B9 in Appendix B for a tabulation of the frequencies of cross-MSA moves among the 2,005 respondents in our sample.

deals with the probability that an individual migrates across MSAs at least once, and the second stage studies the total number of moves, and the total distance moved, respectively. Table 2.8 reports the AMEs of the first stage probit in column 1, whereas columns 2a and 2b display the OLS coefficients from each second stage. Selection is identified, given that the IMR is significantly different from zero at the 5% level for the specification considering the total number of moves, and at the 10% level when considering the total distance moved.

Table 2.8: Risk attitudes, self-selection, and the intensive margin of migration

	(1) First-stage probit stayer or mover		(2a) Second-stage OLS Total number of moves		(2b) Second-stage OLS Total Km moved	
	AME	SE	Coef.	SE	Coef.	SE
Key explanatory variables						
Risk-index°	0.0110**	(0.0053)	-0.0236	(0.0336)	- 61.9438	(73.9107)
Homeownership in all periods°	-0.2401***	(0.0184)				
Inverse Mill's ratio			-0.3658**	(0.1504)	-508.2083*	(275.6045)
Control variables (in 2005)						
Socio-economic charactheristics	Yes		Yes		Yes	
Labour market charactheristics	Yes		Yes		Yes	
Type of industry	Yes		Yes		Yes	
Individuals	2,005					
Selected individuals			432		432	
Baseline migration probability	0.2154					
Pseudo R2	0.1316					
R2			0.0867		0.0755	

Notes: 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 columns (2a) and (2b), where the dependent variable is the total number of cross-MSA moves and the total distance moved, respectively. Standard errors (SEs) are shown in parentheses in column 1. Columns 2a and 2b report bootstrapped standard errors based on 500 replications. ***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. Probit coefficients of the first stage are reported in Table B10 in Appendix B. °Time invariant variable.

Declaring homeownership in every single observed period is negatively associated with the probability of being a mover. This result is statistically significant at the 1% level, which shows the fitness of this covariate as an exclusion variable. Being relatively more willing to take risks is positively and statistically significantly related to the likelihood of self-selecting into migration (first-stage regression), but it does not seem to play a role in determining how often movers migrate, nor how far they move, conditional on moving.

b) Comparability of results

Individuals' attitudes towards risk are shown to be positively and statistically significantly related to migration propensities. However, to evaluate the relevance of these results, it is useful to compare them to the ones obtained in similar studies. In particular, we are interested in a comparison with the results for Germany in order to see whether the migration-risk relationship is linear or affected by country specifics in a non-linear way. For this purpose, the study by Jaeger et al. (2010), who present evidence on the relationship between risk attitudes and migration across German districts, 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 U.S. 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 U.S.

Table 2.9: Comparison of results to Jaeger et al. (2010)

	Jaeger et al. (2010) Cross-section 2000-2006			This paper Cross-section 1999-2005		
	(J1)	(J2)	(J3)	(1)	(2)	(3)
Key explanatory variable						
Risk-index°	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
S.D. of risk-index°	2.7	2.7	2.7	1.88	1.88	1.88
AME*S.D. of risk-index	0.0173	0.0113	0.0070	0.0295	0.02068	0.0144
Baseline migration probability (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%

Notes: Average marginal effects (AMEs) of probit models are reported. ***p<0.01, **p<0.05, p*<0.1.
°Time invariant variable.

Columns 1 to 3 in Table 2.9 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 to J3. Given that they observe migration between 2000 and 2006, our sample period is restricted to 1999 to 2005.[35] Furthermore, the standard deviations of the measures of risk aversion are used to allow comparability between their self-assessed eleven-point 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 U.S., the 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).

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

2.6 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 and Baláž 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 and Van den Berg 2013).

The dataset from the Panel Study of Income Dynamics (PSID) allows us to use U.S. Metropolitan Statistical Areas (MSAs) as geographical units to provide evidence on the positive and strongly significant association between individual willingness to take risks and migration propensities. The results are robust to the inclusion of additional covariates, conducting subsample analyses, and using alternative definitions of migration. 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 seem to be even more important. 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 play an important role in the decision whether to move at least once across MSAs, while this is not the case when considering the number of moves, or the total distance moved, conditional on moving.

A violation of the assumption that the error term, ϵ_i, is independent of the explanatory variables in equation (2.10) would lead to biased estimates (cf. section 2.3). 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. 2011b) 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 2.2). The latter would cast doubt on the exogenous nature of risk preferences. This concern is beyond the scope of this chapter. However, it is addressed in section 4.6.3 in chapter 4.

The insights from this chapter may also be extended by introducing a new source of risk, namely one that is related to the variability of employment opportunities in the location of origin. This type of risk may differently affect individuals with varying degrees of risk-aversion. Risk-averse individuals may be pushed to search for labour market opportunities at more stable locations if risk at the location of origin becomes unbearable. On the other hand, those who are more willing to take risks may favour the risky environment. The following chapter deals with this additional source of risk that leads to a more ambiguous relationship between risk attitudes and migration.

3 Chapter 3
Risk Attitudes, Employment Risk, and Migration: the Role of "Origin-Push" and "Origin-Pull" Effects

3.1 Introduction

Individual attitudes towards risk have long been recognized to play a determinant role in migration propensities. However, the way in which risk attitudes affect migration may be ambiguous (Jaeger et al. 2010). This ambivalent relationship stems from the fact that, for potential migrants, there are two different sources of risk (Conroy 2009), namely, risky conditions at their location of origin and risky conditions at a prospective location. When focusing on risky conditions originated in a prospective location, the risk associated with future income streams and the uncertainty generated through incomplete information about the costs and returns of moving makes migration an inherently risky activity (Jaeger et al. 2010; Williams and Baláž 2012). Given that individuals differ in their risk-taking propensities (Arrow 1965; Pratt 1964), individual attitudes towards risk will eventually determine whether migration indeed takes place. Therefore, a straightforward hypothesis is that, *ceteris paribus*, individuals who are relatively more willing to take risks, are more likely to migrate (see chapter 2).

The latter argument still holds when explicitly accounting for risky conditions in the location of origin—in the form of high variability in employment opportunities or income. However, the picture becomes ambiguous. According to Conroy (2009), the presence of risk in the location of origin would push risk-averse potential migrants into relocating to a more stable location. On the other hand, those who are most willing to take risks may be attracted to more risky locations as a way to increase their chance of receiving above-average earnings (Jaeger et al. 2010), i.e. they are pulled from migrating to more stable locations. The goal of this chapter is to analyze the relationship between individuals' attitudes towards risk and their decision to migrate within the United States (U.S.), when explicitly accounting for what we have denominated the "origin-push" and "origin-pull" effects for risk-averse and risk-seeking individuals, respectively.

The literature considering risky conditions in the origin usually focuses on migration as a risk diversification mechanism for risk-averse families in developing countries (see e.g. Stark 1981; Stark and Levhari 1982). The few studies conducted in developed countries implicitly assume a population of risk-averse individuals, and thus, do not explicitly take into account differences in risk aversion (see e.g. Arzaghi and Rupasingha 2013; Daveri and Faini 1999). In a developing country setting and assuming the household to be an indivisible unit, Conroy (2009) is, to the best of our knowledge, the only empirical work studying the “origin-push” hypothesis for risk-averse individuals that uses a direct measure of individual attitudes towards risk. The present study complements Conroy (2009) in two fundamental ways. First, it introduces and tests the “origin-pull” hypothesis for risk-seeking individuals, together with the “origin-push” hypothesis for the risk-averse. Second, it presents the first evidence of a developed country. The results show that those who are among the most willing to take risks are significantly less likely to migrate (compared to those with higher risk aversion), the higher the risk at the origin, supporting the “origin-pull” hypothesis. No evidence is found in favour of the “origin-push” hypothesis for risk-averse individuals, however.

The remainder of the chapter is structured as follows. The next section reviews the literature on the relationship between risk attitudes and migration with a particular focus on how risk at the location of origin may differently affect individuals with varying degrees of risk aversion. This allows us to derive the “origin-push” and “origin-pull” hypotheses. The third section follows with a description of the data. The empirical strategy is presented in section 3.4 while section 3.5 presents summary and descriptive statistics. The sixth section contains the empirical results, and section 3.7 concludes.

3.2 Related literature and motivation

Migration can be viewed as a human capital investment decision (Sjaastad 1962), in which potential migrants are assumed to choose a location that maximizes their present value of lifetime earnings. To say it differently, individuals tend to base their decision to migrate on their expected income (Todaro 1969). As migrants are not necessarily guaranteed a job upon relocation and, according to Jaeger et al. (2010), are assumed to have less information about other non-monetary potential benefits of moving (e.g. leisure opportunities at the destination), migration can be considered an inherently risky activity. Given that a central feature of the theory of choice under risk and uncertainty is that individuals differ in their risk-taking propensities (Arrow 1965; Pratt 1964), individuals’ attitudes towards risk are likely to play a determinant role in their migration decisions.

Jaeger et al. (2010) is the first empirical study to directly measure the relationship between risk attitudes and migration propensities. They find that those who are relatively more willing to take risks are more likely to move across German districts. Williams and Baláž (2014) study international migration in the U.K. and arrive at similar conclusions. Gibson and McKenzie (2012) find that among high-skilled individuals from three south pacific countries, those who are more willing to take risks are more likely to have ever engaged in international migration. In Akgüç et al. (2016), less risk-averse individuals are found to be more likely to engage in rural-to-urban migration in China. Finally, chapter 2 of this dissertation shows that being relatively more willing to take risks is positively associated with the probability of migrating across Metropolitan Statistical Areas (MSAs) and across states in the U.S. These studies, however, focus only on the argument regarding imperfect and incomplete information in a prospective location and fail to explicitly account for risky conditions at the location of origin.

The literature accounting for risky conditions in the location of origin usually focuses on risk diversification of risk-averse agents in the context of rural-to-urban migration in developing countries.[1] In Todaro's (1969) model, individuals base their decision to migrate on expected income differentials between rural and urban areas. Stark (1981) complements this analysis by allowing for heterogeneous risk preferences and focusing on households as the decision-making unit. The author argues that in the absence of formal insurance mechanisms—as it is usually the case for developing countries—migration is used as a strategy to diversify income risk at the origin. So, a risk-averse rural household may decide to send some of its members to locations whose income is only weakly correlated to the income of the location of origin (Stark and Levhari 1982).

The few studies done in developed countries focus on income correlations across regions as well, but they implicitly assume a population of risk-averse individuals. Thus, they do not explicitly take into account differences in individual attitudes towards risk. Daveri and Faini (1999) use income correlations across regions in Italy and find that households diversify risk by relocating some members to locations with imperfectly correlated income. Also based on family separation, Chen et al. (2003) develop a two-country model of migration in which income correlations across countries play a role in migration decisions.[2] Arzaghi and Rupasingha (2013) find similar results for rural-to-urban cross-county migration in the U.S. However, Arzaghi and Rupasingha (2013) differ in that they assume that households are an indivisible unit in which either all stay or all migrate. Thus, when deciding on relocation, the head of the household acts as a decision-maker that takes into account the expected net gains from migration of all members of the household (Mincer 1978).[3]

According to Conroy (2009), migration can be explained by factors other than income differentials *per se*, given that the simple desire to obtain a more reliable stream of income may induce relocation. To illustrate this point, the author frames his analysis in the context of rural-to-urban migration in a developing county (as in Stark 1981) but assumes that migration is taken by the household as a whole (as in Arzaghi and Rupasingha 2013). Since agricultural production is likely to be the main source of income for rural households

[1]See also Katz and Stark (1986), Dustmann et al. (2017).

[2]The authors present some supporting empirical evidence using data of Hong Kong migrants.

[3]This assumption can be justified by the presence of a dominant head of household (Dustmann et al. 2017), or by a household utility function that is the sum of the utility functions of its individual members, assuming homogeneous preferences for risk (Chen et al. 2003).

in developing countries, the income streams of these households tend to be subject to high variation given that they likely depend on meteorological conditions. Conroy (2009) argues that high variability in income is likely to push risk-averse rural households into migration to urban locations, where income streams are less likely to depend on the volatile agricultural production. He tests his hypothesis using Mexican data that contain a direct measure of individuals' risk attitudes and finds that risk-averse women are more likely to migrate away from rural regions with high agricultural income variability.[4]

These insights, however, need not be exclusive to rural-to-urban migration or developing countries for that matter, provided there is a measure of income opportunities (and its variability) that is applicable to developed countries. For this, we focus on employment as the main source of income of individuals and on regional unemployment rates as a measure of regional employment probabilities (Pissarides and McMaster 1990; Todaro 1969). According to Arzaghi and Rupasingha (2013), the changes in unemployment rates over time tend to shape expectations on actual employment probabilities. Even though employment probabilities can be understood as the probability to find a job at a prospective location (Arzaghi and Rupasingha 2013), they can also serve to signal the stability of labour market conditions at the location of origin, as unemployment rates are found to be positively correlated with job-loss rates (Farber 2015).

If the prospects of job-loss are dire or the employment opportunities are very uncertain, a risk-averse individual may start searching for jobs at more stable locations as an insurance mechanism. This alone would increase the likelihood of migration for three reasons. First, because individuals who are actively looking for jobs are more likely to move than those not engaged in job searching (DaVanzo 1978). Second, because risk-averse job seekers are less selective. This increases the likelihood of migration as they are likely to accept most job offers, given that they tend to set their reservation wage levels quite low (Pannenberg 2007). Third, because searching in alternative locations would manifest an initial intention to migrate, making migration more likely. Intentions are not only a pre-condition for realized behaviour (Ajzen 1991), but also migration intentions have been used as a proxy for the actual decision to migrate (see e.g. Uebelmesser 2006). Therefore, we hypothesize that high variability in employment probabilities (unemployment rates) in the origin is likely to push risk-averse individuals into migrating to alternative locations, in hopes of finding lower variability of employment probabilities. We denominate this as our "origin-push" hypothesis for risk-averse individuals.

Those who are relatively more willing to take risks are expected to react differently to less stable labour market conditions. Similarly to the way that they tend to be attracted

[4]The author does not find significant results for the case of males.

to occupations with higher variability of wages, as their mean wage is usually higher (Pissarides 1974), lower-risk-averse individuals are also drawn to locations with higher variability of income opportunities (Jaeger et al. 2010). Moreover, according to the job search theory, when looking for a job, those who are less risk-averse tend to favour longer search periods hoping for a better match at a higher end of the wage distribution (Feinberg 1977; Pissarides 1974). Not only are risk-takers more likely to have secured a better paid and more stable job match by searching for longer—thus reducing their likelihood of getting fired (Diaz-Serrano and O'Neill 2004)—but higher wages are found to be inversely related to measures of subjective job insecurity (Muñoz de Bustillo and de Pedraza 2010).[5] Thus, those who are more willing to take risks are less likely to actively engage in job-search as a reaction to uncertain labour market conditions, if their livelihood is not directly affected. Furthermore, suppose that two individuals become unemployed, one more risk-averse than the other. The latter would tend to set a higher reservation wage and remain unemployed for longer (Feinberg 1977; Pissarides 1974), whereas the former would likely accept most job offers (Pannenberg 2007), which—given the labour market conditions at the origin—are more likely to come from different locations. Therefore, we hypothesize that high variability in employment probabilities (unemployment rates) in the origin is likely to pull those who are relatively more willing to take risks from migrating to alternative locations. We denominate this as our "origin-pull" hypothesis for risk-takers.

3.3 Data and variables

This chapter uses data from the Panel Study of Income Dynamics (PSID), a representative longitudinal panel survey of households in the U.S. From 1997 to 2015, 10 biennial waves of the PSID are merged with a Geospatial dataset that includes detailed geographical information of survey respondents, and the 1996 wave of the PSID, which includes a series of questions used to elicit individual attitudes towards risk. Additionally, data from the U.S. Bureau of Economic Analysis, U.S. Bureau of Labor Statistics, U.S. Department of Justice, and the U.S. Department of Agriculture are used to capture regional characteristics of individuals' locations of origin.

3.3.1 Key explanatory variables

a) Individual attitudes towards risk

Individual attitudes towards risk are underlying attributes that cannot be directly observed. The 1996 wave of the PSID uses a series of hypothetical-gamble questions as a comprehensive method for the elicitation of risk attitudes (see section 1.4 in the introductory chapter). All heads of household that were employed in 1996 were asked up to five questions on

[5] The authors also hypothesize a negative relationship between the willingness to take risks and subjective job insecurity, but they fail to provide direct evidence.

the selection of a safe job that guarantees their current lifetime income, and a risky job that may double their lifetime income or may cut it by a given fraction. The gambles differ only on the size of the potential negative outcome associated with the risky job. An individual is assumed to accept a risky job only if its expected utility exceeds that of the safe job. Hence, those who exhibit a higher tolerance towards risk are willing to accept jobs with worse potential negative outcomes (Kimball et al. 2009). According to the authors, with constant relative risk aversion (CRRA),[6] i.e. absolute risk-aversion that declines with wealth, gamble responses imply an upper and lower bound on an individual's willingness to take risks, under the assumption of no response error. Following Brown et al. (2012), the responses to the hypothetical gambles are used to build a six-point index (from 0 to 5) of the risk preferences of the heads of household. This *risk-index* is decreasing in risk-aversion given that those who are willing to accept all the hypothetical gambles obtain a 5—the highest value in the index.

A major concern related to risk attitudes has to do with their stability. Josef et al. (2016) shows evidence of both differential stability (between-variations of risk attitudes over time) and individual-level stability (within-variations of risk attitudes over time), and concludes that individual risk-taking propensities can be understood as an individual personality trait—much similar to the Big Five personality traits studied in psychology—with a moderate temporal stability across the life-cycle. Accordingly, Sahm (2012) finds relative temporal stability of risk attitudes elicited through hypothetical-gamble questions about lifetime income. Furthermore, the empirical literature on the relationship of risk attitudes and migration has assumed a temporal stability of the former (see e.g. Conroy 2009; Jaeger et al. 2010). Based on the literature reviewed above we treat our risk-aversion variable as time-invariant.

b) MSA-of-origin risk

Following Arzaghi and Rupasingha (2013), we use unemployment rates as a measure of employment opportunities in the MSA of origin, and the changes in unemployment rates over time to capture its variability, given that these changes are expected to shape expectations on actual employment probabilities (cf. section 3.2). We construct our *MSA-of-origin risk* variable as the ratio of the standard deviation (SD) of the unemployment rate in an MSA across the sample period (1997 to 2015), over the mean of the SDs of unemployment rates of all MSAs. An MSA is labelled as "high-risk" if it exhibits an above-mean SD of its unemployment rate.

[6] Brunnermeier and Nagel (2008) and Chiappori and Paiella (2011) show that CRRA is an empirically relevant measure to explain microeconomic behaviour.

3.3.2 Dependent variable: migration

The geographic units selected for this study are Metropolitan Statistical Areas (MSAs). The U.S. Office of Management and Budget (OMB) defines each MSA as a region that consists of one or more counties in which an urban area with a population of at least 50,000 is found, having a high degree of social and economic integration as measured by commutes to work. The OMB has defined 383 MSAs in the U.S. However, given the size of our dataset, not all MSAs are observed. Our sample consists of 256 of the MSAs defined by the OMB.[7] By definition, MSAs do not cover rural areas. However, the PSID dataset allows us to identify non-MSA regions in each state. Therefore, we further include 44 "artificial MSAs", each one representing each state's non-MSA region, enabling us to also consider rural-to-urban and urban-to-rural migration, as well as rural-to-rural migration that occurs across state lines (see section 2.4 in chapter 2). Overall, our sample consists of 300 MSA and non-MSA regions.[8] In this study, migration entails a move from one MSA to another. *Migration* is a dummy variable that takes the value of 1 if an individual (head of household) moved across MSAs at least once between 1997 and 2015.[9]

3.3.3 Control variables

The literature on the determinants of migration serves to guide our selection of control variables.[10] These variables are categorized into socio-economic, labour market, and MSA-of-origin characteristics.

a) Socio-economic characteristics

We control for individual characteristics of the heads of household like gender and age, factors that are likely exogenous to an individual's decision to migrate (Jaeger et al. 2010). Additionally, marital status and years of education are controlled for, as well as household-level characteristics like the presence of children in the household and the natural logarithm of the family income. A total of 49 missing values were identified for the variable years of education, 13 of which were corrected using the last non-missing observation available for the respective individual. For the remaining missing values, we used the next non-missing observation available only if the individual was 25 years old or older, under the assumption that people of this age are likely to have already finished their educational path.[11] On the other hand, 61 individuals reported negative or zero

[7] See Table B1 in Appendix B.

[8] For simplicity, these regions will be referred to as MSAs, regardless of their type.

