The Effect of Risk Attitudes on the Migration Decision

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The Effect of Risk Attitudes on the Migration Decision

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In this paper, I examine the impact of risk attitudes on migration decision. I use the "Two Sample Two-Stage Instrumental Variable (TS2SIV)" technique to measure relative risk aversion and its impact on migration. Using the probit model, I find that more risk averse people are less likely to migrate. The results also indicate that the impact of risk attitude on migration varies by other demographic characteristics such as age, sex etc. In addition, I test whether there is any network effect on migration and how risk attitudes vary with network effect. I consider two ethnic groups; Asian and Hispanic, and find that the size of one's own ethnic group in a source location has significant effect on the migration decisions. In addition, I also find the evidence that risk attitudes vary with network effect.

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I. Introduction

Migration over the years has emerged as an interesting research topic because of its distinctive importance on the overall economy. The mobility of highly skilled and educated labor from less to more developed countries has gradually become a serious concern for the overall labor market outcome. The efficient outcome in the labor market as well as in the economy depends on the ongoing geographic mobility as Borjas (2001) considered migrants as the grease of the wheels of labor market. The research on migration study has addressed different questions; who migrates, why migrates, where to migrate, what are the consequences of migration. However, there is still an ongoing debate on these migration issues. In my paper, I will focus on the household decision of migration. That is, what are the factors that influence some people to migrate or not to migrate? For this, the US internal migration across state has been considered in this paper.

A simple hypothesis can explain that people will migrate to a place where they will have a higher expected utility than their current location. That is, the factors that derive the individual's expected utility can be considered as the determinants of their moving decision of one place to another. Initially, migration theory failed to explain the reasons behind migration equating expected utility with expected income while deriving the expected utility function. Based on this theory, the expected income differential had widely taken its place as one of the main economic explanations of migration. This explanation originated from Todaro's expected income hypothesis. A number of empirical works studied how the wage and unemployment differentials influence migration flows under the Harris-Todaro (1969) hypothesis for a risk neutral individual. However afterwards, it had been investigated that migrants consider the income variability between their current and destination locations

(Stark 1981, Stark and Levhari 1982). That is, an individual can migrate to a place with no expected income differential if the income variability appeared as lower than in the current location. It is even rational for rural-urban migration when expected urban income is lower than rural income for example. Such findings signify to unobservable characteristics that may also explain the reasons behind the migration decision and why it varies across individuals given the same observable characteristics. This motivates a recent trend in the literature that analyzes how attitudes towards risk influence the decision to migrate. Thereafter, both risk and risk avoidance have appeared as a major significance factor in the mainstream migration theory of economics.

It has been hypothesized that individuals' migration propensities depend on their risk attitudes. On this hypothesis, Jaeger et al. (2010) explains the justification of considering risk attitudes behavior towards the migration decision in a simple way. As individuals derive utility from consumption and leisure and we can reasonably assume that individuals have better information on consumption, income and leisure opportunities in their current location than any other place, leaving this place for some unknown destination is a risky behavior that makes migration as a fundamentally risky activity. In that sense, the existence of the relative uncertainty of a new place tends to make less risk averse people have a higher probability of migration.

However, the new literature on migration in developing countries suggests that it is an opportunity to diversify risk. That is, risk averse people migrate as a means for diversifying risk in the malfunctioning rural credit market. Such studies consider migration as an investment decision for households and part of the family migrates to improve their investment portfolio to avoid foreseeable income risk due to natural hazard for example. The initial uncertainty and cost of migration can be considered as a premium in this case.

The direction of the relationship between risk attitudes and migration is potentially ambiguous. If a risk averse individual decides to stay at a location where income variation is lower, it can be explained by the hypothesis of risk attitudes. Relatively more risk averse individuals are more likely to stay to avoid fluctuation of income. On the other hand, less risk averse people are more likely to take a chance of having a higher level of income. The new migration theories that consider risk attitudes as one of the determinants of migration other than expected income have been mostly developed theoretically. There are very few empirical studies that have attempted to estimate the relationship between risk attitudes and the migration decision.

In my thesis, I will take the opportunity to empirically test the link between migration and risk attitudes behavior. The hypotheses that I want to test are:

H_1: Relative risk aversion has significant effect on migration decision.

H_2: The impact of risk attitudes towards migration varies by demographic characteristics.

H_3: The size of one's own ethnic group in a source location affects the migration decision.

H_4: The impact of risk attitudes varies with different ethnic group.

H_5: The impact of attitudes towards risk varies with network effect.

I consider the US labor market and movement across states as a means of migration in my paper to test the above hypotheses. As I have mentioned earlier, the empirical testing of the link between risk attitudes and the moving decision has not been commonly estimated.

Jaeger at al.(2010) and Conroy (2010) worked on the direct measure of individual risk attitudes and its impact on migration decision using the data from German labor market and the Mexican labor market respectively. These are the two of the very few papers that estimated the link between direct risk measurement and migration. As such, this thesis follows part of the paper of Jaeger et al. (2010) but with the data for the US labor market. As the nature of the US labor market is different from the German labor market, the empirical findings would be a contribution to the literature. In my knowledge, no previous empirical study has examined the relationship between relative risk aversion and migration in US labor market. I allow the interaction terms in the model to estimate the variation of risk attitude impact by demographic characteristics. This thesis also expands to test the network effect due to the increasing size of one's own ethnic group to a source location on the migration decision. In addition, I estimate the variation of attitudes toward risk with network effect. My analysis is also different from previous works since I use the "Two Sample Two-Stage Instrumental Variable (TS2SIV)" technique to measure the relationship between relative risk aversion and migration.

The literature review of migration studies has been mentioned in section II. Section III covers the methodology part and section IV discusses about the data and variables that have been used for this paper. The estimation and result part have been discussed in section V. Section VI is about the concluding remarks.

II. Literature Review

II.A. Link between Relative Risk Aversion and Migration

Fact that the relationship between risk aversion and migration has not been empirically studied by many may be due to the difficulties of measuring individual risk attitudes. However, we can find theoretical studies that approach the linkage between risk and the moving decision. Banerjee and Kanbur (1981) developed a theoretical model with the inclusion of risk averse individual instead risk neutral and tested the importance of income variation rather than conventional migration theory of expected income hypothesis with the rural-urban migration in India. They found that the risk and uncertainty of job search in a new place may have an impact on the rural-urban migration decision in a developing country. Based on Banerjee and Kanbur's prediction, Hatton (1995) found indirect evidence that risk was a determinant of UK immigration in 1870-1913. Stark and Levhari (1982) developed a theoretical model and considered migration as a family strategy to diversify the risk associated with family earnings in the absence of a rural credit market. According to the study, rural households sent their family members for migration even if there was no variation in income to the destination location. This can be explained as improving the household income portfolio to diversify unexpected income fluctuation. This study had a huge contribution by including risk attitude as a major factor in the migration decision. The Stark and Levhari analysis is carried further by Stark and Lucas (1988) who consider that migration of a family member can result from a cooperative arrangement struck between the migrant and his family. Both members are risk averse but acts differently in risks at different times, which make co-insurance mutually advantageous. The migrant is insured by his family while looking for a job. Later on, the family can engage in the adoption of a new agricultural technology knowing that the migrant will be able to compensate adverse shocks. The similar theoretical work had been done by Katz and Stark (1986). They challenged the pioneering work of Todaro's expected income hypothesis migration theory by demonstrating that a small chance of reaping a high reward is sufficient to trigger rural-urban migration even if urban expected income is lower than rural income. Daveri and Faini (1999) studied to test whether risk is a significant determinant of the decision to migrate abroad or inside the country using the aggregate level data from the regions of Southern Italy. The study found a similar result that also indicates migration as an opportunity for family to diversify risk and it may take place even in the absence of significant wage and unemployment differentials especially where financial markets are absent.