[9] Households are assumed to be a unit in which either all stay or all migrate as in Mincer (1978). The terms "individual" and "head of household" are used indistinctly.

[10] See e.g. Greenwood and Sweetland (1972), Shields and Shields (1989), Bodvarsson and Van den Berg (2013).

[11] After applying these corrections, missing observations for 3 individuals remained for the year 1997.

family income. These were recorded to 1 to avoid undefined values of the logarithms of the family income.

b) Labour market characteristics

According to DaVanzo (1978), individuals who are actively looking for jobs are more likely to move than those not engaged in job searching. Hence, a factor variable indicating the employment status of the head of the household is added as a covariate. Additionally, we include controls for nine types of industry, given that, according to Shields and Shields (1989), there are economic activities that require more location-specific capital (human and otherwise) than others, which in turn likely plays a role in migration propensities (DaVanzo 1981).

c) Other MSA-of-origin characteristics

As a more general measure of uncertainty related to income opportunities, we further include the SD of the MSA personal income per capita. To capture a measure of the size of economic conditions at the MSAs in levels, we also include the unemployment rate and the personal income per capita, as such. Other MSA-of-origin regional controls include the natural logarithm of the population, a measure of natural amenities,[12] and the number of violent and non-violent crimes reported per 100,000 inhabitants. Table C1 in Appendix C provides the summary statistics of the regional characteristics variables for the 300 MSAs in our sample.

A total of 2,002 individuals with no missing information, who answered the risk questions in 1996, and remained in the sample in 2015 were included in the analysis.

3.4 Estimation strategy

Given the binary nature of our outcome variable *migration*, a probit specification is used. The decision of an individual, i, to migrate across MSAs is modeled by a continuous latent variable, y_i^*,

$$\begin{gathered} y_i^* = \beta x_i + \epsilon_i, \quad i = 1, ..., N \\ \text{with} \quad y_i = 1 \quad \text{if} \quad y_i^* > 0, \quad \text{and} \quad 0 \quad \text{otherwise} \end{gathered} \tag{3.1}$$

where x_i is a vector of the independent variables described in section 3.3, and ϵ_i represents the standard normally distributed error term, which is assumed to be uncorrelated with the explanatory variable. The response probabilities,

[12]See McGranahan (1999) for more information.

$$
\begin{aligned}
Pr(y_i = 1|x) &= Pr(y_i^* > 0|x) = Pr(\epsilon_i > -\beta x_i|x) \\
&= 1 - \Phi(-\beta x_i') \\
&= \Phi(\beta x_i')
\end{aligned}
\tag{3.2}
$$

can be derived, where Φ,

$$
\Phi(\beta x_i') = \int_{-\infty}^{\beta x_i'} \phi(z) dz \tag{3.3}
$$

is the cumulative distribution function (cdf) of the standard normal distribution, and $\phi(z)$ is the normal density function,

$$
\phi(z) = \frac{exp(-\frac{z^2}{2})}{\sqrt{2\pi}} \tag{3.4}
$$

Following Jaeger et al. (2010), our analysis is a cross-section of the 2,002 individuals in our sample, given that we are interested in the relationship between risk attitudes and the probability of an individual being an overall "Stayer" (one who never moved) or "Mover" (one who moved at least once). To say it differently, our focus lays on the extensive margin of migration.

Individuals in our sample are observed between the years 1997 and 2015. This period is selected as 1997 is the first year of information available after the elicitation of risk attitudes. All time-variant variables in our cross-section analysis are set to 1997. Given that the oldest individual in our sample is 76 years old in 1997 (cf. Table 3.1 in section 3.5), it is likely that some individuals have engaged in migration before our sample period. This would imply a correlation between individual preferences and the characteristics of their MSA of residence in 1997. This issue is addressed in subsection 3.6.2. The regressions do not control for the variability in employment probabilities or other regional characteristics at prospective locations. Following Conroy (2009, p. 23), we take an "agnostic stance" about the characteristics of the set of prospective locations and concentrate instead on testing the "origin-push" and "origin-pull" hypotheses laid out in section 3.2.

3.5 Summary and descriptive statistics

Table 3.1 presents summary statistics of the regression sample of 2,002 heads of household. A total of 431 individuals (21.53%) are movers, whereas 1,571 are stayers (78.47%). The mean of the risk-index of the heads of household is 1.88 and the standard deviation is 1.62.

Table 3.1: Summary statistics of the regression sample

Variable	Obs. (N)	Mean	Std. Dev.	Min.	Max.
Dependent variable					
Migration	2,002	0.2153	0.4111	0	1
Key explanatory variables					
Risk-index°	2,002	1.8846	1.6250	0	5
MSA-of-origin risk	2,002	1.0234	0.3137	0.2045	2.3972
Control variables					
Socio-economic characteristics (1997)					
Female°	2,002	0.1793	0.3837	0	1
Age	2,002	41.4505	10.3113	19	76
Married	2,002	0.6568	0.4748	0	1
Children	2,002	1.0449	1.1841	0	9
Years of education	2,002	13.5759	2.2456	3	17
Log of total family income	2,002	10.6837	1.0879	0	13.3598
Labour market characteristics (1997)					
Employed	2,002	0.9301	0.2550	0	1
Unemployed	2,002	0.0304	0.1719	0	1
Retired	2,002	0.0204	0.1416	0	1
Other employment status	2,002	0.0189	0.1364	0	1
Type of industry (1997)					
Construction / manufacturing	2,002	0.2697	0.4439	0	1
Finance / real state	2,002	0.0489	0.2158	0	1
Mining / agriculture / forestry / fisheries	2,002	0.0244	0.1545	0	1
Transport / communications / utilities	2,002	0.0884	0.2839	0	1
Wholesale / retail trade	2,002	0.1418	0.3489	0	1
Professional / business services	2,002	0.2512	0.4338	0	1
Personal / entertainment services	2,002	0.0334	0.1798	0	1
Public administration	2,002	0.0924	0.2896	0	1
Other	2,002	0.0494	0.2168	0	1
Other MSA-of-origin characteristics (1997)					
Unemployment rate	2,002	4.6244	1.5182	1.5	15.4
High-risk MSA-of-origin	2,002	0.4935	0.5000	0	1
Personal income p.c.	2,002	26.0019	4.6669	14.1874	48.7686
SD of the Personal income p.c.	2,002	7.2929	2.1656	2.9287	27.9907
Natural Amenities Scale	2,002	3.7794	1.2169	2	7
Log of population	2,002	13.8041	1.4306	8.8500	16.6970
Violent crime per 100,000 inhabitants	2,002	420.3150	365.6159	0	1938.0210
Non-violent crime per 100,000 inhabitants	2,002	3,330.0120	1,859.6010	0	8,945.6470
Additional control variables°					
1997 MSA same as MSA of birth	2,002	0.5044	0.5001	0	1
Prime-age individual	2,002	0.7207	0.4487	0	1
First moved between 2001 and 2005	2,002	0.0414	0.1993	0	1
First moved between 2007 and 2011	2,002	0.0299	0.1705	0	1

Notes: Migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse / 5 = least risk-averse. Risk-dummy takes the value of 1 if risk-index = 5. MSA-of-origin risk is the ratio of the SD of the MSA-of-origin unemployment rate over the mean of the SD of the unemployment rate. High-risk MSA-of-origin is a dummy variable that takes the value 1 if the SD of the MSA-of-origin unemployment rate if above the mean. No data on natural amenities is available for the states of Hawaii and Alaska. For these states, the mean value of the national amenities scale is used. °Time invariant variable.

Around 18% of households have female heads. In 1997, the heads of households were, on average, 41 years old, had one child, and had completed 14 years of education. The mean MSA unemployment rate in 1997 was 4.62%. In this year, 49% of individuals resided in a high-risk MSA.

Table 3.2 illustrates the "origin-push" effect for risk-averse individuals and the "origin-pull" effect for risk-takers described in section 3.2. If our sample would consist only of individuals whose MSA-of-origin is a low-risk MSA, the relationship between risk attitudes and migration would be straight forward. Risk-averse individuals would be *ceteris paribus* less inclined to move across MSAs, given the inherent riskiness of migration. Similarly, they would have no additional pressure to leave their current MSA as they reside in a low-risk environment. On the other hand, those who are more willing to take risks would be more likely to engage in migration on account of their risk preferences and their fondness for locations with higher variability of income (Jaeger et al. 2010). If we consider those who initially reside in a high-risk MSA, the effects stemming from risk preferences still hold for both types of individuals. However, the riskiness of their environment would impact risk-averse and risk-takers differently, with the former being pushed into migrating to more stable MSAs, and the latter being pulled into staying in their current MSA.

Table 3.2: Origin-push and origin-pull effects for migration

Attitudes towards risk	Effect	Low-risk MSA-of-origin	High-risk MSA-of-origin
3*Risk-averse	Individual effect	-	-
	Location effect	-	+
	Total effect	-	-/+
3*Risk-taker	Individual effect	+	+
	Location effect	+	-
	Total effect	+	-/+

Given our six-point risk-index, the classification of individuals' risk preferences need not be dichotomous. We are able to analyze the relationship between risk attitudes, variability in employment opportunities, and migration, taking into account different degrees of risk-aversion. The distribution of the risk-index differentiating among stayers and movers is shown in Figure 3.1.[13] Overall, individuals tend to be more risk-averse, with 47% exhibiting the two lowest scores of the risk-index. This share grows to 49% when considering only stayers, whereas 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 far greater than the share of stayers with a similar risk preference. The two highest scores in

[13]Table 3.1 differs from Table 2.1 only in that the latter includes 3 individuals more (cf. chapter 2).

the risk-index correspond to 18% of stayers, whereas more than 30% of movers fall in that group.

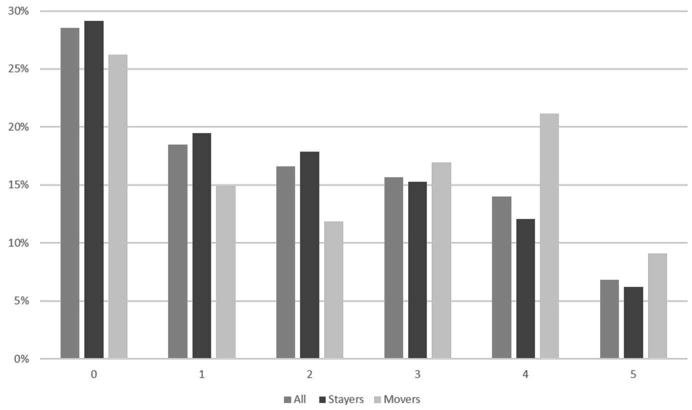

Figure 3.1: Distribution of the risk-index among stayers and movers (2,002 individuals)

Notes: Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse / 5 = least risk-averse.

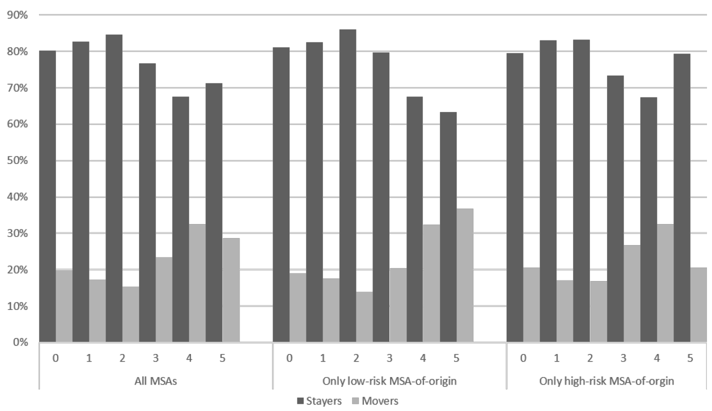

Figure 3.2: Shares of stayers and movers by risk-index, among low-risk and high-risk MSAs

Notes: Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse / 5 = least risk-averse. High-risk MSA-of-origin = 1 if an individual resided in a high-risk MSA in 1997, and zero otherwise.

The results from these comparisons go in line with the hypothesis that movers are likely to be more risk-tolerant than stayers (Jaeger et al. 2010, chapter 2), but they do not consider the role of risky conditions in the origin. Figure 3.2 shows the distribution of stayers and movers by each score in the risk-index for the whole sample, as well as differentiating among the riskiness of respondents' MSA-of-origin.[14] There seems not to be major differences for

[14]Table C2 in Appendix C shows the tabulation of the risk-index among low-risk and high-risk MSAs-of-origin from which Figure 3.2 is built.

risk-averse individuals. For example, around 20% of the most risk-averse (risk-index = 0) are movers. This share remains practically unchanged when considering only those coming from a high-risk MSA, and falls slightly to 19% for those coming from a low-risk MSA. On the other hand, when looking at risk-takers, the contrast between the different levels of risk at the origin seems to be more noticeable. Overall, 71% of those who are among the most willing to take risks (risk-index =5) are stayers. This share falls considerably to 63% when considering those coming from a low-risk MSA and, more important, it grows to 79% for those coming from a high-risk MSA. We interpret this as a first indication in favour of the "origin-pull" hypothesis for the most willing to take risks.

3.6 Empirical results

In a first step, as a benchmark, we study the relationship between risk attitudes and the probability to migrate across MSAs for all individuals. Similarly to Figure 3.2, we compare these results to subsamples separating those coming from low and high-risk environments, respectively. In a second step, we pay special attention to how risk at the MSA-of-origin may differently affect individuals with varying degrees of risk-aversion. For this, an additional term is included in the estimation equations, which interacts the risk-index with our measure of risk at the MSA-of-origin. Furthermore, we assess the robustness of our results when focusing on prime-age individuals for whom the MSA of residence in 1997 is the same MSA in which they were born. Finally, we address the concern of our results being influenced by specific periods of above-trend growth of the unemployment rate.

3.6.1 Risk attitudes and migration decisions

To analyze the relationship between individuals' attitudes towards risk and migration propensities, we present the average marginal effects (AMEs) of probit models (Table 3.3). Column 1 includes only the risk-index, while column 2 additionally considers gender and age, factors that are likely exogenous to an individual's decision to migrate (Jaeger et al. 2010). Column 3, shows the results when also controlling for other socio-economic and labour-market characteristics. Finally, in column 4, the characteristics of the MSA-of-origin of individuals are added as additional regressors.

All specifications show that being more willing to take risks is positively and statistically significantly related to the likelihood of migrating across MSAs. In the most restrictive specification, a one-unit increment in the risk-index increases the probability that an individual migrates between MSAs by 1.34%. This implies that a one-standard-deviation increase (1.62 points) in the willingness to take risks is associated with a 2.17 percentage point increase in the migration probability, which represents around 10% of the baseline cross-MSA migration probability of 21.53%. The results go in line with the empirical literature on the determinants of migration. There is a positive relationship between the years of education and the likelihood of migration whereas the opposite is found for age, coinciding with the findings of Jaeger et al. (2010) and Williams and Baláž (2014). Being a female head of household reduces the probability of migration, in accordance with Akgüç et al. (2016). Looking at other MSA-of-origin characteristics, population size and higher unemployment rates are associated with a reduction in migration probabilities. No significant effect is found for natural amenities or crime. Higher risk related to employment opportunities at the MSA-of-origin is positively and statistically significantly related to the likelihood of engaging in cross-MSA migration. This effect does not differentiate among individuals' degrees of risk-aversion, however.

Table 3.3: Risk attitudes and cross-MSA migration between 1997 and 2015

Dependent variable:	(1)		(2)		(3)		(4)	
cross-MSA migration at least once	AME	SE	AME	SE	AME	SE	AME	SE
Key explanatory variables								
Risk-index°	0.0240***	(0.0054)	0.0195***	(0.0055)	0.0135**	(0.0054)	0.0134**	(0.0054)
MSA-of-origin risk							0.0767**	(0.0347)
Socio-economic characteristics (1997)								
Female°			-0.0797***	(0.0254)	-0.1242***	(0.0314)	-0.1224***	(0.0311)
Age			-0.0039***	(0.0008)	-0.0051***	(0.0009)	-0.0050***	(0.0009)
Married					-0.0772***	(0.0250)	-0.0805***	(0.0250)
Children					-0.0249***	(0.0084)	-0.0241***	(0.0083)
Years of education					0.0232***	(0.0044)	0.0238***	(0.0044)
Log of total family income					-0.0032	(0.0092)	-0.0011	(0.0093)
Labour market characteristics (1997)								
Employed (R.)								
Unemployed					-0.0341	(0.0637)	-0.0146	(0.0665)
Retired					0.1025	(0.0883)	0.0830	(0.0852)
Other employment status					0.0175	(0.0834)	0.0193	(0.0828)
Other MSA-of-origin characteristics (1997)								
Unemployment rate							-0.0152**	(0.0070)
Personal income p.c.							-0.0046	(0.0039)
SD of the Personal income p.c.							0.0177**	(0.0072)
Natural amenities scale							0.0041	(0.0087)
Log of population							-0.0311***	(0.0093)
Violent crime per 100,000 inhabitants							-3.2E-5	(4.4E-5)
Non-violent crime per 100,000 inhabitants							1.2E-5	(8.2E-6)
Type of industry	No		No		Yes		Yes	
Individuals	2,002		2,002		2,002		2,002	
Baseline migration probability	0.2153		0.2153		0.2153		0.2153	
Pseudo R2	0.0091		0.0240		0.0654		0.0826	

Notes: Average marginal effects (AMEs) of probit models are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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. MSA-of-origin risk is the ratio of the SD of the MSA-of-origin unemployment rate over the mean of the SD of the unemployment rate. Probit coefficients are reported in Table C3 in Appendix C. (R.) Reference category. °Time invariant variable.

Table 3.4 presents the results from subsamples separating individuals depending on the riskiness of their MSA-of-origin. When considering only those coming from low-risk MSAs, being more willing to take risks is associated with an increase in the probability of moving that represents around 15% of the base migration probability for this subsample. The size of this effect is around five percentage points larger than the one found in Table 3.3 (10%). This goes in line with the hypothesis that the results in chapter 2, which show a positive

Table 3.4: Risk attitudes and cross-MSA migration:
Low-risk and high-risk MSA-of-origin subsamples

Dependent variable:	(1)		(2)	
	Only low-risk MSA-of-origin		Only high-risk MSA-of-origin	
cross-MSA migration at least once	AME	SE	AME	SE
Key explanatory variable				
Risk-index°	0.0195***	(0.0074)	0.0094	(0.0079)
Socio-economic characteristics (1997)	Yes		Yes	
Labour market characteristics (1997)	Yes		Yes	
Type of industry (1997)	Yes		Yes	
Other MSA-of-origin characteristics (1997)	Yes		Yes	
Individuals	1,014		988	
Baseline migration probability	0.2130		0.2176	
Pseudo R2	0.1338		0.0619	

Notes: Average marginal effects (AMEs) of probit models are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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. High-risk MSA-of-origin is a dummy variable that takes the value 1 if the SD of the MSA-of-origin unemployment rate if above the mean. Probit coefficients are reported in Table C4 in Appendix C. °Time invariant variable.

relationship between risk attitudes and cross-MSA migration but do not account for risky conditions at the origin, should report even stronger effects if risk at the origin is not present. No significant results for the risk-index are found in the subsample of high-risk MSAs-of-origin. This is not surprising given the more ambiguous relationship between risk attitudes and migration when risky conditions exist at the origin (cf. section 3.2 and Table 3.2). Given that depending on their risk preferences, some individuals may be more able than others to cope with high levels of risk, a specification including an interaction between the risk-index and our measure of risk at the origin is explored in the following section.