A more recent article by Wang and Wirjanto (2004) uses a stochastic model to investigate the consequences of different risk attitudes in the migration decision. They found that uncertainty regarding wages at home and abroad have opposite effects on the optimal investment time. Their findings indicate that in the presence of uncertainty at home and abroad, those with average levels of risk aversion will migrate first. Axel Heitmueller (2004) derived the effect of unemployment benefits on the migration decision. His findings support the hypothesis that risk averse individuals are less likely to engage in migration applying theory to the European enlargement context. He provides a model that links risk aversion with the choice of the destination country where the countries differ in terms of welfare provision. The outcome indicates that individuals that migrate to countries with high welfare provision are likely to be more risk averse. Gibson and McKenzie (2009) worked on a paper with a unique survey which tracks worldwide the best and brightest academic performers from three Pacific countries. The study assessed the extent of emigration and returns to migration among the very highly skilled and found that the migration decision mostly depends on risk aversion, patience, and the choice of subjects in secondary school, and not strongly linked to either liquidity constraints or to the gain in income to be had from migrating. In the same way, the decision to return is strongly linked to family and lifestyle reasons, rather than to the income opportunities in different countries.

Among the very few empirical studies that estimate the link between a direct measure of risk attitudes and migration, Jaeger et al. (2010) started to work with empirical data from the German labor market. They used primary data to measure individual risk attitudes. Risk attitudes have been directly measured for this paper using the general risk question that was available in the survey of German Socio-Economic Panel (SOEP). According to their hypothesis testing, they found that individuals who are more willing to take risk are more likely to migrate (by controlling for a variety of demographic characteristics). The impact of more willing to take risks is a positive, statistically significant, and a quantitatively important determinant of migration. They also tested for reverse causality that is, the chance of risk attitudes that are also affected by the migration decision. They did not find any reverse causality in their paper. Conroy (2009) did a similar analysis with a sample of Mexican migration. However, he found a risk preference which is positively related between a person's risk aversion and the likelihood of migrating, especially when the motivations are closely related to family issues. This result is completely opposite of the previous hypothesis, that is more risk averse people are more likely to migrate. As an explanation of this result, Conroy did not rule out the possibility of the significant role of networking in the migration decision.

II.B. Network Effect and Migration

The migration literature has also found that networks play a critical role in migration patterns. Sarah and Garance (2006) analyzed that larger family networks encourage migration, consistent with the job information hypothesis. Community networks also appear to provide job information as larger networks increase the likelihood of migration. Bauer et al. (2000) captured the effects of the usual network variable and two additional origin-village-specific variables on migrants' location choice studying Mexican immigrants in US. They extended their work with another paper (2002) and found that both network externalities and herds have significant effects on the migrant's decision on location choice. They also established that the effects vary in terms of size and significance depending on the migrants' legal status. Janis Umblij (2011) found the variation of risk attitudes with network effect on migration decision in. Their testing hypothesis indicated that when migrant networks are larger, the average migrant will be more risk averse.

II.C. Direct Measures of Risk Aversion from Secondary Data Sets

Most of the previous empirical studies on direct measure of risk attitudes and migration had been done using primary survey data for direct risk measurement. Due to the difficulties of measuring risk aversion in the absence of access to primary data access, there has been less work done on the link between migration and risk attitudes. Different studies that work with secondary data have followed a different approach to measure relative risk aversion. Daveri and Faini (1999) used aggregate level data from the regions of Southern Italy (1970-1980) which has been considered as a natural laboratory to analyze migration as a means for diversifying risk in the absence of effective credit and insurance markets. The indirect measure of risk took into account the coefficient of correlation between income in the home and destination place and also income variability at home. Halek and Eisenhauer (2001) measured relative risk aversion using life insurance data from Wave I of the University of Michigan Health and Retirement Study (HRS) for the estimation purpose of demography of risk aversion. Janis Umblij (2011) followed the same approach but used data of homeowner insurance from the American Community Survey and found that when migrant networks are larger, the average migrant will be more risk averse. Feng-Teng Lin (2009) also used household life insurance expenditure to explain the theories of optimal risk taking behavior in the presence of background risk.

Based on the other literatures, I found property insurance, health insurance and life insurance purchase data that can be used for direct measurement of risk. As my objective of this paper is to explore the link between relative risk attitudes and migration choice, I have ruled out the possibility of using property insurance data. Because, it is a reasonable assumption that most of the migrants will not have their own property. In the same way, using health insurance as a proxy of risk measurement has its own limitation. There might be less variation in health insurance purchase and it also largely depends on health status. Therefore, health insurance purchase might not capture individual risk attitudes behavior significantly. Counting these facts, it is reasonable to use the purchase of life insurance as a proxy of relative risk aversion.

III. Methodology

To test the hypothesis of any significant relationship between risk attitudes and migration choice, I include the proxy of relative risk aversion as an independent variable along with other demographic characteristics into the migration model.

(1) $$M_i = \alpha_0 + \alpha_1 R_i + \alpha_2 W_i + \omega_i$$

Where 'R' is the proxy of risk aversion and 'W' is the vector of other independent variables that include the variables of age, age square, year of education, dummy variables of gender, race, marital status, citizenship status, number of children, and place of birth. I use Probit to estimate the model where the dependent variable is the binary indicator of migration decision. The interpretation of probit model is not so straight forward. To interpret the model in probability terms, I use marginal effect using the direct command "dprobit" from stata. "dprobit" reports the marginal effects at the overall mean of the predictors and estimates maximum-likelihood probit models. Rather than reporting coefficients, dprobit reports the change in the probability for a marginal change in each independent, continuous variable and, by default, the discrete change in the probability for dummy variables.

In addition, I also include the interaction term of risk and demographic characteristics to capture the variation of risk attitude impact on moving decision by demographic characteristics.

(2) $$M_i = \alpha'_0 + \alpha'_1 R_i + \alpha'_2 W_i + \alpha'_3 R_i W_i + \omega'_i$$

To check the network effect on the migration decision, my testable hypothesis is that, when migrant networks are larger, that is, more individuals from the same ethnic group are present in the current place; they are less likelihood to migrate than other groups. For this, I include dummy variables for two ethnic groups (Asian and Hispanic) and their share of the state level population according to their original location before migration. The model also estimates the marginal coefficients of the interaction term of those variables.

$$M_i = \alpha''_0 + \alpha''_1 R_i + \alpha''_2 W_i + \alpha''_3 D_i + \alpha''_4 S_i + \alpha''_5 D_i S_i + \omega''_i \tag{3}$$

Where, 'D' represents the vector of dummy variables for Asian and Hispanic and 'S' is their share of the state level population according to their original location before migration. The estimated marginal effect of the interaction variable of ethnic group and their corresponding share reflects the network effect.

I also test the hypothesis to check if risk attitudes on the moving decision vary by ethnic group as well as with the network effect. For the first case, I include the interaction terms of risk and ethnic group in the model.

$$M_i = \alpha'''_0 + \alpha'''_1 R_i + \alpha'''_2 W_i + \alpha'''_3 D_i + \alpha'''_4 S_i + \alpha'''_5 D_i S_i + \alpha'''_6 R_i D_i + \omega'''_i \tag{4}$$

To test the risk attitudes variation with network effect, I include the triple interaction effect by multiplying the corresponding population share of ethnic group with the above interaction variables.

$$M_i = \alpha^{iv}{}_0 + \alpha^{iv}{}_1 R_i + \alpha^{iv}{}_2 W_i + \alpha^{iv}{}_3 D_i + \alpha^{iv}{}_4 S_i + \alpha^{iv}{}_5 D_i S_i + \alpha^{iv}{}_6 R_i D_i + \alpha^{iv}{}_7 R_i D_i S_i + \omega^{iv}{}_i \tag{5}$$

Estimating the usual model of migration requires data that contain a direct measure of or a proxy for risk aversion and migration information along with other economic and demographic characteristics. But as a matter of fact, no large-scale nationally representative survey has all the necessary information been available to me. I have one data set where all other required variables are available except a measure of risk aversion. I have another data set that includes information on life insurance, my proxy for risk aversion. To deal with such limitation of data unavailability, I use “Two Sample Two-Stage Instrumental Variable (TS2SIV)” technique following Angrist (1990) and Angrist and Kruegers’ (1992) similar technique of “Two Sample Instrumental Variable (TSIV)”.