3.6.2 Risk attitudes, employment risk and migration decisions

In order to assess whether there are differentiated effects of residing in a high-risk environment when comparing individuals with different degrees of risk-aversion, an additional term is included in the estimation equations, which interacts the risk-index with our measure of risk at the MSA-of-origin. The risk-index variable is included as a factor variable, with risk-index = 3 set as reference category. This allows analyzing whether the migration patterns differ for individuals in the upper and lower bounds of the willingness to take risks as a function of the risky conditions at the origin. Table 3.5 shows the coefficients of the probit estimations. A negative, highly significant relationship can be observed between being among the most willing to take risks and a high level of risk at the origin, compared to the reference category in terms of risk aversion. Nonetheless, due to the non-linear

Table 3.5: Risk attitudes and cross-MSA migration:
Interactions between risk-index and MSA-of-origin risk

Dependent variable:	(1)		(2)		(3)		(4)	
cross-MSA migration at least once	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Key explanatory variables								
Risk-index° = 0	0.2807	(0.3461)	0.3080	(0.3504)	0.3590	(0.3613)	0.3250	(0.3604)
Risk-index° = 1	0.2168	(0.3804)	0.2306	(0.3820)	0.3127	(0.3923)	0.2331	(0.3940)
Risk-index° = 2	0.1062	(0.3928)	0.1180	(0.3992)	0.1211	(0.4089)	0.1273	(0.4119)
Risk-index° = 3 (R.)								
Risk-index° = 4	0.5704	(0.3698)	0.4945	(0.3736)	0.3770	(0.3846)	0.3779	(0.3870)
Risk-index° = 5	1.4890***	(0.4939)	1.4749***	(0.4666)	1.4496***	(0.4895)	1.3792***	(0.4961)
MSA-of-origin risk	0.4019	(0.2504)	0.3970	(0.2531)	0.3712	(0.2612)	0.5891**	(0.2711)
Risk-index° = 0 X MSA-of-origin risk	-0.3866	(0.3193)	-0.3413	(0.3226)	-0.3155	(0.3323)	-0.2916	(0.3314)
Risk-index° = 1 X MSA-of-origin risk	-0.4151	(0.3512)	-0.3975	(0.3524)	-0.4259	(0.3616)	-0.3755	(0.3633)
Risk-index° = 2 X MSA-of-origin risk	-0.3840	(0.3633)	-0.3998	(0.3692)	-0.3417	(0.3777)	-0.3566	(0.3806)
Risk-index° = 4 X MSA-of-origin risk	-0.2826	(0.3415)	-0.2040	(0.3448)	-0.0887	(0.3540)	-0.1079	(0.3567)
Risk-index° = 5 X MSA-of-origin risk	-1.3216***	(0.4438)	-1.3041***	(0.4448)	-1.2810***	(0.4659)	-1.2114***	(0.4716)
Socio-economic characteristics (1997)	No		Yes		Yes		Yes	
Labour-market characteristics (1997)	No		No		Yes		Yes	
Type of industry (1997)	No		No		Yes		Yes	
Other MSA-of-origin characteristics (1997)	No		No		No		Yes	
Individuals	2,002		2,002		2,002		2,002	
Baseline migration probability	0.2153		0.2153		0.2153		0.2153	
Pseudo R2	0.0217		0.0384		0.0785		0.0946	

Notes: Coefficients (Coef.) of probit models are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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. MSA-of-origin risk is the ratio of the SD of the MSA-of-origin unemployment rate over the mean of the SD of the unemployment rate. (R.) Reference category. °Time invariant variable.

nature of the underlying probit models, neither the coefficients nor the marginal effects can be directly interpreted (see Greene 2010). Furthermore, the interpretation of the interaction effects is conditional on the independent variables. Based on specification 4 from Table 3.5, Figure 3.3 displays the average marginal effects of belonging to the group of the most risk-averse (risk-index = 0) and the group of the most willing to take risks (risk-index = 5)—relative to the reference category (risk-index = 3)—on the probability of migrating across MSAs, depending on the level of risk at the MSA-of-origin.[15] Those who are among the most willing to take risks are consistently less likely to migrate the higher the risk at their MSA-of-origin, compared to the reference category. The results are statistically significantly different from zero at the 95% level for MSA-of-origin risk equal or below to 0.75 and equal or greater to 1.75 (see Panel B). On the other hand, no significant differences are found for the most risk-averse (see Panel A). Although the results for other risk-index categories show statistically significant differences for a few levels of MSA-of-origin risk, no consistent trend is observed (cf. Table C5). We interpret these results as a first confirmation of our "origin-pull" hypothesis for the most willing to take risks. However, there seems to be no evidence in favour of the "origin-push" hypothesis for the most risk-averse.

[15] The results for other risk-index categories are not displayed to ease readability. The statistical significance of the interaction effects for all degrees of risk aversion are found in Table C5 in Appendix C.

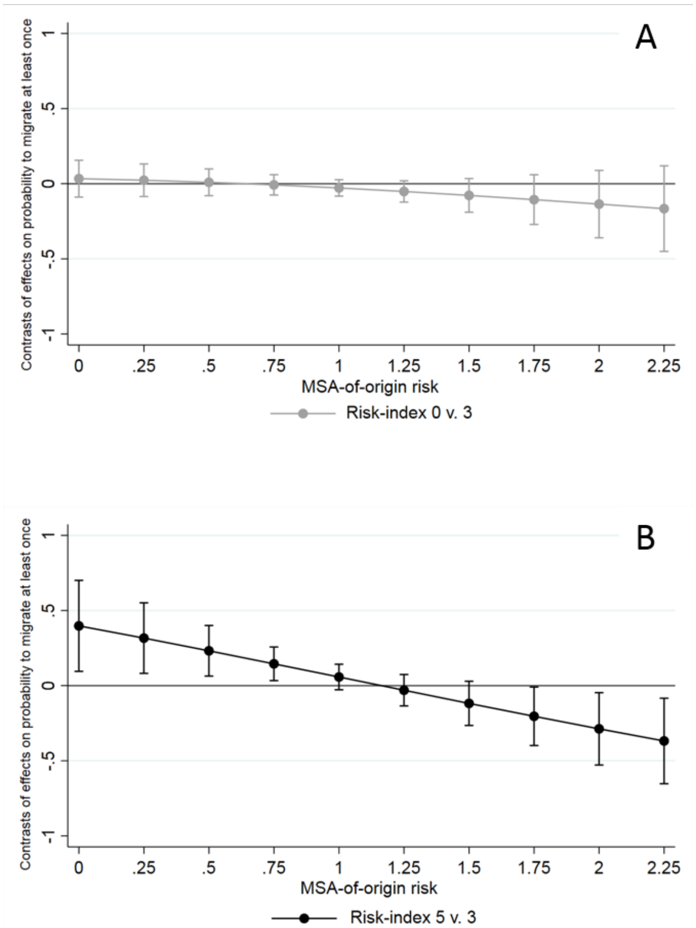

Figure 3.3: Interactions between risk-index and risk at the MSA-of-origin.

Notes: Predicted probabilities based on contrasts of average marginal effects with 95% confidence intervals. Panel A and Panel B show the contrasts of risk-index = 0 and risk-index = 5 with the reference category, respectively. MSA-of-origin risk is the ratio of the SD of the MSA-of-origin unemployment rate over the mean of the SD of the unemployment rate. Reference category: risk-index = 3.

In the following, we explore the robustness of our results in favour of the "origin-pull" hypothesis for the most willing to take risks. As significant evidence has been found only for this category of risk-aversion, for ease of interpretation of the results, the focus is shifted to analyzing the contrast of the migration patterns of the most willing to take risks compared to the rest of individuals. The risk-index is thus replaced by the binary variable *risk-dummy*, that takes the value of 1 if an individual exhibits the highest score in the risk-index, and zero otherwise. Furthermore, we pay special attention to two potential problems that may be driving our results. First, senior citizens reaching retirement may relocate for reasons unrelated to labour market considerations, e.g. moving to locations with a warmer climate. Second, some individuals may have already moved before first being observed in our sample, which would mean that the MSA in which they reside in 1997 does not represent their "true" MSA-of-origin (cf. section 3.4). To account for these potential problems, we focus on 753 prime-age individuals who were between 18 and 65 years of age during the whole sample period, and who in 1997 lived in the same MSA in which they were born.[16] When this subsample is considered, the results are still consistently in favour of the "origin-pull" hypothesis for the most willing to take risks (see Figure 3.4). Compared to individuals with lower degrees of risk-aversion, belonging to the upper-bound of the risk-taking distribution is associated with a reduced probability of migration, the higher the risk at the MSA-of-origin.[17]

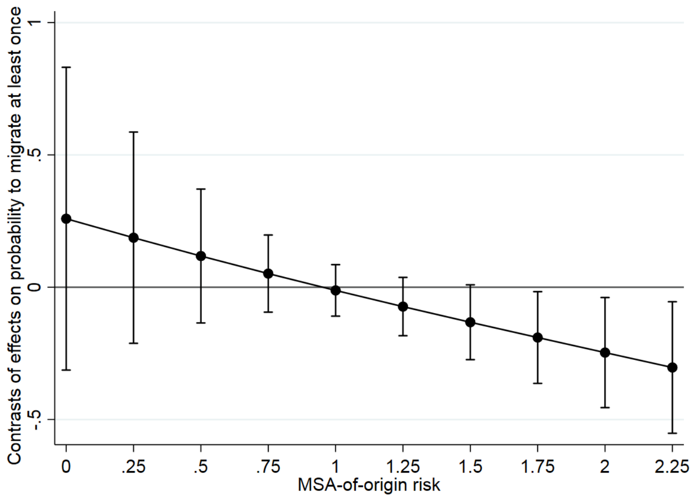

Figure 3.4: Interaction between risk-dummy and risk at the MSA-of-origin: 1997 MSA same as MSA of birth, prime-age individuals

Notes: Predicted probabilities based on contrasts of average marginal effects with 95% confidence intervals. MSA-of-origin risk is the ratio of the SD of the MSA-of-origin unemployment rate over the mean of the SD of the unemployment rate. Risk-dummy takes the value of 1 if risk-index = 5.

3.6.3 Accounting for macroeconomic shocks

A final concern that we address is the possibility of macroeconomic shocks—which are assumed to affect all individuals—having an influence on migration patterns. During our sample period, the U.S. economy experienced two major economic crises, the dot-com crash and the subprime mortgage crisis, that lead to periods of above-trend growth of the unemployment rate between 2001 and 2004, and 2007 and 2011, respectively (see Figure 3.5). Our "origin-pull" hypothesis is retested, excluding from the sample those who

[16] Information on the MSA of birth is collected retrospectively in 1997. We are not able to identify return migrants (if any) who may have migrated from and back to their MSA of birth before being observed in 1997.

[17] Probit coefficients and the statistical significance of the interaction effects are found in Table C6 in Appendix C.

migrated for the first time during the above-mentioned periods. The focus is on first-time migration acts, as these are the ones that determine whether someone is a stayer or a mover.

Figure 3.5: Unemployment rate in the U.S.

Source: U.S. Bureau of Labor Statistics (2019).

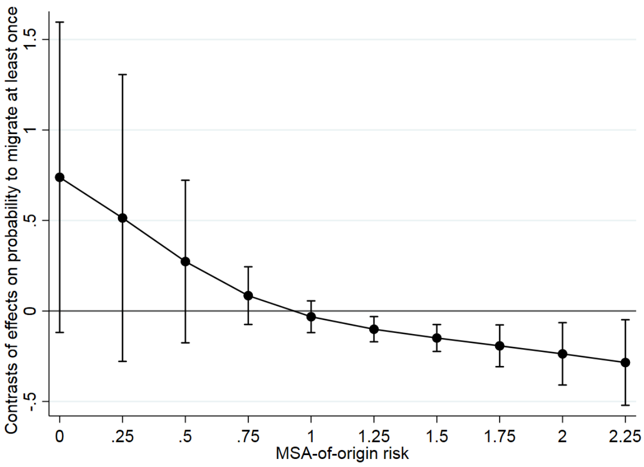

Figure 3.6: Interaction between risk-dummy and risk at the MSA-of-origin: No first-moves during financial crisis.

Notes: Predicted probabilities based on contrasts of average marginal effects with 95% confidence intervals. MSA-of-origin risk is the ratio of the SD of the MSA-of-origin unemployment rate over the mean of the SD of the unemployment rate. Risk-dummy takes the value of 1 if risk-index = 5.

The results for this subsample of 709 individuals, shown in Figure 3.6, are consistent with the ones presented in section 3.6.2. Those who are among the most willing to take risks are significantly less likely to be movers, the higher the risk at the MSA-of-origin, starting from a 1.25 ratio of the SD of the MSA-of-origin unemployment rate relative to the mean.[18]

[18]Probit coefficients and the statistical significance of the interaction effects are found in Table C7 in

3.7 Conclusions

The established relationship between individual attitudes towards risk and migration propensities may be ambiguous when explicitly accounting for risk at the location of origin—in the form of high variability in employment opportunities. This ambivalent relationship stems from the fact that risk at the origin may differently affect individuals with varying degrees of risk aversion. Risk-averse individuals may be pushed to search for labour market opportunities at more stable locations if risk at the origin becomes unbearable. On the other hand, those who are more willing to take risks may favour the risky environment.

This chapter studies the relationship between individuals' attitudes towards risk and their decision to migrate within the U.S., with a particular focus on what we have denominated as "origin-push" and "origin-pull" effects for risk-averse and risks-seeking individuals, respectively. The paper contributes to the still scarce literature on the relationship between risk attitudes and migration decisions that focuses on risk at the origin, by introducing and testing the "origin-pull" hypothesis for risk-seeking individuals, and presenting the first evidence for a developed country. Using probit specifications we find that being among the most willing to take risks is significantly related to a lower probability to move across MSAs (compared to those with higher risk aversion), the higher the risk at the MSA-of-origin. No evidence is found in favour of the "origin-push" hypothesis for risk-averse individuals, however.

The question may arise as to whether high-risk locations not only motivate those who are most willing to take risks to stay but also whether risk-seeking potential migrants specifically target more uncertain prospective locations. This is left for future research.

Appendix C.

4 Chapter 4
Childhood Migration Experience and the Decision to Migrate as an Adult

4.1 Introduction

Migration experience has long been shown to have a positive effect on future migration propensities (DaVanzo 1981, 1983; Eldridge 1965). For movers, the stock of location-specific capital acquired in alternative locations and a general reduction in information costs are identified as the main mechanisms through which repeat migration is explained. Migration, however, is more often than not a household decision. The above-mentioned reasoning is similarly relevant for all members of the household who are exposed to the migration experience, regardless of whether they acted as the decision-makers. Childhood migrants are also likely to develop ties to more than one location and to benefit from a "Learning- by-doing" effect related to adapting to unfamiliar environments and processing information that is relevant for the migration process. This would imply a reduction in the costs associated with migration, increasing the probability to migrate in the future.

The goal of this chapter is to analyze the relationship between individuals' childhood migration experience and their decision to migrate as adults within the United States (U.S.). The study is based on data for the period 1997-2015 from the Panel Study of Income Dynamics (PSID). The dataset includes detailed geographical, socio-economic and labour market information, as well as retrospective information on respondents' childhood and parental characteristics. To the best of our knowledge, no study has analyzed the relationship between childhood migration experience and migration propensities during adulthood. Childhood mobility has been shown to have an effect on future educational attainment (Hango 2006), social integration during adulthood (Myers 1999), and health outcomes through the life-cycle (Jelleyman and Spencer 2008), to name a few. However, its long-term effects on migration patterns have not been addressed. On the other hand, the migration literature has extensively analyzed the relationship between previous migration experience and repeat migration (DaVanzo 1981, 1983; DaVanzo and Morrison 1981; Grant and Vanderkamp 1986), but no focus has been put on the role of childhood migration experience. This chapter seeks to fill the gaps in both streams of literature by arguing that the conceptual framework of repeat migration, with its emphasis on information costs and location-specific capital, is also applicable for migration experience during childhood.

Using a recursive bivariate probit model of simultaneous equations to account for the endogenous nature of childhood migration and its joint determination with migration during adulthood, we find that being a childhood migrant is positively and statistically significantly related to the likelihood of cross-MSA adult migration. Childhood migration is even more important when removing from the sample those who moved during childhood and return to their MSA of birth as adults, i.e. return childhood migrants. Accounting for the distance between MSAs of residence during childhood leads to no substantial differences between nearer and farther childhood moves. When considering individual attitudes towards risk, childhood migration experience seems to be more important for the most risk-averse.

The remainder of the chapter is structured as follows. The next section reviews the literature on repeat migration, describes its conceptual framework, and motivates its application to childhood migration. Section 4.3 proceeds with a description of the data. Section 4.4 follows with summary and descriptive statistics. The empirical strategy is presented in section 4.5. The sixth section contains the empirical results, and section 4.7 concludes.

4.2 Related literature and motivation

Migration is a human capital investment decision in which potential migrants choose a location that maximizes the present value of their lifetime earnings, accounting for the costs related to moving (Sjaastad 1962). To say it differently, potential migrants base their decision on their expected income (Todaro 1969) and are assumed to have complete and perfect information, being able to accurately calculate the relative costs and benefits of the migration and non-migration options (DaVanzo 1983). However, the latter argument fails to account for three essential features of the migration decision-making process.

First, individuals may also decide to migrate for reasons other than better income opportunities (Bodvarsson and Van den Berg 2013). For example, migration decisions are likely to be influenced by the availability of market and non-market amenities (Rosen 1974; Tiebout 1956), including consumption and leisure goods (Shields and Shields 1989). Likewise, the costs of migration are not necessarily related to income and may include, among other things, psychological costs from leaving family and friends behind (Schwartz 1973). Second, individuals have imperfect and incomplete information about the expected pay-offs from migration. The decision to migrate involves a great deal of uncertainty given that potential migrants have less information about income, leisure, and consumption opportunities in locations with which they are not familiar (Jaeger et al. 2010). If the search for information is costly, potential migrants would invest in search up to a certain threshold in which the search costs surpass the perceived gains from additional information (Simon 1956), limiting their set of choices to a few heuristically preselected locations (DaVanzo 1981). Third, it is unlikely that the pool of migrants is randomly determined. According to Borjas (1991), migrants tend to exhibit certain inherent characteristics (e.g.

ability, risk preference, weak ties to the current location), that made them self-select into migration in the first place. The intensity of such selectivity may be affected by the availability (and accuracy) of information about prospective locations, which shapes the expectations about the potential gains from moving (Allen 1979), causing some potential migrants to overestimate the net benefits from migration (DaVanzo 1983).

Migration, however, is not a once in a lifetime occurrence. An individual who self-selects into migration due to an overestimation of its net benefits may be inclined to either move back to the location of origin (return migration) or may instead decide to move to a third location (onward migration), as corrective measures to the disappointing migration experience (Allen 1979; Yezer and Thurston 1976). Similarly to their initial move, these potential repeat migrants would need to form expectations on the net benefits of the repeat migration act (Dierx 1988; Grant and Vanderkamp 1986), with two key fundamental differences, however. First, potential migrants with previous migration experience would arguably be better at gathering and processing information that is relevant for the migration process compared to individuals who have never moved before (DaVanzo 1981, 1983). This is due to a "Learning- by-doing" effect that reduces the costs of subsequent migration (Bowman and Myers 1967; Morrison 1971). The implication is that potential repeat migrants would exhibit higher propensities of migration than those who never moved (DaVanzo and Morrison 1981; Eldridge 1965). Second, and specific to potential return migrants, knowledge about income, leisure, and consumption opportunities in the location of origin is likely to persist, facilitating the recuperation of foregone location-specific capital like local reputation, social networks, and close friendships (DaVanzo 1981, 1983). If location-specific capital in a particular location reduces the costs of migrating to it, individuals with location-specific capital in more than one location would be more likely to migrate than those with no migration experience.

The human capital model tends to focus on the individual as the decision-maker. However, migration is more often than not a household decision. If the household is assumed to be an indivisible unit in which either all stay or all migrate, the head of the household could be thought of as a decision-maker that, when deciding on relocation, takes into account the expected net benefits from migration of all members of the household (Mincer 1978).[1] Analogously, the conceptual framework of repeat migration described above, with its emphasis on information costs and location-specific capital, is just as relevant for other members of the household, including the offspring of the decision-maker. Even though they were not the ones who decided to migrate, childhood migrants are more likely to migrate during adulthood than immobile children for two reasons. First, childhood

[1] According to Chen et al. (2003) this assumption can be justified by a household utility function that is the sum of the utility functions of its individual members.

migration not only hinders the ability of children and adolescents to develop strong social ties in their local community (Coleman 1988; Hango 2006), but it also provides them with opportunities to make new friends and expand their social networks (Myers 1999). Mobile children are thus more likely to have location-specific capital in more than one location and are less attached to one particular location, making them more likely to move during adulthood. Second, mobile children are faced with the challenge of learning how to develop new relationships and adjusting to, for example, a new neighbourhood or a new school (Myers 1999). Therefore, individuals with migration experience during childhood are likely to have benefited from a "Learning- by-doing" effect related to adapting to unfamiliar environments, which reduces the costs of migration, increasing the probability of adult migration.

Even though the decision to migrate during adulthood is made by the individuals themselves whereas childhood mobility was determined by their parents, studying the relationship between childhood and adulthood migration implies analyzing the determinants of the same outcome at two points in time during the life-cycle of individuals. Childhood migration is thus likely to be endogenous and jointly determined with adult migration, given that among the conventional determinants of migration there may be lingering factors that influenced the decision of parents and play a role, either directly or indirectly, on migration patterns of their adult children.