In general, Two-Sample Instrumental variable estimators may be used whenever a set of instruments is common to two data sets, but endogenous regressors and the dependent variable are included in only one or the other data sets (Angrist and Kruger, 1992). The technique of TSIV has been used by Dee and Evans (2003) to examine the effect of teen drinking on educational attainment. In a later study, Inoue and Solon (2005) discussed a slightly different model than Angrist and Kruger named “Two Sample Two-Stage Instrumental Variable (TS2SIV)” technique to serve the same purpose. I follow the same TS2SIV technique to predict the likelihood of life insurance purchase for one data set using the information from another data set. Both data sets meet the requirement of having a common set of instruments, but the endogenous regressor (relative risk aversion proxy) and the dependent variable (migration decision) are included in only one or the other data set.

III.A. Model Specification

The model of interest is:

$$M_i = \alpha_0 + \alpha_1 R_i + \alpha_2 W_i + \omega_i$$

where M_i is an indicator of the migration decision for person i; W_i is a vector of independent variables other than the risk measurement variable R_i and η_i is a mean zero random error. As I use life insurance purchases as a proxy of individual's risk aversion and I do not have one data set including all information of above regression equation, I follow the TS2SIV technique to predict the likelihood of life insurance purchase for one data sample using the information of another sample.

III.B. Two Sample Two-Stage Instrumental Variable Technique

To illustrate how TS2SIV estimates are generated, consider the reduced form equation for one data set indicated by '1' for k observations;

(1B) $$M_{i_1} = \beta_0 + \beta_1 Z_{i_1} + \varepsilon_{i_1}$$

And the regression equation for another data set indicating by '2' for i observations;

(2B) $$L_{i_2} = \pi_0 + \pi_1 Z_{i_2} + \upsilon_{i_2}$$

The TS2SIV procedure requires one set of data "1" with a set of IV vector, Z_1 and another set of data "2" with same set of IV vector, Z_2. Our first sample of data set "1" is based on the Census Bureau's 2010 IPUMS. We use the information on the migration variable M_1 and a set of IVs Z_1 as age, marital status, race, gender, year of education, income and health insurance from this survey. Our second set of data "2" is from 2010 survey data generated by University of Michigan Health and Retirement Study (HRS) that provides the information on life insurance purchases L_2 and the same set of IVs, Z_2. The link between the two data sets is established by these set of instruments Z. These data sets are described in more detail in the next section.

First Stage

The first stage of this process is to estimate the binary indicator of life insurance using the HRS data "2". Then I use the estimated coefficients to predict the likelihood of life insurance purchases for the data set "1" from IPUMS. I use Probit to estimate the model where the dependent variable is the indicator of life insurance. I prefer the probit estimation because it provides the probability change of dependent variable due to the change in independent variable that lies within 0-1 interval. It also allows for a non-linear relationship between the probability of the insurance and marginal impacts of the independent variables. The parameters are typically estimated by maximum likelihood.

Now estimate the equation 3 with probit regression for life insurance:

(3B) $$\hat{L}_{i_2} = \hat{\pi}_0 + \hat{\pi}_1 Z_{i_2}$$

Then I use these estimated coefficients from above regression to predict the probability of having life insurance, $\hat{L}_{i_1}$ for the sample of data set "1". The predicted probabilities are given by the formula:

(4B) $$\hat{L}_{i_1} = F(Z_{i_1} * \hat{\pi})$$

where, F is the cumulative normal of standard distribution, Z_{i_1} is the data vector for the i^th observation from data set "1", and π hat is the vector of coefficient estimates from equation (4).

That is, $\hat{L}_{i_1}$ is the predicted probability of insurance purchase for IPUMS observations using a set of estimated coefficients from the HRS data. This serves as our predicted value of relative risk aversion.

Second Stage

Now we are able to run the second stage migration model with the predicted measure of risk aversion. Here, migration, M is also a binary variable.

(5B) $$M_{i_1} = \beta_0 + \beta_1 \hat{L}_{i_1} + \beta_2 W_{i_1} + e_{i_1}$$

β_1 is the coefficient of relative risk aversion, W_{i_1} is the data vector for the i^th observation from IPUMS that might influence individual's migration decision. This is the general model that I use to test the hypothesis about the relationship between relative risk aversion and migration using the TS2SIV technique.