Consider education as a determinant of migration. Higher educational attainment increases the expected payoffs from migration making individuals, in general, more likely to move (Bodvarsson and Van den Berg 2013; Shields and Shields 1989). This holds as well for parents when they are the decision-makers. Higher parental education is thus associated with a higher probability of childhood migration. However, parental education is also likely to have an effect on the offspring's future educational attainment (Chevalier et al. 2013), which, as already mentioned, is related to the likelihood of migration. Another example, and one that is particularly relevant for a conceptualization of household migration as in Mincer (1978), is related to household size. A greater number of household members (e.g. the number of children) increases the costs of moving, decreasing the likelihood of migration (Bodvarsson and Van den Berg 2013; Shields and Shields 1989). Analogously, the number of siblings an individual had during childhood is associated with a lower probability of childhood migration. According to Rainer and Siedler (2009), however, mobility patterns of young adults are influenced by competition among adult siblings regarding decisions about the care of their elder parents. Only children do not face this type of competition and thus exhibit lower adult migration propensities.

The empirical strategy presented in section 4.5 accounts for the endogenous character of childhood migration and its joint determination with migration during adulthood. The selection of the method is guided by the binary nature of both our dependent variable and our key explanatory variable, whose construction is presented in the following.

4.3 Data and variables

This study uses data from the Panel Study of Income Dynamics (PSID), a representative longitudinal panel survey of households in the U.S. From 1997 to 2015, 10 biennial waves of the PSID with information on socio-economic and labour market characteristics, as well as retrospective information on childhood and parental characteristics are merged with a Geospatial dataset that includes detailed geographical information of survey respondents. Additionally, data from the 1996 wave of the PSID is used to elicit individual attitudes towards risk, an attribute that has been shown to play a significant role in migration propensities (Jaeger et al. 2010, chapter 2).

4.3.1 Dependent variable: Adult migration

The geographic units selected for this study are Metropolitan Statistical Areas (MSAs). The U.S. Office of Management and Budget (OMB) defines each MSA as a region that consists of one or more counties in which an urban area with a population of at least 50,000 is found, having a high degree of social and economic integration as measured by commutes to work. The OMB has defined 383 MSAs in the U.S. During our sample period (1997-2015), individuals in our sample resided in 254 of the MSAs defined by the OMB.[2]

By definition, MSAs do not cover rural areas. However, the PSID dataset allows us to identify non-MSA regions in each state. Therefore, we further include 44 "artificial MSAs", each one representing each state's non-MSA region,[3] enabling us to also consider urban-to-rural migration and rural-to-urban, as well as rural-to-rural migration that occurs across state lines. A total of 298 MSA and non-MSA regions are used to build our adult migration variable.[4] Adult migration is defined as a move from one MSA to another during adulthood. *Adult migration* is a dummy variable that takes the value of 1 if an individual (head of household) moved across MSAs at least once between 1997 and 2015.[5]

[2]The number of OMB MSAs in the sample differs from the ones in chapters 2 and 3, due to the reduced sample size in this chapter (see subsection 4.3.2).

[3]Chen and Rosenthal (2008) follow a similar approach. Delaware, the District of Columbia, New Jersey, and Rhode Island do not have non-MSA regions. Furthermore, between 1997 and 2015, we do not have individuals in rural areas in Connecticut, Maine, and Maryland.

[4]For simplicity, these regions will be referred to as MSAs, regardless of their type.

[5]Households are assumed to be indivisible as in Mincer (1978). The terms "individual" and "head of household" are used indistinctly.

4.3.2 Key explanatory variable: Childhood migration

To analyze individuals' childhood migration histories, ideally one would prefer to build a sample comprised of individuals who have been followed and re-interviewed throughout their whole life. For this, however, the households in our sample would need to be "splitoffs" of an original household that participated in the first PSID wave in 1968. Although many "splitoff households" indeed exist, relying solely on them to build a sample would considerably reduce the number of observations for three reasons. First, because attrition across waves occurs in the PSID as with any long-standing longitudinal panel dataset. Second, because in order to maintain the representativeness of their dataset, the PSID conducts periodic sample refreshments, meaning that they add additional households besides those who took part in the original survey. Third, and related to the latter, because it would imply the exclusion of individuals who either were born or grew up abroad. As an alternative, we rely on retrospective information provided by respondents about two specific moments of their life-cycle. Specifically, individuals are asked about their county and state of birth and the county and state in which they grew up. Although working with retrospective information poses the problem of the possibility of recall error (Smith and Thomas 2003), information about the place of birth and place of residence whilst growing up are unlikely to be misremembered. Nonetheless, a total of 75 missing values were identified for the variable denoting the MSA in which individuals grew up. 30 of these were corrected by using information reported in waves before our sample period. Additionally, two individuals who reported only state-level information and for which the state of birth differed from the state in which they grew up were included in the sample and coded as childhood migrants. Our sample consists of 1,962 individuals for which no missing information in any variable remains, including those listed in subsection 4.3.3.

Pairing county and state-level information allows us to identify the corresponding MSAs. *Childhood migration* is a dummy variable that takes the value of 1 if the MSA in which an individual grew up differs from the MSA of birth. Appending the retrospective geographic information entails the inclusion in our sample of 50 further OMB MSAs plus two "artificial MSAs" representing non-MSA regions in the states of Maine and Maryland. Furthermore, an additional "artificial MSA" is coded to signal whether an individual resided abroad. Therefore, our sample consists of 304 of the MSAs defined by the OMB,[6] plus 47 "artificial MSAs", totalling 351 MSA and non-MSA regions.

[6]See Table B1 in Appendix B. One of the MSAs included in the samples of chapters 2 and 3 is not part of the sample of this chapter. On the other hand, a total of 49 MSAs are used only in this chapter. Finally, 255 MSAs are common to all the chapters of this dissertation.

4.3.3 Control variables

The literature on the determinants of migration serves to guide our selection of control variables.[7] These variables are categorized into socio-economic and idiosyncratic, labour market, childhood, and parental characteristics. The first two groups refer to individuals' attributes during adulthood, whereas the latter two are constructed based on retrospective information about their childhood.

a) Socio-economic and idiosyncratic characteristics (during adulthood)

Characteristics of the heads of household like gender, age, and ethnicity are factors that are determined at birth and are likely exogenous to an individual's decision to migrate (Jaeger et al. 2010; Shields and Shields 1989). They are included as covariates. Additional controls include marital status and years of education, as well as household-level characteristics like the presence of children in the household and the natural logarithm of the family income. A total of 49 missing values were identified for the variable years of education. 13 of these were corrected by using the last non-missing observation available for the respective individual. For the remaining 36, we used the next non-missing observation available if the individual was 25 years old or older, under the assumption that at this age, educational paths should be finished. Furthermore, 61 households reported negative or zero income. These were recorded to 1 to avoid undefined values of the logarithms of the family income. Furthermore, we control for individuals' attitudes towards risk, underlying attributes that can be considered to be a stable personality trait (Josef et al. 2016). Following Brown et al. (2012), we use hypothetical-gamble questions posed in the 1996 wave of the PSID to built a six-point (from 0 to 5) *risk-index* that is decreasing in risk-aversion (see section 1.4 in the introductory chapter). Additionally, we include a binary *risk-indicator* that takes the value of 1 if the risk-index is larger than or equal to 3.[8]

b) Labour market characteristics (during adulthood)

Unemployed individuals who are actively looking for jobs are more likely to move than those not engaged in job searching (DaVanzo 1978). Hence, a variable indicating the employment status of individuals is added as an additional covariate. According to Shields and Shields (1989), there are economic activities that require more location-specific capital than others, which in turn likely plays a role in migration propensities (DaVanzo 1981). Therefore, we control for nine types of industry in which individuals work during our sample period.

[7]See e.g. Greenwood and Sweetland (1972), Shields and Shields (1989), Bodvarsson and Van den Berg (2013).

[8]See Table D1 in Appendix D for a tabulation of the six-point risk-index and the binary risk-indicator.

c) Childhood characteristics

We control whether an individual was an only child. A larger number of children in the household is likely to have increased the costs of moving for parents. On the other hand, the number of siblings may influence adult migration propensities (cf. section 4.2). Additionally, we include two dummy variables, one indicating if individuals were born in a rural area, and the other signalling whether they were born abroad.

d) Parental characteristics

Educational attainments of both parents are signalled by two dummy variables, each taking the value of 1 if the mother and the father of an individual had at least 12 years of schooling, respectively. Following Shields and Shields (1989), we also control for nine types of industry in which fathers worked.[9] The same cannot be done for mothers due to the arguably low share of female labour market participation in the generation of the parents of survey respondents. Instead, we add a dummy variable that takes the value of 1 if the mother did not actively participate in the labour market.

4.4 Summary and descriptive statistics

Table 4.1 presents summary statistics of the regression sample of 1,962 individuals. A total of 569 individuals (29%) have migrated during childhood, whereas 418 (21.3%) are adult movers. Around 18% of households have female heads. In 2005, the heads of households were, on average, 49 years old and had completed 14 years of education. The mean of the risk-index of the heads of household is 1.87 and the standard deviation is 1.62. Approximately 28% of respondents were born in a rural area, whereas only 2% were born abroad. Looking at parental characteristics, although mothers seem to be more educated than fathers, 53% of mothers did not actively participate in the labour market.[10]

A cross-tabulation of the binary variables signalling childhood and adulthood migration is presented in Table 4.2. The probability to migrate as an adult drops to 0.1981 when looking only at immobile children. The probability to migrate as an adult conditional on being a childhood stayer is 0.1981. More importantly, the probability to move as an adult conditional on having childhood migration experience increases to 0.2495. We interpret this as a first indication suggesting the presence of a bivariate relationship between childhood and adult migration.

[9] These are assumed to directly influence childhood migration propensities only. However, an indirect effect is transmitted back to adult migration propensities (cf. section 4.5).

[10] Table D2 in Appendix D presents summary statistics of additional control variables.

Table 4.1: Summary statistics of the regression sample

Variable	Obs. (N)	Mean	Std. Dev.	Min.	Max.
Dependent variable°					
Migration	1,962	0.2130	0.4095	0	1
Key explanatory variable°					
Childhood migration	1,962	0.2900	0.4538	0	1
Control variables					
Socio-economic / idiosyncratic characteristics (2005)					
Female°	1,962	0.1794	0.3837	0	1
Age	1,962	49.4913	10.2928	27	83
Ethnicity°					
White-American	1,962	0.7130	0.4524	0	1
African-American	1,962	0.2675	0.4428	0	1
Native-American	1,962	0.0045	0.0675	0	1
Asian-American	1,962	0.0056	0.0746	0	1
Other ethnicity	1,962	0.0091	0.0953	0	1
Married	1,962	0.6799	0.4666	0	1
Children	1,962	0.7456	1.0726	0	7
Years of education	1,962	13.5902	2.2482	3	17
Log of total family income	1,962	11.0194	1.0175	0	15.5202
Risk-index°	1,962	1.8776	1.6256	0	5
Labour market characteristics (2005)					
Employed	1,962	0.8639	0.3429	0	1
Unemployed	1,962	0.0219	0.1464	0	1
Retired	1,962	0.0774	0.2674	0	1
Other employment status	1,962	0.0366	0.1880	0	1
Type of industry (2005)					
Construction / manufacturing	1,962	0.2344	0.4237	0	1
Finance / real state	1,962	0.0524	0.2230	0	1
Mining / agriculture / forestry / fisheries	1,962	0.0188	0.1360	0	1
Transport / communications / utilities	1,962	0.0973	0.2965	0	1
Wholesale / retail trade	1,962	0.1172	0.3217	0	1
Professional / business services	1,962	0.2798	0.4490	0	1
Personal / entertainment services	1,962	0.0336	0.1803	0	1
Public administration	1,962	0.0713	0.2574	0	1
Other	1,962	0.0948	0.2930	0	1
Childhood characteristics°					
Born in a rural area	1,962	0.2818	0.4500	0	1
Born abroad	1,962	0.0188	0.1360	0	1
Only child	1,962	0.0453	0.2081	0	1
Parental characteristics°					
Education of father at least 12 years	1,962	0.5917	0.4916	0	1
Education of mother at least 12 years	1,962	0.6860	0.4642	0	1
Mother did not work	1,962	0.5310	0.4991	0	1
Type of industry of the father°					
Construction / manufacturing	1,962	0.3496	0.4769	0	1
Finance / real state	1,962	0.0270	0.1621	0	1
Mining / agriculture / forestry / fisheries	1,962	0.1182	0.3229	0	1
Transport / communications / utilities	1,962	0.0917	0.2887	0	1
Wholesale / retail trade	1,962	0.0993	0.2992	0	1
Professional / business services	1,962	0.0840	0.2776	0	1
Personal / entertainment services	1,962	0.0728	0.2600	0	1
Public administration	1,962	0.0703	0.2557	0	1
Other	1,962	0.0866	0.2813	0	1

Notes: Adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Childhood migration is a dummy variable that takes the value of 1 if the MSA of birth differs from the MSA in which an individual grew up. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse / 5 = least risk-averse. °Time invariant variable.

Table 4.2: Cross-tabulation of childhood and adulthood migration

	Childhood stayer	Childhood mover	Total
Adult stayer	1,117	427	1,544
Adult mover	276	142	418
Total	1,393	569	1,962
Adult mover conditional on childhood migration	0.1981	0.2495	0.2130

Notes: Adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Childhood migration is a dummy variable that takes the value of 1 if the MSA of birth differs from the MSA in which an individual grew up.

4.5 Estimation strategy

Our analysis is a cross-section of the 1,962 individuals in our sample, given that we are interested in the relationship between the probability of an individual being a "childhood stayer" (one who never moved during childhood) or "childhood mover" (one who moved at least once), and the probability of being an "adult stayer" or an "adult mover". To say it differently, our focus lays on the extensive margin of migration. All time-variant variables are set to the year 2005, the mid-point in our sample period. As pointed out in section 4.2, there may be some factors that influence both childhood and adult migration patterns, meaning that our key explanatory variable is likely to be of an endogenous nature and jointly determined with the outcome. Furthermore, both variables are dichotomous by construction (cf. section 4.3). According to Wooldridge (2010), conventional two-stage instrumental variable methods assume endogenous regressors to be continuous. Their application with a discrete endogenous regressor, particularly a binary one, may thus not be appropriate (Freedman and Sekhon 2010), with simultaneous likelihood estimation procedures often being regarded as a preferred alternative (Marra and Radice 2011).

Consider thus the following bivariate probit model, in which the binary parental decision to migrate across MSAs during the childhood of individual i is modelled by the latent variable, r_i^*,

$$r_i^* = \alpha w_i + u_i, \quad i = 1, ..., N \tag{4.1}$$
$$\text{with} \quad r_i = 1 \quad \text{if} \quad r_i^* > 0 \quad \text{and} \quad r_i = 0 \quad \text{otherwise,}$$

and the binary decision of individual i to migrate across MSAs during adulthood is modelled by the latent variable, y_i^*,

$$y_i^* = \beta x_i + \delta r_i + \epsilon_i, \quad i = 1, ..., N \tag{4.2}$$
$$\text{with} \quad y_i = 1 \quad \text{if} \quad y_i^* > 0 \quad \text{and} \quad y_i = 0 \quad \text{otherwise},$$

The latter takes the form of a recursive bivariate probit model of simultaneous equations (Greene 1998), given that the endogenous variable r_i appears on the right-hand side of equation (4.2) and the outcome variable y_i is not included as a regressor in any equation (Kassouf and 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 not to be independent of each other and to have a bivariate normal distribution (Greene 2003). The correlation between unobservables in both equations is determined by the correlation coefficient, ρ,

$$\rho \quad = \quad Cov[u_i, \epsilon_i | w_i, x_i] \tag{4.3}$$

whose statistical significance determines if the binary variables signaling childhood and adult migration are indeed jointly determined. 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 (4.1) and (4.2) 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 4.2. 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 4.2 consist only of direct effects. Finally, the marginal effects of the endogenous variable, r_i, in the outcome equation can be evaluated by the difference between the conditional probabilities of adult migration when childhood migration equals one and when childhood migration equals zero, i.e.

$$Prob(y_i = 1 | w_i, x_i, r_i = 1) - Prob(y_i = 1 | w_i, x_i, r_i = 0) \tag{4.4}$$

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

4.6 Empirical results

In a first step, we study the relationship between childhood migration experience and the probability to migrate across MSAs as adults for all individuals, accounting for the endogenous nature of childhood migration and its joint determination with adult migration propensities. We proceed with a series of subsample analyses excluding certain groups of respondents who may be affecting our results in a given direction. Furthermore, we explore whether our results are robust to different characterizations of childhood migration according to the distance moved. Finally, we focus on how these effects may differ for individuals with varying degrees of risk aversion.

4.6.1 Childhood migration experience and the decision to migrate as an adult

To analyze the relationship between childhood and adult migration propensities, we present average marginal effects (AMEs) of a recursive bivariate probit model of simultaneous equations (Table 4.3).[11] Column 1 presents the results for the determinants of the endogenous variable. These include childhood and parental characteristics, as well as individual factors that were determined at birth. Depending on whether a covariate appears on the right-hand side of equation (4.1), (4.2), or both, column 2 presents direct and indirect AMEs on adult migration, as well as total AMEs defined as the summation of both (cf. section 4.5). The correlation coefficient ρ (-0.4655) is statistically significant at the 10% level, which we interpret as evidence of the joint determination of childhood and adult migration. Having childhood migration experience is shown to be positively and statistically significantly related to adult migration propensities. Being a childhood mover increases the probability of migrating between MSAs as an adult by 1.34%. We regard this effect as economically significant given that it represents a bit more than 6% of the base adult migration probability of 21.30% (cf. Table 4.1).

Overall, the results seem to conform with the literature on the determinants of migration. There is a positive and strongly significant relationship between years of education and the likelihood of adult migration. This goes in line with the results of Williams and Baláž (2014). An analogous association is found for years of education of the father and childhood migration. Although maternal education does not seem to play a role in the probability of being a child mover, it has a positive effect on the likelihood of moving as an adult. The latter is not surprising given the lasting effect of mothers' education on their children's educational attainment documented in the literature (see e.g. Behrman 1997). Surprisingly, a negative effect of mothers' non-participation in the labour market is observed. Non-working mothers are likely to have greater involvement in childcare, which positively influences children's future educational outcomes (Bettinger et al. 2014). In Datcher-Loury (1988), however, this effect is only significant for highly educated mothers. Being a female head of household reduces the probability of being an adult mover, as in Akgüç et al. (2016) and Hao et al. (2014), while it does not have a significant effect on childhood migration.

[11] Estimation coefficients are presented in Table D3 in Appendix D.

Table 4.3: Childhood migration and the probability of adult migration

Dependent variable:	(1) Childhood migration		(2) Adult migration			
	Direct AME	SE	Direct AME	Indirect AME	Total AME	SE
Key explanatory variable°						
Childhood migration	-	-	0.0134***	-	0.0134***	(0.0039)
Socio-economic and idiosyncratic characteristics (2005)						
Female°	0.0077	(0.0279)	-0.0820***	-0.0467**	-0.1288***	(0.0453)
Age	-0.0030***	(0.0010)	-0.0049***	-0.0035***	-0.0085***	(0.0024)
Ethnicity°						
White-American (R.)						
African-American	-0.0623**	(0.0254)	-0.0994***	-0.0668***	-0.1663***	(0.0414)
Native-American	0.2828*	(0.1572)	-0.1257	-0.0436	-0.1683	(0.1796)
Asian-American	-0.1083	(0.1131)	-0.1114	-0.0782	-0.1896	(0.1651)
Other ethnicity	0.0932	(0.1133)	0.0109	0.0253	0.0362	(0.1602)
Married	-	-	-0.0524**	-	-0.0524**	(0.0264)
Children	-	-	-0.0078	-	-0.0078	(0.0091)
Years of education	-	-	0.0209***	-	0.0209***	(0.0046)
Log of total family income	-	-	-0.0284***	-	-0.0284***	(0.0099)
Risk-index°	-	-	0.0116**	-	0.0116**	(0.0052)
Labour market characteristics (2005)						
Employed (R.)						
Unemployed	-	-	0.0137	-	0.0137	(0.0574)
Retired	-	-	0.1435**	-	0.1435**	(0.0586)
Other employment status	-	-	0.0417	-	0.0417	(0.0605)
Type of industry (2005)						
Construction / manufacturing (R.)						
Finance / real state	-	-	0.0695*	-	0.0695*	(0.0428)
Mining / agriculture / forestry / fisheries	-	-	-0.1477***	-	-0.1477***	(0.0438)
Transport / communications / utilities	-	-	0.0342	-	0.0342	(0.0329)
Wholesale / retail trade	-	-	0.0104	-	0.0104	(0.0296)
Professional / business services	-	-	0.0055	-	0.0055	(0.0241)
Personal / entertainment services	-	-	0.0923*	-	0.0923*	(0.0532)
Public administration	-	-	0.0589	-	0.0589	(0.0374)
Other	-	-	0.0106	-	0.0106	(0.0152)
Childhood characteristics°						
Born in a rural area	-0.0003	(0.0236)	0.0501**	0.0313*	0.0815**	(0.0353)
Born abroad	0.2036**	(0.0889)	-0.1181**	-0.0469	-0.1651**	(0.0724)
Only child	0.0219	(0.0491)	-0.0530	-0.0281	-0.0812	(0.0599)
Parental characteristics°						
Education of father at least 12 years	0.0732***	(0.0248)	-0.0421*	-0.0128	-0.0550	(0.0345)
Education of mother at least 12 years	0.0001	(0.0259)	0.0364*	0.0220	0.0585*	(0.0358)
Mother did not work	0.0018	(0.0211)	-0.0430**	-0.0262**	-0.0693**	(0.0260)
Type of industry of the father°						
Construction / manufacturing (R.)						
Finance / real state	0.1507**	(0.0671)	-	0.0257**	0.0257**	(0.0116)
Mining / agriculture / forestry / fisheries	0.0229	(0.0343)	-	0.0041	0.0041	(0.0062)
Transport / communications / utilities	-0.0215	(0.3500)	-	-0.0040	-0.0040	(0.0065)
Wholesale / retail trade	-0.0369	(0.3230)	-	-0.0069	-0.0069	(0.0064)
Professional / business services	0.0240	(0.0372)	-	0.0043	0.0043	(0.0066)
Personal / entertainment services	0.1298***	(0.0422)	-	0.0223***	0.0223***	(0.0087)
Public administration	0.2399***	(0.0458)	-	0.0400***	0.0400***	(0.0116)
Other	0.0586	(0.0401)	-	0.0103	0.0103	(0.0073)
Individuals	1,962				1,962	
Base migration probability	0.2900				0.2130	
Errors terms correlation:	Coef.				SE	
Rho	-0.4655*				(0.2032)	
	χ^2				$P > \chi^2$	
Wald test of Rho = 0	3.7766				0.0520	

Notes: Average marginal effects (AMEs) of a recursive bivariate probit model of simultaneous equations are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. Adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Childhood migration is a dummy variable that takes the value of 1 if the MSA of birth differs from the MSA in which an individual grew up. (R.) Reference category. °Time invariant variable.

In accordance with the results of Jaeger et al. (2010) and chapter 2, those who are relatively more willing to take risks are more likely to migrate as adults. Compared to employed individuals, those who are retired are more likely to engage in adult migration. Being born abroad makes an individual less likely to move as an adult. According to Goodwin-White (2007), the foreign-born children of immigrants are more likely to remain in their parents' original location. The latter may be explained by the higher degree of urbanization among first-generation immigrants in the U.S (Chiswick and Miller 2004) and the greater employment opportunities available in larger metropolitan areas. On the other hand, being born in a rural area is associated with a higher probability of adult migration.

Table 4.4: Childhood migration and the probability of adult migration: Prime-age individuals and alternative definition of adult migration

Dependent variable:	(1) No older than 65 years of age in 2015		(2) Cross-state adult migration	
	Total AME	SE	Total AME	SE
Key explanatory variable°				
Childhood migration	0.0132***	(0.0051)	0.0055*	(0.0031)
Socio-economic and idiosyncratic characteristics (2005)	Yes		Yes	
Labour market characteristics (2005)	Yes		Yes	
Type of industry (2005)	Yes		Yes	
Childhood characteristics°	Yes		Yes	
Parental characteristics°	Yes		Yes	
Type of industry of the father°	Yes		Yes	
Individuals	1,411		1,962	
Base migration probability	0.2244		0.1544	
Errors terms correlation:	Coef.	SE	Coef.	SE
Rho	-0.4950**	(0.1981)	-0.4429*	(0.2281)
	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$
Wald test of Rho = 0	4.2775	0.0386	2.8117	0.0936

Notes: Average marginal effects (AMEs) of the outcome equation of a recursive bivariate probit model of simultaneous equations are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. Adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Childhood migration is a dummy variable that takes the value of 1 if the MSA of birth differs from the MSA in which an individual grew up. (R.) Reference category. Estimation coefficients are reported in Table D4 in Appendix D. °Time invariant variable.

Along with fathers who worked in finance or real state, and personal or entertainment services, working in public administration significantly increases the probability of migration of fathers compared to those who work in construction or manufacturing. The latter in particular may be due to the fact that the public administration category includes those working in the military, who may be more likely to be relocated more frequently. On the other hand, although no significant effect is found for public administration when looking at the type of industry of respondents in our sample, working in mining, agriculture, forestry or fisheries strongly and significantly decreases the probability of migration compared to the reference category. This may be due to these industries depending on region-specific characteristics like the availability of natural resources.

The first column in Table 4.4 deals with a particular group of individuals who may be directly driving the outcome. The base specification is re-estimated on a subsample of prime-age individuals, i.e. those who were 65 years of age or younger during the entire sample period. Senior citizens reaching retirement age are thus excluded, given that being retired was shown to have a quite strong association with adult migration probabilities (cf. Table 4.3). The significance of the correlation coefficient is increased (going to the 5% level), however, a slight reduction in the size of the effect of being a childhood mover is observed. The average marginal effect represents around 6% of the base migration probability for this subsample. Column 2 explores the robustness of our results to alternative characterizations of the outcome. Specifically, we redefine the adult migration variable and consider migration across states instead of cross-MSA migration. This is done given that moving across states should lead to higher costs together with higher uncertainty (cf. subsection 2.5.1 in chapter 2). Having moved during childhood is associated with an increase in the probability to migrate across states as an adult that represents almost 4% of the respective base migration probability, a smaller effect than the one found for cross-MSA adult migration.

Table 4.5 explores how the relationship between childhood and adult migration propensities changes when excluding certain individuals who may be affecting the probability of being a childhood mover, which in turn would indirectly affect the outcome. In column 1, individuals with fathers that worked in public administration are removed. Column 2 considers only individuals with no foreign background, meaning that only those who were born and grew up in the U.S. are included. The results from the first column show that having moved during childhood is associated with an increase in the probability of moving as an adult of around 6% of the base adult migration probability for this subsample. A very similar result can be found when excluding those with foreign background. Finally, column 3 estimates a specification without childhood movers who at the beginning of the sample period resided in the same MSA in which they were born, i.e. return childhood migrants. Migrants are likely to preserve some location-specific capital in their location of origin, increasing their likelihood of return migration. However, as return migration may ensue as a corrective measure to a possible disappointing migration experience (Allen 1979; Yezer and Thurston 1976), it may imply a reduction in future migration propensities, particularly when compared to the mobility patterns of onward migrants. Being a non-return childhood migrant increases the probability of moving as an adult by around 13% of the base probability for this subsample. The effect more than doubles the size of the one observed in Table 4.3.

Table 4.5: Childhood migration and the probability of adult migration: Subsamples according to childhood and parental characteristics

Dependent variable:	(1)		(2)		(3)	
	No father worked in public administration		No foreign background		No return migrants	
	Total AME	SE	Total AME	SE	Total AME	SE
Key explanatory variable°						
Childhood migration	0.0133***	(0.0041)	0.0132***	(0.0040)	0.0291***	(0.0040)
Socio-economic and idiosyncratic characteristics (2005)	Yes		Yes		Yes	
Labour market characteristics (2005)	Yes		Yes		Yes	
Type of industry (2005)	Yes		Yes		Yes	
Childhood characteristics°	Yes		Yes		Yes	
Parental characteristics°	Yes		Yes		Yes	
Type of industry of the father°	Yes		Yes		Yes	
Individuals	1,824		1,923		1,819	
Base migration probability	0.2083		0.2142		0.2166	
Errors terms correlation:	Coef.	SE	Coef.	SE	Coef.	SE
Rho	-0.6032**	(0.2061)	-0.5310**	(0.1824)	-0.3928*	(0.2011)
	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$
Wald test of Rho = 0	4.6439	0.0312	5.4190	0.0199	3.0466	0.0.0809

Notes: Average marginal effects (AMEs) of the outcome equation of a recursive bivariate probit model of simultaneous equations are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. Adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Childhood migration is a dummy variable that takes the value of 1 if the MSA of birth differs from the MSA in which an individual grew up. Estimation coefficients are reported in Table D5 in Appendix D. (R.) Reference category. °Time invariant variable.

4.6.2 Childhood migration distance

In the human capital model, the costs of migration are related to distance (Sjaastad 1962), including non-monetary costs like leaving family and friends behind (Schwartz 1973). In Table 4.6 we explore whether our results are robust to alternative characterizations of childhood migration according to the distance moved. Following Sinnot (1984), distance is measured using the straight-line of the “great circle” distance calculated based on the latitude and longitude of each MSA’s internal central point. Whenever an individual was born or grew up in a rural area, the coordinates of the counties are used. Due to the unavailability of data on the countries of residence of those with foreign background, this group is excluded from the sample. Therefore, the results from column 2 in Table 4.5 are used as a benchmark (around 6% of the base probability). The binary childhood migration variable is recoded to zero if the distance moved was less than 25 km (column 1), 50 km (column 2), 75 km (column 3), and 200 km (column 4). The effects of being a childhood mover represent 6.93%, 7.09%, 5.38%, and 6.00% of the base probability, respectively for each column. These results do not show a clear trend regarding the role played by the distance of childhood migration on adult migration. We conclude that our results seem to be robust to this alternative specification.

Table 4.6: Childhood migration and the probability of adult migration: Childhood migration distance

Dependent variable:	(1) Childhood migration at least 25 km		(2) Childhood migration at least 50 km		(3) Childhood migration at least 75 km		(4) Childhood migration at least 200 km	
	Total AME	SE	Total AME	SE	Total AME	SE	Total AME	SE
Key explanatory variable°								
Childhood migration	0.0148***	(0.0040)	0.0151***	(0.0040)	0.0115***	(0.0040)	0.0128***	(0.0041)
Socio-economic and idiosyncratic characteristics (2005)	Yes		Yes		Yes		Yes	
Labour market characteristics (2005)	Yes		Yes		Yes		Yes	
Type of industry (2005)	Yes		Yes		Yes		Yes	
Childhood characteristics°	Yes		Yes		Yes		Yes	
Parental characteristics°	Yes		Yes		Yes		Yes	
Type of industry of the father°	Yes		Yes		Yes		Yes	
Individuals	1,923		1,923		1,923		1,923	
Base migration probability	0.2142		0.2142		0.2142		0.2142	
Errors terms correlation:	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Rho	-0.5315**	(0.1801)	-0.5055**	(0.1829)	-0.5304**	(0.1708)	-0.5064**	(0.1777)
	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$
Wald test of Rho = 0	5.5646	0.0183	5.1292	0.0235	6.1768	0.0129	5.4470	0.0196

Notes: Average marginal effects (AMEs) of the outcome of a recursive bivariate probit model of simultaneous equations are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. Adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Childhood migration is a dummy variable that takes the value of 1 if the MSA of birth differs from the MSA in which an individual grew up, and the distance between MSAs is of at least 25 km (column 1), 50 km (column 2), 75 km (column 3), and 200 km (column 4). Estimation coefficients are reported in Table D6 in Appendix D (R.) Reference category. °Time invariant variable.

4.6.3 The role of individual attitudes towards risk

The conceptualization of repeat migration in which this paper is framed, with its emphasis on information costs and location-specific capital, characterizes migration as an inherently risky activity. Indeed, individual attitudes towards risk have been shown to play an important role in migration propensities (Jaeger et al. 2010; Williams and Baláž 2012, chapter 2). If the "Learning- by-doing" effect from migration experience hypothesized by DaVanzo (1981, 1983) reduces the costs and the overall uncertainty related to migration, a question may arise as to whether there is a trade-off between the role played by individual attitudes towards risk and migration experience on the decision to migrate. If this is the case, the role played by migration experience should be particularly relevant for risk-averse individuals, and less so for the most willing to take risks. Column 1 in Table 4.7 removes from the sample respondents who obtained the highest score in the risk-index, i.e. those who are the most willing to take risks. The effect of childhood migration represents around 7% of the base probability. On the other hand, column 2 focuses only on the most risk-averse individuals. Being a childhood mover is associated with an increase in the probability to migrate as an adult of a bit over 12% of the respective base probability. The size of this effect is almost twice as large as the one found in the base specification (cf.

Table 4.7: Childhood migration, adult migration
and individual attitudes towards risk

Dependent variable:	(1) No risk-index = 5		(2) Only risk-index = 0		(3) No risk-index	
	Total AME	SE	Total AME	SE	Total AME	SE
Key explanatory variable°						
Childhood migration	0.0144***	(0.0038)	0.0243***	(0.0079)	0.0139***	(0.0038)
Socio-economic and idiosyncratic characteristics (2005)	Yes		Yes		Yes	
Labour market characteristics (2005)	Yes		Yes		Yes	
Type of industry (2005)	Yes		Yes		Yes	
Childhood characteristics°	Yes		Yes		Yes	
Parental characteristics°	Yes		Yes		Yes	
Type of industry of the father°	Yes		Yes		Yes	
Individuals	1,829		563		1,962	
Base migration probability	0.2083		0.1972		0.2130	
Errors terms correlation:	Coef.	SE	Coef.	SE	Coef.	SE
Rho	-0.4927**	(0.1726)	-0.7400**	(0.2196)	-0.4576*	(0.2054)
	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$
Wald test of Rho = 0	5.6056	0.0179	3.8306	0.0503	3.6184	0.0571

Notes: Average marginal effects (AMEs) of the outcome equation of a recursive bivariate probit model of simultaneous equations are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. Adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Childhood migration is a dummy variable that takes the value of 1 if the MSA of birth differs from the MSA in which an individual grew up. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse / 5 = least risk-averse. Estimation coefficients are reported in Table D7 in Appendix D. (R.) Reference category. °Time invariant variable.

Table 4.3), meaning that childhood migration experience seems to be especially important in explaining the adult migration patterns of those whose mobility is constrained by their risk preferences.

A final concern relates to the formation of risk preferences. Dohmen et al. (2011a) find evidence of an intergenerational link between the risk attitudes of parents and children, nonetheless, they highlight the importance of socialization in this transmission process. For their part, Zumbuehl et al. (2013) show that the similarities in attitudes towards risk are particularly important for parents who are more involved with their child's education. The latter may cast doubt on the exogenous nature of risk preferences. Column 3 re-estimates the base specification without including the risk-index as a covariate. No substantial differences are found. The direction and statistical significance of the effects (and of the correlation coefficient) remain unchanged, with the relation to the base probability differing by just 0.23 percentual points.

To directly address the concern of the potential endogenous nature of risk attitudes and its joint determination with adult migration probabilities, the recursive bivariate probit model of simultaneous equations presented in section 4.5 is estimated, with two fundamental differences. First, the latent variable, r_i^*, in equation 4.1 no longer denotes childhood migration and instead represents a dichotomous measure of the attitudes towards risk of individual i. This binary *risk-indicator* takes the value of 1 if a respondent obtains a score of 3 or higher in the risk-index. Second, the vector w_i no longer includes the variable signalling the types of industry in which fathers worked. This covariate is replaced by a factor variable that denotes whether the parents of individuals smoked. Given that a higher willingness to take risks is associated with a higher propensity to smoke (Dohmen et al. 2011b; Jenks 1992), a more direct association can be established between parental smoking behaviour and their children's attitudes towards risk. Column 1 of Table 4.8 presents the results from the outcome of the above mentioned recursive bivariate probit, whereas column 2 shows the results of the second step estimated using a simple probit specification to allow for comparisons. These columns use the estimation sample of this chapter, which consists of 1,962 individuals due to the missing information regarding the MSA in which individuals grew up (cf. section 4.3). Columns 3 and 4 repeat the comparison exercise, but using instead the complete sample used in chapter 2 (2,005 individuals).

Table 4.8: Risk attitudes and the probability of adult migration: Endogenous nature of risk attitudes

Dependent variable: Adult migration at least once	(1) Recursive Bivariate probit		(2) Probit		(3) Recursive Bivariate probit		(4) Probit	
	Chapter 4 sample		Chapter 4 sample		Chapter 2 sample		Chapter 2 sample	
	Total AME	SE	AME	SE	Total AME	SE	AME	SE
Key explanatory variable°								
Risk-indicator	0.0638***	(0.0038)	0.0638***	(0.0183)	0.0641***	(0.0038)	0.0643***	(0.0181)
Socio-economic and idiosyncratic characteristics (2005)	Yes		Yes		Yes		Yes	
Labour market characteristics (2005)	Yes		Yes		Yes		Yes	
Type of industry (2005)	Yes		Yes		Yes		Yes	
Childhood characteristics°	Yes		Yes		Yes		Yes	
Parental characteristics°	Yes		Yes		Yes		Yes	
Parents smoked°	Yes		Yes		Yes		Yes	
Individuals	1,962		1,962		2,005		2,005	
Base migration probability	0.2130		0.2130		0.2154		0.2154	
Pseudo R2			0.0852				0.0858	
Errors terms correlation:	Coef.	SE			Coef.	SE		
Rho	-0.7059***	(0.1715)			-0.7287***	(0.1514)		
	χ^2	$P > \chi^2$			χ^2	$P > \chi^2$		
Wald test of Rho = 0	6.6064	0.0102			8.2177	0.0041		

Notes: Average marginal effects (AMEs) of the outcome equation of recursive bivariate probit models of simultaneous equations (columns 1 and 3), and probit models (columns 2 and 4) are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. Adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Risk-indicator takes the value of 1 if risk-index is greater than or equal to 3. Estimation coefficients are reported in Table D8 in Appendix D. °Time invariant variable.

The values of ρ in the first and the third columns are -0.7059 and -0.7287, respectively. Both are statistically significant at the 1% level, signalling that our binary measure of attitudes towards risk and the dichotomous migration decision to migrate as an adult may indeed be jointly determined. Being more willing to take risks is positively and statistically significantly related to the likelihood of engaging in adult migration across MSAs. The marginal effect of the binary risk-indicator calculated following equation (4.4) (cf. section 4.5), is 0.063892 (column 1), whereas the AME estimated using a probit model amounts to 0.063888 (column 2). The effect remains practically unchanged given that they differ just slightly, starting on the fifth decimal. These effects represent 30% of the respective base migration probability of 21.30%. Using a sample of 2,005 individuals, the effect of the binary risk-indicator after running a bivariate probit is 0.064159 (column 3). Again, this effect differs just slightly from the AME of 0.064302 found when, in column 4, the outcome equation is estimated by a simple probit (i.e. without taking into account the endogenous nature of attitudes towards risk). Given that not only the direction of the effects of risk attitudes on adult migration and their strong statistical significance remain identical (at the 1% level), but also that removing the endogeneity bias barely changes the size of the effects, we interpret our results as robust to accounting for unobservable cofounders.

4.7 Conclusions

Migration is more often than not a household decision. The conceptual framework of repeat migration, with its emphasis on location-specific capital and information costs, is relevant for all members of the household who are exposed to the migration experience, regardless of whether they acted as the decision-makers. Childhood migrants are also likely to acquire location-specific capital in more than one place of residence, and to benefit from a "Learning- by-doing" effect related to adapting to unfamiliar environments and processing information that is relevant for the migration process. The associated reduction of migration costs would lead to an increase in the probability of future migration.

To the best of our knowledge, no study has analyzed the relationship between childhood migration experience and the decision to migrate as an adult. This chapter contributes to both the literature on repeat migration and the literature on the consequences of childhood migration. The dataset from the Panel Study of Income Dynamics (PSID) allows us to use U.S. metropolitan statistical areas (MSAs) to provide evidence on the positive and statistically significant association between being a childhood mover and cross-MSA migration propensities during adulthood. The results are robust to conducting subsample analyses and to alternative characterisations of childhood and adult migration.

Given the inherent riskiness of migration, there may be a trade-off between the role played by individual attitudes towards risk and migration experience, especially during childhood, on the decision to migrate. Childhood migration experience seems to be especially important in explaining the adult migration patterns of those whose mobility is constrained by their risk preferences. Considering the formation of risk preferences, there is evidence favouring the hypothesis that risk attitudes may be endogenously determined with adult migration. Nonetheless, removing the endogeneity bias leads to no noticeable changes in the statistical significance, the magnitude, nor the direction of the effects as compared to the ones estimated without taking into account the endogenous nature of individual attitudes towards risk. Future research may be directed to studying adult migration propensities, accounting for both the potential endogenous nature of childhood migration and risk attitudes.