IV. Data Analysis

IV.A. Data Description

The data I have used in this paper come from two different surveys. One of them is the 2010 survey of the University of Michigan Health and Retirement Study (HRS). HRS is a national longitudinal study of the economic, health, marital, and family status, as well as public and private support systems, of older Americans funded by the National Institute on Aging at NIH, with supplemental support from the Social Security Administration (SSA)[1]. I use the RAND HRS data files. The RAND Center for the Study of Aging creates the RAND HRS with the goal of making the data more accessible to researchers. This is a very large data set allowing us to have the information on life insurance purchase along with other economic variables and demographic characteristics. I get the information of having life insurance or not, either individually or through a group, on the primary respondent, whom they assume to be the head of the household. This survey contains information on individual assets, wealth, level of education, place of residence, place they are coming from, age, place of birth along with all demographic characteristics. I use this data set for the purpose of predicting the probability of life insurance purchase for the individuals of another data set. The HRS data will be used in first stage of the TS2SIV technique that I mentioned earlier. The 2010 HRS data set has 4929 observations after I cleaned the missing values.

To have the migration data, I use the Census Bureau's 2010 IPUMS survey in the second stage of TS2SIV after predicting the probability of life insurance purchase for these observations. The integrated Public Use Microdata Series (IPUMS) is the world's largest individual-level population database consisting of microdata samples from United States

[1] RAND HRS Data Documentation, November 2011

(IPUMS-USA) and international (IPUMS-International) census records[2]. The 2010 IPUMS data set has 1,523,689 individual level observations and 815,385 household level observations (considering head of household as primary respondent) after cleaning the missing values.

In need of using these two data sets, I restrict the sample age to be between 27 to 65 years old. The purpose of this restriction follows in two ways. As I have the sample information on age beginning at 27 in HRS data set, such restriction on both data set will allow keeping the same cohort of observations for two data sets. The TS2SIV techniques would not be viable if both data sets of use do not contain the same set of variables for the same cohort. Another reason for restricting age to lie between 27 and 65 is to consider the fact that most of the people decide to migrate from one state to another during this age. The advantage of using the IPUMS and HRS surveys is that same set of variables are available as required for TS2SIV. However, using these two different samples might potentially weaken the validity of the estimation due to their differing age distribution. As HRS data set mostly consists with older people, I follow the same methodology for the selective age group of 50-65 to check the robustness of the result.

There is another important limitation of the HRS data for this work. It does not mention anything about when the insurance was purchased. The characteristics of the household may have changed since the time that the life insurance was purchased. Using the current characteristics of the household to estimate a decision made in the past may introduce measurement error.

[2] IPUMS Data Documentation, 2011

IV.B. First Stage Variables of Interest in TS2SIV Technique

The dependent variable in the analysis is the binary indicator of life insurance purchase that is included in the HRS data set. The data shows that 3162 of 4929 individuals or 64.15% of the total sample own life insurance. The same set of instrumental variables included in the IPUMS data has been used as the independent variables in the life insurance regression. These variables are expected to influence life insurance purchase based on the literature of insurance demand. The definitions and summary statistics of the variables from the HRS and IPUMS data can be found in Appendix A.

Age: In general, life insurance demand decreases as individual's age. This is because the accumulated wealth along with age can reach the level that mostly meets the needs of the survivor. I impose a restriction on age to be between 27-65 years old.

Education: Education gives individuals opportunities to understand the importance of risk management especially through insurance purchases. Burnett and Palmer (1984) show that life insurance demand is positively related to the education level of an individual.

Earnings: The effect of the household income on the life insurance demand is ambiguous. Some studies suggest that an increase in income will reduce the individual's willingness to insure (e.g., Chavas (2004). On the other hand, numerous studies (e.g., Goldsmith (1983)) found a positive relationship between these two. We hence expect that the higher the income, the greater are life insurance holdings. I take the log of total yearly income of individuals.

Marital Status: In both the HRS and IPUMS data set, 65% to75% of observations are found to be married in the age range of 27-65. People may become more risk averse after marriage. We expect a positive relation between married and insurance purchase. 66% of married couples hold life insurance in our data.

Race: I consider black and other race (neither black nor white) as two explanatory dummy variables. Black people consist of 10%-15% and the people from other race consist of 9%-10% of total observations in both data sets. White people are expected to be a larger share that is 76% to 80%. Both whites and backs that hold life insurance is about 65% of the HRS sample population. This percentage is a lower for other race which is about 43%. The relationship between life insurance purchase and race may vary.