5 Chapter 5 Conclusions

5.1 Summary

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 and Baláž 2012). Given that a central feature of the theory of choice under risk and uncertainty is that individuals differ in their tolerance towards risk (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 and Van den Berg 2013). The latter argument still holds when explicitly accounting for risky conditions in the origin location—in the form of high variability in employment opportunities. However, the picture becomes ambiguous. This ambivalent relationship stems from the fact that risk at the origin may differently affect individuals with varying degrees of risk-aversion. High variability in employment probabilities in the location of origin may push risk-averse individuals to start searching for jobs at more stable locations as an insurance mechanism, increasing the likelihood of migration. Those who are among the most willing to take risks are expected to react differently to less stable labour market conditions. Similarly to the way that they tend to be attracted to occupations with higher variability of wages, as their mean wage is usually higher (Pissarides 1974), lower-risk-averse individuals are also drawn to locations with higher variability of income opportunities (Jaeger et al. 2010). Furthermore, risk-takers are less likely to actively engage in job-search as a reaction to uncertain labour market conditions. High variability in employment probabilities in the location of origin is likely to pull those who are relatively more willing to take risks from migrating to alternative locations.

Migration, however, is not a once in a lifetime occurrence. Migration experience may decrease the costs associated with future migration decisions due to a "Learning-by-doing" effect related to adapting to unfamiliar environments and processing information that is relevant for the migration process, and the acquisition of location-specific capital in more than one location. Therefore, individuals who have moved before are more likely to migrate again. Migration, however, is more often than not a household decision. The conceptual framework of repeat migration, with its emphasis on location-specific capital and information costs, is relevant for all members of the household who are exposed to the migration experience, regardless of whether they acted as the decision-makers, e.g. children.

This dissertation contributes to the still scarce literature on the relationship between risk attitudes, migration experience, and migration decisions. The dataset from the Panel Study of Income Dynamics (PSID) allows us to use U.S. Metropolitan Statistical Areas (MSAs) as geographical units to provide evidence on the positive and strongly significant association between individual willingness to take risks and migration propensities, when focusing on the argument regarding imperfect and incomplete information about prospective locations (cf. chapter 2). The analysis is complemented by studying migration across states and across larger distances, which potentially entail higher levels of risk and uncertainty. We find that risk attitudes seem to be even more important for arguably riskier moves. 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 play an important role in the decision to move at least once across MSAs, while this is not the case when considering the number of moves, or the distance moved, conditional on moving.

Chapter 3 studies the relationship between individuals' attitudes towards risk and their decision to migrate within the U.S., with a particular focus on what we have denominated as "origin-push" and "origin-pull" effects for risk-averse and risks-seeking individuals, respectively. The chapter contributes to the still scarce literature on the relationship between risk attitudes and migration decisions that focuses on risk at the origin, by introducing and testing the "origin-pull" hypothesis for risk-seeking individuals, and presenting the first evidence for a developed country. The results show that being among the most willing to take risks is significantly related to a lower probability to move across MSAs (compared to those with higher risk aversion), the higher the risk at the MSA-of-origin. No evidence is found in favour of the "origin-push" hypothesis for risk-averse individuals, however.

To the best of our knowledge, no study has analyzed the relationship between childhood migration experience and the decision to migrate as an adult. Chapter 4 contributes to both the literature on repeat migration and the literature on the consequences of childhood migration. Using a recursive bivariate probit model of simultaneous equations to account for the endogenous nature of childhood migration and its joint determination with migration during adulthood, we find a positive and statistically significant association between being a childhood mover and cross-MSA migration propensities during adulthood.

Finally, we find that the results on the positive association between individual willingness to take risks and migration propensities, when focusing on the argument regarding imperfect and incomplete information about prospective locations, seem to be robust to accounting for the potentially endogenous nature of attitudes towards risk.

5.2 Limitations

A critical concern related to risk attitudes has to do with their temporal 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. Nonetheless, some studies have found that at an individual level, risk tolerance is expected to progressively decline as people get older (see e.g. Barsky et al. 1997; Dohmen et al. 2011a; Sahm 2012).

A major limitation related to this study has to do with the unavailability of data to elicit individual attitudes towards risk throughout the life cycle of respondents. The hypothetical-gamble questions reviewed in section 1.4 were only asked in the 1996 wave of the PSID. Although the temporal stability of risk attitudes has been assumed in the literature (see section 2.4), this dissertation would have definitely benefited from measuring risk attitudes at different points in time for three reasons. First, because it would imply the relaxation of the rather strong assumption that risk attitudes are time-invariant across the sample period. This would, in turn, allow for the use of fixed-effects specifications to capture unobserved heterogeneity, particularly in chapter 2. Second, because it would lead to an increase in the sample size. As pointed out in section 2.4, only individuals who answered the risk questions in 1996 and remained in the sample in 2015 were included in the analysis.[1] Asking the risk questions in different years would have allowed for the inclusion in the sample of individuals who either were not heads of household or were not employed in 1996. Third, and related to the latter, a larger sample size would have probably permitted conducting multigenerational studies. In section 4.3, sample size reduction is mentioned as a disadvantage of working with "splitoff households" and used as justification for working with retrospective information instead. This dissertation would have benefited from properly addressing the topic of the formation of risk attitudes by directly comparing the risk preferences of parents and children.

5.3 Policy recommendations and future research

Understanding the role played by risk attitudes in the decision to migrate is important given its implications for the efficient functioning of labour markets. In the same sense that being relatively more willing to take risks makes an individual more likely to migrate if risky conditions are not present in the origin, population-averaged tolerance towards risk may impact aggregated internal migration propensities in different economies. For

[1] In chapter 4, the sample size is further reduced due to missing information on the MSAs in which respondents' grew up.

example, Fehr et al. (2006) find that Germans tend to be more risk-averse than U.S. Americans. According to Jaeger et al. (2010), the latter may explain the higher mobility rates observed in the U.S., which in turn may contribute to the lower frictions in the U.S. labour market (Molloy et al. 2011). Even if labour 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 labour 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 and 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 that risk attitudes play in migration decisions, and expand the analysis to include migration across international borders. This would require a relative standardization across panel surveys in different countries. To our knowledge, there is one such a project already in progress. The Cross-National Equivalent File (CNEF) seeks to provide equivalently defined variables from major household panel studies in the U.S., Germany, Great Britain, Canada, Australia, Switzerland, South Korea, and Russia. Given that the Panel Study of Income Dynamics (PSID) and the German Socio-Economic Panel Study (SOEP) are part of the CNEF, the comparability exercise carried out in subsection 2.5.2 could be revisited in more detail.

Supporting the "origin-pull" hypothesis, chapter 3 presents evidence that those who are among the most willing to take risks are significantly less likely to migrate (compared to those with higher risk aversion), the higher the risk at the origin. The question may arise as to whether high-risk locations not only motivate those who are most willing to take risks to stay but also whether risk-seeking potential migrants specifically target more uncertain prospective locations. If this the case, once could ask oneself whether more unstable—and perhaps economically weak—regions can reckon with the fact that they may receive an immigration flow of risk-seekers, which would, for example, foster entrepreneurial activity. This, in our opinion, opens up an interesting avenue for future research.

Given the inherent riskiness of migration, there may be a trade-off between the role played by individual attitudes towards risk and migration experience, especially during childhood, on the decision to migrate. Future research may be directed to studying adult migration propensities, accounting for both the potential endogenous nature of childhood migration and risk attitudes.

Compliance with Ethical Standards

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

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Appendix A

Following Heitmueller (2005), the first order derivative of equation (2.4) with respect to γ is given by

$$\begin{aligned}\frac{\partial E(Y_{i,t}^{j}(w_s^j,p^j,\gamma))}{\partial\gamma} &= \\ & \frac{p^j(w_1^j)^{1-\gamma}[1+(\gamma-1)\ln(w_1^j)]}{(1-\gamma)^2} + \\ & \frac{(1-p^j)(w_2^j)^{1-\gamma}[1+(\gamma-1)\ln(w_2^j)]}{(1-\gamma)^2} \leq 0\end{aligned} \tag{A1}$$

An analytical solution becomes increasingly difficult, given the non-linearity of (A1). Nonetheless, given the parameter restrictions in the framework ($0 < p^j < 1$, w_1^j, $w_2^j > 1$, and $\gamma \neq 1$), it can be shown numerically that (A1) holds. Simplifying (A1) leads to

$$\alpha\delta + \beta\psi \geq \frac{\alpha+\beta}{(1-\gamma)} \tag{A2}$$

where

$$\alpha = p^j(w_1^j)^{(1-\gamma)} \tag{A3}$$
$$\beta = (1-p^j)(w_2^j)^{(1-\gamma)} \tag{A4}$$
$$\delta = \ln(w_1^j) \tag{A5}$$
$$\psi = \ln(w_2^j) \tag{A6}$$

As can be easily seen, (A3) and (A4) are zero for $\gamma \to \infty$. Therefore, the left-hand-side of (A2) is also zero for $\gamma \to \infty$. Similarly, the numerator of the right-hand-side of (A2) is zero in the limit. The total effect on Υ_i^{kj} is negative, given that $Y_i^k(e,w_s^k)$ is not affected by changes in the parameter of risk aversion, γ.

Appendix B

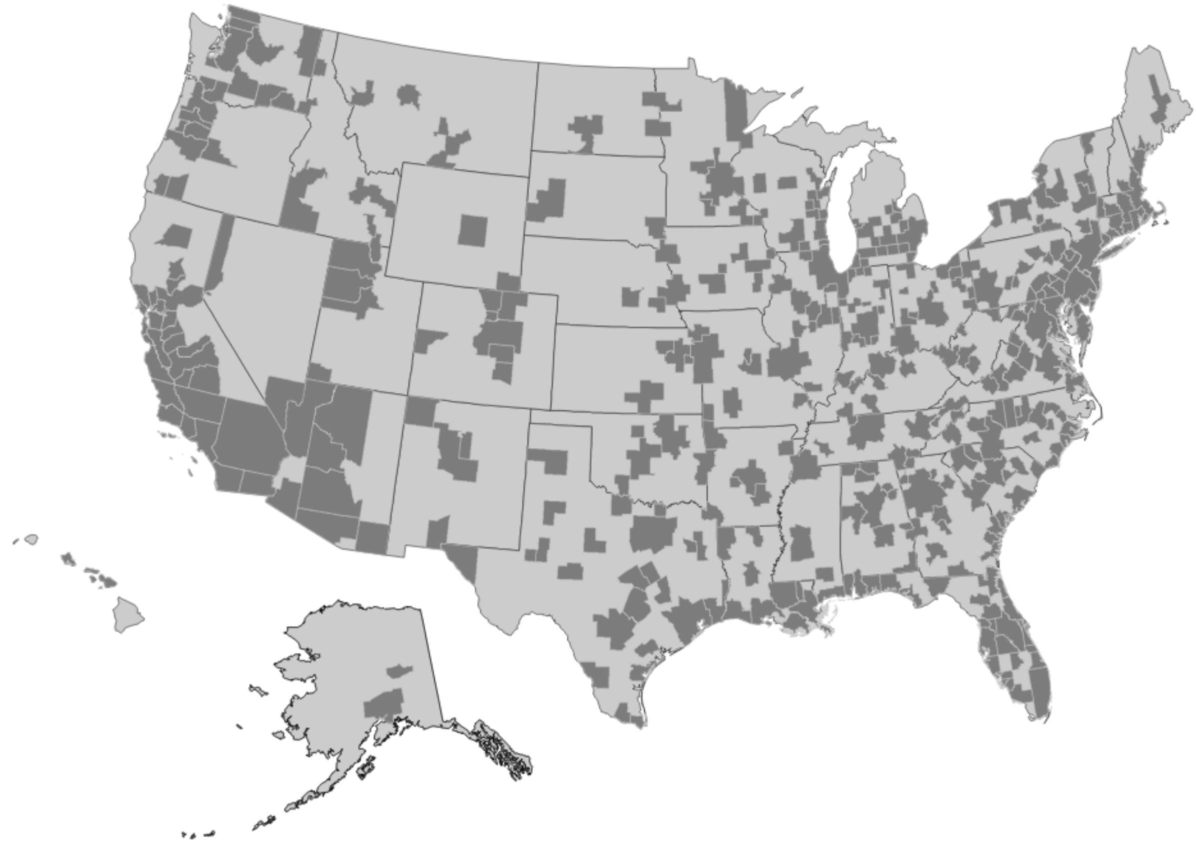

Figure B1: Metropolitan Statistical Areas in the U.S.

Source: U.S. Bureau of Economic Analysis. (2018).

Table B1: MSAs (with geographic codes), by state

1. Anniston-Oxford-Jacksonville, AL [11500]
2. Auburn-Opelika, AL [12220]°
3. Birmingham-Hoover, AL [13820]
4. Columbus, GA-AL [17980]°
5. Daphne-Fairhope-Foley, AL [19300]
6. Dothan, AL [20020]
7. Florence-Muscle Shoals, AL [22520]
8. Huntsville, AL [26620]
9. Montgomery, AL [33860]
10. Tuscaloosa, AL [46220]°
11. Anchorage, AK [11260]
12. Fairbanks, AK [21820]°
13. Flagstaff, AZ [22380]°
14. Lake Havasu City-Kingman, AZ [29420]
15. Phoenix-Mesa-Scottsdale, AZ [38060]
16. Prescott, AZ [39140]
17. Tucson, AZ [46060]
18. Fayetteville-Springdale-Rogers, AR-MO [22220]
19. Fort Smith, AR-OK [22900]
20. Hot Springs, AR [26300]
21. Jonesboro, AR [27860]
22. Little Rock-North Little Rock-Conway, AR [30780]
23. Pine Bluff, AR [38220]
24. Bakersfield, CA [12540]
25. Chico, CA [17020]
26. Fresno, CA [23420]
27. Hanford-Corcoran, CA [25260]°
28. Los Angeles-Long Beach-Anaheim, CA [31080]
29. Madera, CA [31460]
30. Modesto, CA [33700]
31. Napa, CA [34900]°
32. Oxnard-Thousand Oaks-Ventura, CA [37100]
33. Redding, CA [39820]°
34. Riverside-San Bernardino-Ontario, CA [40140]
35. Sacramento–Roseville–Arden-Arcade, CA [40900]
36. Salinas, CA [41500]
37. San Diego-Carlsbad, CA [41740]
38. San Francisco-Oakland-Hayward, CA [41860]
39. San Jose-Sunnyvale-Santa Clara, CA [41940]
40. San Luis Obispo-Paso Robles-Arroyo Grande, CA [42020]*
41. Santa Cruz-Watsonville, CA [42100]°
42. Santa Maria-Santa Barbara, CA [42200]°
43. Santa Rosa, CA [42220]
44. Vallejo-Fairfield, CA [46700]
45. Visalia-Porterville, CA [47300]
46. Boulder, CO [14500]
47. Colorado Springs, CO [17820]
48. Denver-Aurora-Lakewood, CO [19740]
49. Fort Collins, CO [22660]
50. Grand Junction, CO [24300]
51. Greeley, CO [24540]
52. Bridgeport-Stamford-Norwalk, CT [14860]
53. Hartford-West Hartford-East Hartford, CT [25540]
54. New Haven-Milford, CT [35300]
55. Norwich-New London, CT [35980]
56. Worcester, MA-CT [49340]
57. Dover, DE [20100]
58. Philadelphia-Camden-Wilmington, PA-NJ-DE-MD [37980]
59. Salisbury, MD-DE [41540]
60. Washington-Arlington-Alexandria, DC-VA-MD-WV [47900]
61. Cape Coral-Fort Myers, FL [15980]
62. Crestview-Fort Walton Beach-Destin, FL [18880]
63. Deltona-Daytona Beach-Ormond Beach, FL [19660]
64. Homosassa Springs, FL [26140]
65. Jacksonville, FL [27260]
66. Lakeland-Winter Haven, FL [29460]
67. Miami-Fort Lauderdale-West Palm Beach, FL [33100]
68. Naples-Immokalee-Marco Island, FL [34940]
69. North Port-Sarasota-Bradenton, FL [35840]
70. Ocala, FL [36100]
71. Orlando-Kissimmee-Sanford, FL [36740]
72. Palm Bay-Melbourne-Titusville, FL [37340]
73. Panama City, FL [37460]
74. Pensacola-Ferry Pass-Brent, FL [37860]
75. Port St. Lucie, FL [38940]
76. Punta Gorda, FL [39460]
77. Sebring, FL [42700]
78. Tallahassee, FL [45220]
79. Tampa-St. Petersburg-Clearwater, FL [45300]
80. The Villages, FL [45540]
81. Albany, GA [10500]°
82. Athens-Clarke County, GA [12020]°
83. Atlanta-Sandy Springs-Roswell, GA [12060]
84. Augusta-Richmond County, GA-SC [12260]
85. Hinesville, GA [25980]
86. Macon-Bibb County, GA [31420]°
87. Rome, GA [40660]
88. Savannah, GA [42340]
89. Warner Robins, GA [47580]
90. Kahului-Wailuku-Lahaina, HI [27980]
91. Urban Honolulu, HI [46520]
92. Boise City, ID [14260]
93. Idaho Falls, ID [26820]°
94. Lewiston, ID-WA [30300]
95. Bloomington, IL [14010]
96. Carbondale-Marion, IL [16060]°
97. Champaign-Urbana, IL [16580]
98. Chicago-Naperville-Elgin, IL-IN-WI [16980]
99. Davenport-Moline-Rock Island, IA-IL [19340]
100. Decatur, IL [19500]°
101. Kankakee, IL [28100]
102. Peoria, IL [37900]
103. Rockford, IL [40420]
104. Springfield, IL [44100]
105. St. Louis, MO-IL [41180]
106. Bloomington, IN [14020]
107. Elkhart-Goshen, IN [21140]
108. Evansville, IN-KY [21780]
109. Fort Wayne, IN [23060]
110. Indianapolis-Carmel-Anderson, IN [26900]
111. Kokomo, IN [29020]
112. Lafayette-West Lafayette, IN [29200]°
113. Louisville/Jefferson County, KY-IN [31140]
114. Michigan City-La Porte, IN [33140]
115. South Bend-Mishawaka, IN-MI [43780]
116. Terre Haute, IN [45460]°
117. Ames, IA [11180]
118. Cedar Rapids, IA [16300]°
119. Des Moines-West Des Moines, IA [19780]
120. Dubuque, IA [20220]°
121. Omaha-Council Bluffs, NE-IA [36540]
122. Sioux City, IA-NE-SD [43580]
123. Waterloo-Cedar Falls, IA [47940]
124. Kansas City, MO-KS [28140]
125. Topeka, KS [45820]

Note: *Included only in the regression samples of chapters 2 and 3. °Included only in the regression sample of chapter 4.

Table B1: Continued

126. Wichita, KS [48620]	192. Rochester, NY [40380]
127. Bowling Green, KY [14540]	193. Syracuse, NY [45060]
128. Cincinnati, OH-KY-IN [17140]	194. Utica-Rome, NY [46540]
129. Elizabethtown-Fort Knox, KY [21060]	195. Watertown-Fort Drum, NY [48060]
130. Lexington-Fayette, KY [30460]	196. Asheville, NC [11700]
131. Owensboro, KY [36980]	197. Charlotte-Concord-Gastonia, NC-SC [16740]
132. Alexandria, LA [10780]°	198. Durham-Chapel Hill, NC [20500]
133. Baton Rouge, LA [12940]	199. Fayetteville, NC [22180]
134. Houma-Thibodaux, LA [26380]	200. Goldsboro, NC [24140]
135. Lake Charles, LA [29340]	201. Greensboro-High Point, NC [24660]
136. Monroe, LA [33740]	202. Greenville, NC [24780]
137. New Orleans-Metairie, LA [35380]	203. Hickory-Lenoir-Morganton, NC [25860]
138. Shreveport-Bossier City, LA [43340]°	204. Myrtle Beach-Conway-North Myrtle Beach, SC-NC [34820]
139. Portland-South Portland, ME [38860]	205. New Bern, NC [35100]
140. Baltimore-Columbia-Towson, MD [12580]	206. Raleigh, NC [39580]
141. California-Lexington Park, MD [15680]	207. Rocky Mount, NC [40580]
142. Barnstable Town, MA [12700]	208. Virginia Beach-Norfolk-Newport News, VA-NC [47260]
143. Boston-Cambridge-Newton, MA-NH [14460]	209. Wilmington, NC [48900]
144. Pittsfield, MA [38340]°	210. Winston-Salem, NC [49180]
145. Providence-Warwick, RI-MA [39300]	211. Bismarck, ND [13900]
146. Springfield, MA [44140]°	212. Akron, OH [10420]
147. Ann Arbor, MI [11460]	213. Canton-Massillon, OH [15940]
148. Battle Creek, MI [12980]°	214. Cleveland-Elyria, OH [17460]
149. Detroit-Warren-Dearborn, MI [19820]	215. Columbus, OH [18140]
150. Flint, MI [22420]	216. Dayton, OH [19380]
151. Grand Rapids-Wyoming, MI [24340]	217. Lima, OH [30620]
152. Jackson, MI [27100]	218. Mansfield, OH [31900]°
153. Kalamazoo-Portage, MI [28020]	219. Toledo, OH [45780]
154. Lansing-East Lansing, MI [29620]	220. Wheeling, WV-OH [48540]°
155. Monroe, MI [33780]	221. Enid, OK [21420]°
156. Niles-Benton Harbor, MI [35660]°	222. Lawton, OK [30020]°
157. Saginaw, MI [40980]	223. Oklahoma City, OK [36420]
158. Duluth, MN-WI [20260]	224. Tulsa, OK [46140]
159. Fargo, ND-MN [22020]°	225. Albany, OR [10540]°
160. Mankato-North Mankato, MN [31860]°	226. Bend-Redmond, OR [13460]
161. Minneapolis-St. Paul-Bloomington, MN-WI [33460]	227. Eugene, OR [21660]
162. Rochester, MN [40340]	228. Grants Pass, OR [24420]°
163. St. Cloud, MN [41060]°	229. Medford, OR [32780]
164. Gulfport-Biloxi-Pascagoula, MS [25060]	230. Portland-Vancouver-Hillsboro, OR-WA [38900]
165. Hattiesburg, MS [25620]°	231. Salem, OR [41420]
166. Jackson, MS [27140]	232. Bloomsburg-Berwick, PA [14100]
167. Memphis, TN-MS-AR [32820]	233. East Stroudsburg, PA [20700]
168. Columbia, MO [17860]	234. Erie, PA [21500]
169. Jefferson City, MO [27620]	235. Gettysburg, PA [23900]
170. Joplin, MO [27900]°	236. Harrisburg-Carlisle, PA [25420]
171. Springfield, MO [44180]	237. Lancaster, PA [29540]
172. Grand Island, NE [24260]°	238. Pittsburgh, PA [38300]
173. Lincoln, NE [30700]	239. Reading, PA [39740]
174. Carson City, NV [16180]	240. Scranton–Wilkes-Barre–Hazleton, PA [42540]
175. Las Vegas-Henderson-Paradise, NV [29820]	241. Williamsport, PA [48700]
176. Reno, NV [39900]	242. York-Hanover, PA [49620]
177. Manchester-Nashua, NH [31700]	243. Youngstown-Warren-Boardman, OH-PA [49660]
178. Allentown-Bethlehem-Easton, PA-NJ [10900]	244. Charleston-North Charleston, SC [16700]
179. Atlantic City-Hammonton, NJ [12100]	245. Columbia, SC [17900]
180. New York-Newark-Jersey City, NY-NJ-PA [35620]	246. Greenville-Anderson-Mauldin, SC [24860]
181. Ocean City, NJ [36140]°	247. Hilton Head Island-Bluffton-Beaufort, SC [25940]
182. Trenton, NJ [45940]	248. Spartanburg, SC [43900]
183. Vineland-Bridgeton, NJ [47220]	249. Sumter, SC [44940]°
184. Albuquerque, NM [10740]	250. Rapid City, SD [39660]
185. Las Cruces, NM [29740]	251. Sioux Falls, SD [43620]
186. Albany-Schenectady-Troy, NY [10580]	252. Chattanooga, TN-GA [16860]
187. Binghamton, NY [13780]	253. Clarksville, TN-KY [17300]
188. Buffalo-Cheektowaga-Niagara Falls, NY [15380]	254. Jackson, TN [27180]
189. Elmira, NY [21300]°	255. Kingsport-Bristol-Bristol, TN-VA [28700]
190. Ithaca, NY [27060]°	
191. Kingston, NY [28740]	

Note: °Included only in the regression sample of chapter 4.

Table B1: Continued

256. Knoxville, TN [28940]	281. Salt Lake City, UT [41620]
257. Nashville-Davidson-Murfreesboro-Franklin, TN [34980]	282. Burlington-South Burlington, VT [15540]
258. Abilene, TX [10180]	283. Blacksburg-Christiansburg-Radford, VA [13980]
259. Amarillo, TX [11100]	284. Richmond, VA [40060]
260. Austin-Round Rock, TX [12420]	285. Roanoke, VA [40220]
261. Beaumont-Port Arthur, TX [13140]	286. Bellingham, WA [13380]
262. Brownsville-Harlingen, TX [15180]	287. Bremerton-Silverdale, WA [14740]
263. College Station-Bryan, TX [17780]°	288. Kennewick-Richland, WA [28420]
264. Corpus Christi, TX [18580]	289. Longview, WA [31020]°
265. Dallas-Fort Worth-Arlington, TX [19100]	290. Mount Vernon-Anacortes, WA [34580]
266. El Paso, TX [21340]°	291. Olympia-Tumwater, WA [36500]
267. Houston-The Woodlands-Sugar Land, TX [26420]	292. Seattle-Tacoma-Bellevue, WA [42660]
268. Killeen-Temple, TX [28660]	293. Spokane-Spokane Valley, WA [44060]
269. Longview, TX [30980]	294. Wenatchee, WA [48300]
270. Lubbock, TX [31180]	295. Beckley, WV [13220]°
271. Midland, TX [33260]	296. Charleston, WV [16620]°
272. Odessa, TX [36220]	297. Huntington-Ashland, WV-KY-OH [26580]
273. San Antonio-New Braunfels, TX [41700]	298. Fond du Lac, WI [22540]°
274. Texarkana, TX-AR [45500]	299. Green Bay, WI [24580]
275. Tyler, TX [46340]	300. Madison, WI [31540]
276. Waco, TX [47380]°	301. Milwaukee-Waukesha-West Allis, WI [33340]
277. Wichita Falls, TX [48660]	302. Appleton, WI [11540]
278. Logan, UT-ID [30860]	303. Sheboygan, WI [43100]
279. Ogden-Clearfield, UT [36260]	304. Cheyenne, WY [16940]
280. Provo-Orem, UT [39340]	305. Casper, WY [16220]

Note: °Included only in the regression sample of chapter 4.

Table B2: Distribution of the risk-index and the binary risk-indicator—chapter 2

Risk-index	Individuals (n)	Percent	Cum.
0	572	28.53	28.53
1	371	18.50	47.03
2	332	16.56	63.59
3	313	15.61	79.20
4	281	14.01	93.22
5	136	6.78	100.00
Total	2,005		
Binary risk-indicator	**Individuals (n)**	**Percent**	**Cum.**
0	1,275	63.59	63.59
1	730	36.41	100.00
Total	2,005		

Notes: Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse / 5 = least risk-averse. Binary risk-indicator is a dummy variable that takes the value of 1 if risk-index is equal to 3 or higher.

Table B3: Summary statistics of the regression sample of chapter 2

Variable	Obs. (N)	Mean	Std. Dev.	Min.	Max.
Dependent variable					
Migration	18,028	0.0417	0.2000	0	1
Key explanatory variable					
Risk-index°	18,028	1.8839	1.6239	0	5
Control variables					
Socio-economic characteristics					
Female°	18,028	0.1792	0.3835	0	1
Age	18,028	51.5591	11.5370	21	94
Married	18,028	0.6720	0.4694	0	1
Children	18,028	0.6489	1.0321	0	8
Years of education	18,028	13.7077	2.2444	3	17
Home ownership	18,028	0.7840	0.4114	0	1
Log of total family income	18,028	11.0140	1.0820	0	15.5202
Labour-market characteristics					
Employed	18,028	0.7776	0.4158	0	1
Unemployed	18,028	0.0378	0.1909	0	1
Retired	18,028	0.1451	0.3522	0	1
Other employment status	18,028	0.0393	0.1945	0	1
Type of industry					
Finance / real state	18,028	0.0521	0.2224	0	1
Mining / agriculture / forestry / fisheries	18,028	0.0247	0.1555	0	1
Construction / manufacturing	18,028	0.2167	0.4120	0	1
Transport / communications / utilities	18,028	0.0914	0.2882	0	1
Wholesale / retail trade	18,028	0.1069	0.3090	0	1
Professional / business services	18,028	0.2593	0.4383	0	1
Personal / entertainment services	18,028	0.0297	0.1700	0	1
Public administration	18,028	0.0758	0.2647	0	1
Other	18,028	0.1429	0.3500	0	1
Additional control variables					
Previous migration experience					
Moved before in the sample period	18,028	0.1496	0.3567	0	1
Ethnicity°					
White	18,028	0.7099	0.4537	0	1
African-American	18,028	0.2681	0.4430	0	1
Native-American	18,028	0.0062	0.0785	0	1
Asian-American	18,028	0.0059	0.0768	0	1
Other ethnicity	18,028	0.0097	0.0983	0	1
Changes in employment status					
Employed to employed	18,028	0.7360	0.4407	0	1
Employed to unemployed	18,028	0.0270	0.1622	0	1
Unemployed to employed	18,028	0.0234	0.1513	0	1
Unemployed to unemployed	18,028	0.0082	0.0905	0	1
Other changes	18,028	0.2051	0.4038	0	1

Notes: Migration is a dummy variable that takes the value 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. °Time invariant variable.

Table B4: Risk attitudes and the probability of migrating across MSAs between 1997 and 2015—random-effects probit coefficients

Dependent variable:	(1)		(2)		(3)		(4)	
cross-MSA migration since t-1	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Key explanatory variable								
Risk-index°	0.0844***	(0.0190)	0.0653***	(0.0019)	0.0466**	(0.0185)	0.0466**	(0.0182)
Control variables (t-1)								
Socio-economic characteristics								
Female°			-0.3260***	(0.0909)	-0.5120***	(0.1017)	-0.5182***	(0.1013)
Age			-0.0178***	(0.0024)	-0.0262***	(0.0028)	-0.0244***	(0.0031)
Married					-0.3225***	(0.0688)	-0.3333***	(0.0689)
Children					-0.1069***	(0.0262)	-0.0999***	(0.0262)
Years of education					0.0801***	(0.0141)	0.0745***	(0.0142)
Log of total family income					0.0145	(0.0239)	0.0136	(0.0243)
Labour market characteristics								
Employed (R.)								
Unemployed							0.3245***	(0.1053)
Retired							0.3165***	(0.1086)
Other employment status							0.1741	(0.1446)
Type of industry								
Construction / manufacturing (R.)								
Finance / real state							0.1336	(0.1159)
Mining / agriculture / forestry / fisheries							-0.1382	(0.1822)
Transport / utilities / communications							0.0453	(0.0955)
Wholesale / retail trade							-0.0779	(0.0899)
Professional / business serv.							0.0062	(0.0737)
Personal / entertainment serv.							-0.0055	(0.1419)
Public administration							0.1661*	(0.0985)
Other							-0.0115	(0.1136)
Financial crisis dummy							-0.0560	(0.0497)
State dummies							Yes	
Observations	18,028		18,028		18,028		18,028	
Individuals	2,005		2,005		2,005		2,005	
Baseline migration probability	0.0417		0.0417		0.0417		0.0417	
Rho	0.4290		0.4184		0.3896		0.3612	

Notes: Coefficients of random-effects probit models are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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. (R.) Reference category. °Time invariant variable.

Table B5: Risk attitudes and the probability of migrating across MSAs: Alternative controls—random-effects probit coefficients

Dependent variable: cross-MSA migration since t-1	(1) Previous migration experience		(2) Ethnicity		(3) Change in employment status	
	Coef.	SE	Coef.	SE	Coef.	SE
Key explanatory variable						
Risk-index°	0.0318**	(0.0143)	0.0383**	(0.0180)	0.0473***	(0.0184)
Previous migration experience						
Moved before in the sample period	0.5127***	(0.0876)				
Ethnicity°						
White (R.)						
African-American			-0.4699***	(0.0853)		
Native-American			-0.0690	(0.2950)		
Asian-American			-0.8362*	(0.4790)		
Other ethnicity			0.0386	(0.2510)		
Changes in employment status						
Employed to employed (R.)						
Employed to unemployed					0.5703***	(0.1203)
Unemployed to employed					0.5290***	(0.1106)
Unemployed to unemployed					0.4010*	(0.2186)
Other changes					0.5920***	(0.0752)
Control variables (t-1)						
Socio-economic characteristics	Yes		Yes		Yes	
Labour market characteristics	Yes		Yes		No	
Type of industry	Yes		Yes		Yes	
Financial crisis dummy	Yes		Yes		Yes	
State dummies	Yes		Yes		Yes	
Observations	18,028		18,028		18,028	
Individuals	2,005		2,005		2,005	
Baseline migration probability	0.0417		0.0417		0.0417	
Rho	0.1600		0.3429		0.3659	

Notes: Coefficients of random-effects probit models are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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. (R.) Reference category. °Time invariant variable.

Table B6: Risk attitudes and the probability of migrating across MSAs: Subsample analyses—random-effects probit coefficients

Dependent variable: cross-MSA migration since t-1	(1) No younger than 30 in 1997		(2) No older than 65 in 2015		(3) No international migration background		(4) No public administration type of industry	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Key explanatory variable								
Risk-index°	0.0527**	(0.0207)	0.0594***	(0.0219)	0.0422**	(0.0191)	0.0434**	(0.0202)
Control variables (t-1)								
Socio-economic characteristics	Yes		Yes		Yes		Yes	
Labour market characteristics	Yes		Yes		Yes		Yes	
Type of industry	Yes		Yes		Yes		Yes	
Financial crisis dummy	Yes		Yes		Yes		Yes	
State dummies	Yes		Yes		Yes		Yes	
Observations	15,414		12,931		16,913		14,790	
Individuals	1,714		1,438		1,881		1,645	
Baseline migration probability	0.0366		0.0458		0.0420		0.0396	
Rho	0.3751		0.3733		0.3705		0.3576	

Notes: Coefficients of random-effects probit models are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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. °Time invariant variable.

Table B7: Risk attitudes and the probability of migrating: Alternative definitions of migration—random-effects probit coefficients

Dependent variable:	(1) All migration types		(2) Cross-state migration		(3) Migration distance larger than 75 Km	
	Coef.	SE	Coef.	SE	Coef.	SE
Key explanatory variable						
Risk-index°	0.0460***	(0.0178)	0.0443**	(0.0207)	0.0496***	(0.0190)
Control variables (t-1)						
Socio-economic characteristics	Yes		Yes		Yes	
Labour market characteristics	Yes		Yes		Yes	
Type of industry	Yes		Yes		Yes	
Financial crisis dummy	Yes		Yes		Yes	
State dummies	Yes		Yes		Yes	
Observations	18,028		18,028		18,028	
Individuals	2,005		2,005		2,005	
Baseline migration probability	0.0458		0.0280		0.0361	
Rho	0.3629		0.3775		0.3631	

Notes: Coefficients of random-effects probit models are reported. Standard errors (SEs) are shown in parentheses. ***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. Financial crisis is a dummy variable that takes the value of 1 if t>=2009. °Time invariant variable.

Table B8: Risk attitudes and migration, by total number of moves—probit coefficients

Dependent variable: Cross-MSA migration at least once	(1) Max 1 move		(2) Max 2 moves		(3) Max 3 moves		(4) All moves	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Key explanatory variable								
Risk-index°	0.0476**	(0.0237)	0.0502**	(0.0209)	0.0541***	(0.0201)	0.0560***	(0.0200)
Control variables (in 2005)								
Socio-economic characteristics	Yes		Yes		Yes		Yes	
Labour market characteristics	Yes		Yes		Yes		Yes	
Type of industry	Yes		Yes		Yes		Yes	
Individuals	1,804		1,933		1,972		2,005	
Baseline migration probability	0.1280		0.1862		0.2023		0.2154	
Pseudo R2	0.0348		0.0474		0.0564		0.0597	

Notes: Coefficients of probit models are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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. °Time invariant variable.

Table B9: Frequencies of moves across MSAs

Number of moves	Individuals (n)	Percent	Cum.
0	1,573	78.45	78.45
1	231	11.52	89.97
2	129	6.43	96.40
3	39	1.95	98.35
4	22	1.10	99.45
5	8	0.40	99.85
6	1	0.05	99.9
7	2	0.10	100.00
Total	2,005		

Table B10: Risk attitudes, self-selection, and the intensive margin of migration—probit coefficients of the first-stage of Heckman selection model

	(1) First-stage probit stayer or mover	
	Coef.	SE
Key explanatory variables		
Risk-index°	0.0436**	(0.0202)
Homeownership in all periods°	-0.9460***	(0.0809)
Control variables (in 2005)		
Socio-economic charactheristics	Yes	
Labour market charactheristics	Yes	
Type of industry	Yes	
Individuals	2,005	
Baseline migration probability	0.2154	
Pseudo R2	0.1316	

Notes: Probit coefficients of the first-stage of a Heckman selection model are reported. 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. Standard errors (SEs) are shown in parentheses. ***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. °Time invariant variable.

Appendix C

Table C1: Summary statistics of the MSA regional characteristics

Variable	Obs. (N)	Mean	Std. Dev.	Min.	Max.
MSA regional characteristics					
Unemployment rate	300	4.9431	2.1466	1.5	15.4
SD of the Unemployment rate	300	1.9565	0.6883	0.4001	4.6905
MSA-of-origin risk	300	1.0000	0.3517	0.2045	2.3972
High-risk MSA-of-origin	300	0.4566	0.4989	0	1
Personal income p.c.	300	24.0742	4.2487	13.7166	48.7686
SD of the personal income p.c.	300	6.8934	2.3823	2.9287	27.9907
Natural Amenities Scale	300	3.9276	1.2613	2	7
Population	300	664,303	1,523,364	6,975	17,800,000
Violent crime per 100,000 inhabitants	300	413.7052	316.9588	0	1,938.0210
Non-violent crime per 100,000 inhabitants	300	3,613.5950	1,842.0210	0	8,945.6470

Notes: MSA-of-origin risk is the ratio of the SD of the MSA-of-origin unemployment rate over the mean of the SD of the unemployment rate. High-risk MSA-of-origin is a dummy variable that takes the value 1 if the SD of the MSA-of-origin unemployment rate if above the mean. No data on natural amenities is available for the states of Hawaii and Alaska. For these states, the mean value of the national amenities scale is used.

Table C2: Distribution of the risk-index by stayers and movers, among low-risk and high-risk MSAs

Risk-index	All MSAs			Only low-risk MSAs			Only high-risk MSAs		
	Stayers	Movers	Total	Stayers	Movers	Total	Stayers	Movers	Total
0	458	113	571	222	52	274	236	61	297
1	306	64	370	150	32	182	156	32	188
2	281	51	332	148	24	172	133	27	160
3	240	73	313	133	34	167	107	39	146
4	189	91	280	102	49	151	87	42	129
5	97	39	136	43	25	68	54	14	68
Total	1,571	431	2,002	798	216	1,014	773	215	988

Notes: Migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse / 5 = least risk-averse. High-risk MSA-of-origin is a dummy variable that takes the value 1 if the SD of the MSA-of-origin unemployment rate if above the mean.

Table C3: Risk attitudes and cross-MSA migration between 1997 and 2015—probit coefficients

Dependent variable:	(1)		(2)		(3)		(4)	
cross-MSA migration at least once	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Key explanatory variables								
Risk-index°	0.0831***	(0.0191)	0.0683***	(0.0194)	0.0496**	(0.0201)	0.0502**	(0.0203)
MSA-of-origin risk							0.2864**	(0.1301)
Socio-economic characteristics (1997)								
Female°			-0.2793***	(0.0894)	-0.4551***	(0.1161)	-0.4570***	(0.1173)
Age			-0.0137***	(0.0031)	-0.0188***	(0.0035)	-0.0187***	(0.0036)
Married					-0.2828***	(0.0924)	-0.3007***	(0.0941)
Children					-0.0913***	(0.0309)	-0.0901***	(0.0313)
Years of education					0.0852***	(0.0164)	0.0888***	(0.0168)
Log of total family income					-0.0119	(0.0337)	-0.0043	(0.0348)
Labour-market characteristics (1997)								
Employed (R.)								
Unemployed					-0.1320	(0.2592)	-0.0561	(0.2596)
Retired					0.3373	(0.2673)	0.2833	(0.2696)
Other employment status					0.0629	(0.2934)	0.0707	(0.2956)
Other MSA-of-origin characteristics (1997)								
Unemployment rate							-0.0569**	(0.0262)
Personal income p.c.							-0.0172	(0.0148)
SD of the Personal income p.c.							0.0662**	(0.0270)
Natural amenities scale							0.0154	(0.0326)
Log of population							-0.1161***	(0.0349)
Violent crime per 100,000 inhabitants							-0.0001	(0.0001)
Non-violent crime per 100,000 inhabitants							4.7E-5	(3.1E-5)
Type of industry	No		No		Yes		Yes	
Individuals	2,002		2,002		2,002		2,002	
Baseline migration probability	0.2153		0.2153		0.2153		0.2153	
Pseudo R2	0.0091		0.0240		0.0654		0.0826	

Notes: Coefficients (Coef.) of probit models are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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. MSA-of-origin risk is the ratio of the SD of the MSA-of-origin unemployment rate over the mean of the SD of the unemployment rate. (R.) Reference category. °Time invariant variable.

Table C4: Risk attitudes and cross-MSA migration: Low-risk and high-risk MSA-of-origin subsamples—probit coefficients

Dependent variable:	(1) Only low-risk MSA-of-origin		(2) Only high-risk MSA-of-origin	
cross-MSA migration at least once	Coef.	SE	Coef.	SE
Key explanatory variable				
Risk-index°	0.0779***	(0.0297)	0.0343	(0.0290)
Socio-economic characteristics (1997)	Yes		Yes	
Labour-market characteristics (1997)	Yes		Yes	
Type of industry (1997)	Yes		Yes	
Other MSA-of-origin characteristics (1997)	Yes		Yes	
Individuals	1,014		988	
Baseline migration probability	0.2130		0.2176	
Pseudo R2	0.1338		0.0619	

Notes: Coefficients (Coef.) of probit models are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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. High-risk MSA-of-origin is a dummy variable that takes the value 1 if the SD of the MSA-of-origin unemployment rate if above the mean. °Time invariant variable.

Table C5: Significance of interactions effects (risk-index 0,1,2,4,5 v. 3) for different degrees of MSA-of-origin risk

Dependent variable:	Risk-index 0 v. 3 Delta-method		Risk-index 1 v. 3 Delta-method		Risk-index 2 v. 3 Delta-method	
cross-MSA migration at least once	*dy/dx*	SE	*dy/dx*	SE	*dy/dx*	SE
MSA-of-origin risk:						
0.2	0.0253	(0.0567)	0.0165	(0.0625)	-0.0048	(0.0609)
0.5	0.0091	(0.0453)	-0.0054	(0.0490)	-0.0273	(0.0482)
0.8	-0.0117	(0.0323)	-0.0329	(0.0346)	-0.0553	(0.0343)
1.1	-0.0374	(0.0292)	-0.0658**	(0.0312)	-0.0886***	(0.0312)
1.4	-0.6730	(0.0482)	-0.1036**	(0.0509)	-0.1267**	(0.0512)
1.7	-0.1005	(0.0791)	-0.1454*	(0.0831)	-0.1686**	(0.0837)
2.0	-0.1360	(0.1148)	-0.1901	(0.1202)	-0.2132*	(0.1214)
2.3	-0.1722	(0.1519)	-0.2361	(0.1590)	-0.2590	(0.1610)
Individuals	2,002		2,002		2,002	

Dependent variable:	Risk-index 4 v. 3 Delta-method		Risk-index 5 v. 3 Delta-method	
cross-MSA migration at least once	*dy/dx*	SE	*dy/dx*	SE
MSA-of-origin risk:				
0.2	0.0903	(0.0710)	0.3315***	(0.1261)
0.5	0.0948*	(0.0562)	0.3315***	(0.0852)
0.8	0.0966**	(0.0401)	0.1263**	(0.0523)
1.1	0.0954***	(0.0367)	0.0207	(0.0449)
1.4	0.0911	(0.0586)	-0.0846	(0.0661)
1.7	0.0837	(0.0934)	-0.1883**	(0.0948)
2.0	0.0736	(0.1322)	-0.2890**	(0.1233)
2.3	0.6160	(0.1708)	-0.3851***	(0.1497)
Individuals	2,002		2,002	

Notes: Migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse / 5 = least risk-averse. *dy/dx* for factor levels is the discrete change from the base level. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. MSA-of-origin risk is the ratio of the SD of the MSA-of-origin unemployment rate over the mean of the SD of the unemployment rate. Reference category: Risk-index = 3.

Table C6: Risk attitudes, MSA-of-origin risk and cross-MSA migration: 1997 MSA same as MSA of birth, prime-age individuals—with significance of interactions effects (risk-dummy 1 v. 0) for different degrees of MSA-of-origin risk

Dependent variable:	MSA-of-origin risk	
cross-MSA migration at least once	Coef.	SE
Key explanatory variables		
Risk-dummy° =1	1.2343	(0.9693)
MSA-of-origin risk	0.5679*	(0.2909)
Risk-dummy° X MSA-of-origin risk	-1.3199	(0.9414)
Socio-economic characteristics (1997)	Yes	
Labour-market characteristics (1997)	Yes	
Type of industry (1997)	Yes	
Other MSA-of-origin characteristics (1997)	Yes	
Individuals	753	
Baseline migration probability	0.1514	
Pseudo R2	0.1290	
Dependent variable:	Risk-dummy 1 v. 0 Delta-method	
cross-MSA migration at least once	*dy/dx*	SE
MSA-of-origin risk:		
0.2	0.2000	(0.2188)
0.5	0.1167	(0.1278)
0.8	0.0375	(0.0659)
1.1	-0.0377	(0.0498)
1.4	-0.1098*	(0.0658)
1.7	-0.1796**	(0.0854)
2.0	-0.2479**	(0.1065)
2.3	-0.3155**	(0.1317)
Individuals	753	

Notes: Coefficients (Coef.) of probit models are reported in the upper panel. In the lower panel, *dy/dx* for factor levels is the discrete change from the base level. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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-dummy takes the value of 1 if risk-index = 5. MSA-of-origin risk is the ratio of the SD of the MSA-of-origin unemployment rate over the mean of the SD of the unemployment rate. Reference category: risk-dummy = 0. °Time invariant variable.

Table C7: Risk attitudes, MSA-of-origin risk and cross-MSA migration: No first moves during economic crises—with significance of interactions effects (risk-dummy 1 v. 0) for different degrees of MSA-of-origin risk

Dependent variable:	MSA-of-origin risk	
cross-MSA migration at least once	Coef.	SE
Key explanatory variables		
Risk-dummy° =1	2.9982*	(1.6543)
MSA-of-origin risk	0.6891**	(0.3382)
Risk-dummy° X MSA-of-origin risk	-3.4484*	(1.8902)
Socio-economic characteristics (1997)	Yes	
Labour-market characteristics (1997)	Yes	
Type of industry (1997)	Yes	
Other MSA-of-origin characteristics (1997)	Yes	
Individuals	709	
Baseline migration probability	0.9870	
Pseudo R2	0.1770	
Dependent variable:	Risk-dummy 1 v. 0	
	Delta-method	
cross-MSA migration at least once	*dy/dx*	SE
MSA-of-origin risk:		
0.2	0.5583	(0.4247)
0.5	0.2691	(0.2256)
0.8	0.0537	(0.0652)
1.1	-0.0646	(0.0408)
1.4	-0.1319***	(0.0343)
1.7	-0.1846***	(0.0542)
2.0	-0.2376***	(0.0883)
2.3	-0.2957**	(0.1280)
Individuals	709	

Notes: Coefficients (Coef.) of probit models are reported in the upper panel. In the lower panel, *dy/dx* for factor levels is the discrete change from the base level. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. 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-dummy takes the value of 1 if risk-index = 5. MSA-of-origin risk is the ratio of the SD of the MSA-of-origin unemployment rate over the mean of the SD of the unemployment rate. Reference category: risk-dummy = 0. °Time invariant variable.

Appendix D

Table D1: Distribution of the risk-index—chapter 4

Risk-index	Individuals (n)	Percent	Cum.
0	563	28.69	28.69
1	364	18.55	47.24
2	325	16.56	63.81
3	303	15.44	79.25
4	274	13.96	93.22
5	133	6.77	100.00
Total	1,962		
Binary risk-indicator	**Individuals (n)**	**Percent**	**Cum.**
0	1,252	63.81	63.81
1	710	36.18	100.00
Total	1,962		

Notes: Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse / 5 = least risk-averse. Binary risk-indicator is a dummy variable that takes the value of 1 if risk-index is equal to 3 or higher.

Table D2: Summary statistics of additional control variables

Variable	Obs. (N)	Mean	Std. Dev.	Min.	Max.
Additional control variables°					
Cross-state adult migration	1,962	0.1544	0.3614	0	1
Return childhood migrant	1,962	0.0530	0.2241	0	1
Foreign background	1,962	0.0198	0.1396	0	1
Childhood migration more than 25 km*	1,923	0.2797	0.4488	0	1
Childhood migration more than 50 km*	1,923	0.2542	0.4354	0	1
Childhood migration more than 75 km*	1,923	0.2418	0.4281	0	1
Childhood migration more than 200 km*	1,923	0.1752	0.3801	0	1

Notes: Complete adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015 and the MSA in which an individual grew up differs from the MSA of residence in 1997. Foreign background is a dummy variable that takes the value of 1 if an individual was born or grew up abroad. °Time invariant variable. *Calculated on a subsample of individuals with no foreign background.

Table D3: Childhood migration and the probability of adult migration

Dependent variable:	(1) Childhood migration		(2) Adult migration	
	Coef.	SE	Coef.	SE
Key explanatory variable°				
Childhood migration	-	-	0.8477**	(0.3471)
Socio-economic and idiosyncratic characteristics (2005)				
Female°	-0.0092***	(0.0032)	-0.3319***	(0.1193)
Age	0.0237	(0.0852)	-0.0188***	(0.0048)
Ethnicity°				
White-American (R.)				
African-American	-0.1961**	(0.0822)	-0.3964***	(0.0894)
Native-American	0.7621*	(0.4201)	-0.5199	(0.5601)
Asian-American	-0.3589	(0.4268)	-0.4535	(0.5582)
Other ethnicity	0.2630	(0.3065)	0.0377	(0.3287)
Married	-	-	-0.1938**	(0.0957)
Children	-	-	-0.0295	(0.0344)
Years of education	-	-	0.0789***	(0.0173)
Log of total family income	-	-	-0.1072***	(0.0376)
Risk-index°	-	-	0.0439**	(0.0196)
Labour-market characteristics (2005)				
Employed (R.)				
Unemployed	-	-	0.0527	(0.2164)
Retired	-	-	0.4890***	(0.1842)
Other employment status	-	-	0.1546	(0.2161)
Type of industry (2005)				
Construction / manufacturing (R.)				
Finance / real state	-	-	0.2505*	(0.1475)
Mining / agriculture / forestry / fisheries	-	-	-0.7876**	(0.3380)
Transport / communications / utilities	-	-	0.1280	(0.1208)
Wholesale / retail trade	-	-	0.0401	(0.1134)
Professional / business services	-	-	0.0215	(0.0932)
Personal / entertainment services	-	-	0.3257*	(0.1763)
Public administration	-	-	0.2143*	(0.1320)
Other	-	-	0.0409	(0.1949)
Childhood characteristics°				
Born in a rural area	-0.0009	(0.0725)	0.1846**	(0.0744)
Born abroad	0.5635**	(0.2332)	-0.5370**	(0.2674)
Only child	0.0663	(0.1464)	-0.2137	(0.1661)
Parental characteristics°				
Education of father at least 12 years	0.2255***	(0.0771)	-0.1584*	(0.0841)
Education of mother at least 12 years	0.0003	(0.0796)	0.1397*	(0.0865)
Mother did not work	0.0055	(0.0650)	-0.1618**	(0.0694)
Type of industry of the father°				
Construction / manufacturing (R.)				
Finance / real state	0.4297**	(0.1793)	-	-
Mining / agriculture / forestry / fisheries	0.0715	(0.1058)	-	-
Transport / communications / utilities	-0.0702	(0.1158)	-	-
Wholesale / retail trade	-0.1222	(0.1099)	-	-
Professional / business services	0.0748	(0.1144)	-	-
Personal / entertainment services	0.3742***	(0.1162)	-	-
Public administration	0.6606***	(0.1212)	-	-
Other	0.1772	(0.1177)	-	-
Individuals	1,962		1,962	
Base migration probability	0.2900		0.2130	
Errors terms correlation:	Coef.		SE	
Rho	-0.4655**		(0.2032)	
	χ^2		$P > \chi^2$	
Wald test of Rho = 0	3.7766		0.0520	

Notes: Coefficients (Coef.) of a recursive bivariate probit model of simultaneous equations are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. Adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Childhood migration is a dummy variable that takes the value of 1 if the MSA of birth differs from the MSA in which an individual grew up. (R.) Reference category. °Time invariant variable.

Table D4: Childhood migration and the probability of adult migration: Prime-age individuals and alternative definition of adult migration—estimation coefficients

Dependent variable:	(1) No older than 65 years of age in 2015		(2) Cross-state adult migration	
	Coef.	SE	Coef.	SE
Key explanatory variable°				
Childhood migration	0.8904***	(0.3365)	0.7906**	(0.3972)
Socio-economic and idiosyncratic characteristics (2005)	Yes		Yes	
Labour-market characteristics (2005)	Yes		Yes	
Type of industry (2005)	Yes		Yes	
Childhood characteristics°	Yes		Yes	
Parental characteristics°	Yes		Yes	
Type of industry of the father°	Yes		Yes	
Individuals	1,411		1,962	
Base migration probability	0.2244		0.1544	
Errors terms correlation:	Coef.	SE	Coef.	SE
Rho	-0.4950**	(0.1981)	-0.4429*	(0.2281)
	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$
Wald test of Rho = 0	4.2775	0.0386	2.8117	0.0936

Notes: Coefficients of the outcome equation of a recursive bivariate probit model of simultaneous equations are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. Adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Childhood migration is a dummy variable that takes the value of 1 if the MSA of birth differs from the MSA in which an individual grew up. (R.) Reference category. °Time invariant variable.

Table D5: Childhood migration and the probability of adult migration: Subsamples according to childhood and parental characteristics—estimation coefficients

Dependent variable:	(1)		(2)		(3)	
	No father worked in public administration		No foreign background		No return migrants	
	Coef.	SE	Coef.	SE	Coef.	SE
Key explanatory variable°						
Childhood migration	1.0990***	(0.3669)	0.9631***	(0.3143)	0.7951**	(0.3458)
Socio-economic and idiosyncratic characteristics (2005)	Yes		Yes		Yes	
Labour-market characteristics (2005)	Yes		Yes		Yes	
Type of industry (2005)	Yes		Yes		Yes	
Childhood characteristics°	Yes		Yes		Yes	
Parental characteristics°	Yes		Yes		Yes	
Type of industry of the father°	Yes		Yes		Yes	
Individuals	1,824		1,923		1,1819	
Base migration probability	0.2083		0.2142		0.2166	
Errors terms correlation:	Coef.	SE	Coef.	SE	Coef.	SE
Rho	-0.6032**	(0.2061)	-0.5310**	(0.1824)	-0.3928*	(0.2011)
	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$
Wald test of Rho = 0	4.6439	0.0312	5.4190	0.0199	3.0466	0.0.0809

Notes: Coefficients of the outcome equation of a recursive bivariate probit model of simultaneous equations are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. Adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Childhood migration is a dummy variable that takes the value of 1 if the MSA of birth differs from the MSA in which an individual grew up. (R.) Reference category. °Time invariant variable.

Table D6: Childhood migration and the probability of adult migration: Childhood migration distance—estimation coefficients

Dependent variable:	(1)		(2)		(3)		(4)	
	Childhood migration at least 25 km		Childhood migration at least 50 km		Childhood migration at least 75 km		Childhood migration at least 200 km	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Key explanatory variable°								
Childhood migration	0.9723***	(0.3109)	0.9441***	(0.3204)	0.9830***	(0.3053)	0.9986***	(0.3341)
Socio-economic and idiosyncratic characteristics (2005)	Yes		Yes		Yes		Yes	
Labour-market characteristics (2005)	Yes		Yes		Yes		Yes	
Type of industry (2005)	Yes		Yes		Yes		Yes	
Childhood characteristics°	Yes		Yes		Yes		Yes	
Parental characteristics°	Yes		Yes		Yes		Yes	
Type of industry of the father°	Yes		Yes		Yes		Yes	
Individuals	1,923		1,923		1,923		1,923	
Base migration probability	0.2142		0.2142		0.2142		0.2142	
Errors terms correlation:	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Rho	-0.5315**	(0.1801)	-0.5055**	(0.1829)	-0.5304**	(0.1708)	-0.5064**	(0.1777)
	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$
Wald test of Rho = 0	5.5646	0.0183	5.1292	0.0235	6.1768	0.0129	5.4470	0.0196

Notes: Coefficients of the outcome equation of a recursive bivariate probit model of simultaneous equations are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. Adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Childhood migration is a dummy variable that takes the value of 1 if the MSA of birth differs from the MSA in which an individual grew up, and the distance between MSAs is of at least 25 km (column 1), 50 km (column 2), 75 km (column 3), and 200 km (column 4). (R.) Reference category. °Time invariant variable.

Table D7: Childhood migration, adult migration and individual attitudes towards risk—estimation coefficients

Dependent variable:	(1) No risk-index = 5		(2) Only risk-index = 0		(3) No risk-index	
	Coef.	SE	Coef.	SE	Coef.	SE
Key explanatory variable°						
Childhood migration	0.9021***	(0.2973)	1.4112***	(0.4088)	0.8357**	(0.3504)
Socio-economic and idiosyncratic characteristics (2005)	Yes		Yes		Yes	
Labour-market characteristics (2005)	Yes		Yes		Yes	
Type of industry (2005)	Yes		Yes		Yes	
Childhood characteristics°	Yes		Yes		Yes	
Parental characteristics°	Yes		Yes		Yes	
Type of industry of the father°	Yes		Yes		Yes	
Individuals	1,829		563		1,962	
Base migration probability	0.2083		0.1972		0.2130	
Errors terms correlation:	Coef.	SE	Coef.	SE	Coef.	SE
Rho	-0.4927**	(0.1726)	-0.7400**	(0.2196)	-0.4576*	(0.2054)
	χ^2	$P > \chi^2$	χ^2	$P > \chi^2$		
Wald test of Rho = 0	5.6056	0.0179	3.8306	0.0503	3.6184	0.0571

Notes: Coefficients of the outcome equation of a recursive bivariate probit model of simultaneous equations are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. Adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Childhood migration is a dummy variable that takes the value of 1 if the MSA of birth differs from the MSA in which an individual grew up. Risk-index is an ordinal variable that is decreasing in risk aversion: 0 = most risk-averse / 5 = least risk-averse. (R.) Reference category. °Time invariant variable.

Table D8: Risk attitudes and the probability of adult migration: Endogenous nature of risk attitudes—estimation coefficients

Dependent variable: Adult migration at least once	(1) Recursive Bivariate probit Chapter 4 sample		(2) Probit Chapter 4 sample		(3) Recursive Bivariate probit Chapter 2 sample		(4) Probit Chapter 2 sample	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Key explanatory variable°								
Risk-indicator	1.3714***	(0.2742)	0.2406***	(0.0694)	1.4049***	(0.2417)	0.2407***	(0.0685)
Socio-economic and idiosyncratic characteristics (2005)	Yes		Yes		Yes		Yes	
Labour-market characteristics (2005)	Yes		Yes		Yes		Yes	
Type of industry (2005)	Yes		Yes		Yes		Yes	
Childhood characteristics°	Yes		Yes		Yes		Yes	
Parental characteristics°	Yes		Yes		Yes		Yes	
Parents smoked°	Yes		Yes		Yes		Yes	
Individuals	1,962		1,962		2,005		2,005	
Base migration probability	0.2130		0.2130		0.2154		0.2154	
Pseudo R2			0.0852				0.0858	
Errors terms correlation:	Coef.	SE			Coef.	SE		
Rho	-0.7059***	(0.1715)			-0.7287***	(0.1514)		
	χ^2	$P > \chi^2$			χ^2	$P > \chi^2$		
Wald test of Rho = 0	6.6064	0.0102			8.2177	0.0041		

Notes: Coefficients of the outcome equation of recursive bivariate probit models of simultaneous equations (columns 1 and 3), and probit models (columns 2 and 4) are reported. Standard errors (SEs) are shown in parentheses. ***p<0.01, **p<0.05, p*<0.1. Adult migration is a dummy variable that takes the value 1 if the individual moved across MSAs at least once between 1997 and 2015. Risk-indicator takes the value of 1 if risk-index is greater than or equal to 3. °Time invariant variable.

Attached documents

Explanation of co-authorships

The present thesis is a publication-based (cumulative) dissertation consisting of five chapters based on three individual research papers. Chapter 2 and chapter 3 are a joint work with my doctoral supervisor Prof. Dr. Silke Uebelmesser (Friedrich Schiller University of Jena and CESifo). In these papers, the conception of the studies, the respective reviews of literature, the compilation of data, and the preliminary analyses of data are of my own development. Prof. Dr. Silke Uebelmesser contributed to the collaborative development and application of the empirical strategies, drafting of the manuscripts and final revisions. Chapter 4 is based on a single-authored paper.

Jena, 10.07.2020