Gender: The male-female ratio is 2:3 in the HRS data and it is almost half for the IPUMS sample. The HRS data shows that 67% of male and 61% of females hold life insurance.

Health Insurance: Both data sets include the information of public and private level health insurance purchase. In HRS data, 75% of private health insurance holders and 50% of public health insurance holders have life insurance.

IV.C. Second Stage Variables of Interest in TS2SIV Technique

The Second stage that has been explained in the methodology section focuses on the actual interest of this thesis. I use the 2010 IPUMS data set for this part. In order to examine the link between relative risk aversion and the migration decision, I use the binary migration variable as dependant variable. Here, I limit the sample information of IPUMS to the head of household. The purpose of considering only the household head is that migration is a household decision. All the family members may move together regardless of any other individual characteristics. The head of household consideration limits the IPUMS sample size to 815,385 observations. The migration status has been considered based on the available data on last year's (2009 to 2010) decision to move or not. One of the limitations of considering just one year is that I find only 15,685 observations out of 815385 who migrate in the last year according to the IPUMS 2010 data set. This is only a 2% share of the whole data. However, one year status reduces the common problem of measurement error that occurs when individuals fail to identify remigration. About using the explanatory variables, I have to drop some variables of use that provides only the current information (after migration information) like current income; current unemployment status etc. rather than information of last year (before migration information). As I am concern about migration decision, I can only use those explanatory variables that are available before the migration decision of the sample. The definitions and summary statistics of the explanatory variables are given in Appendix B.

Relative Risk Aversion: This is the predicted probability of life insurance purchase. The prediction is done using the coefficient estimates obtained using the HRS data set. The value of this variable indicates that the individual becomes more risk averse as the value goes from 0 to 1. The negative relationship that is, migrants are less risk averse can be established by the significant negative sign of the coefficient for this variable. The relationship is ambiguous as it varies in different migration literatures.

Age, Gender, Race: These are the variables that are reasonably exogenous to an individual's mobility decision and are not related to their current location. I include two dummy variables for race; black and other race includes American Indian, Alaskan Native, Asian, Native Hawaiian, and Pacific Islander.

Marital Status, Citizenship, Number of child, Years of Education, Place of Birth: These are the additional variables. Some of them may be jointly determined with migration decisions, as well as variables that may determine an individual's initial locations. I control the place of birth variable for the people who were not born in the US. In addition, I also control for Mexican born and Canadian born separately as they are from neighbor country but they do not experience the same entry process into the US.

Interaction Effect: The interaction terms of the risk variable with other demographic variables has been used to capture the risk variation effect by demographic characteristics.

IV.D. Network Effect and Migration

In order to capture the network effect of own ethnic group on the migration decision, I consider two ethnic groups; Asian and Hispanic. I use the share of their state population before migration from the aggregated data of the 2007-2009 American Community Survey. However, the state level data may not be the appropriate use to estimate the network effect; I do not have the access to a more disaggregated level data for this purpose at this moment. The coefficient of interaction variable of ethnic group and their corresponding population share shows the network effect. I also control for the triple interaction effect to see if the risk impact on the moving decision varies with the network effect.

V. Empirical Result

V.A. Predicted Likelihood Indicator of Life Insurance

As I discussed in the methodology section, the probit regression results using the HRS data set are given in Table 1. The likelihood ratio chi-square of 984.24 with a p-value of 0.0000 tells us that our model as a whole is statistically significant. All the variables are also statistically significant. The probit regression coefficients give the change in the cumulative normal probability or probit index for a one unit change in the predictor. A year of increase in age increases the probability by 0.02 that an individual would have a life insurance. In the same way, an increase in one unit of income or one year of education has positive and significant effects on the probability of having life insurance. Blacks' probability of having life insurance is more than non-black by 0.35 whereas other race has a lower probability of having life insurance. The probability of having life insurance increases by 0.28 for married individuals and 0.10 for males compare to non-married individuals and females respectively.

Table 1: Predicting Likelihood of Life Insurance[a]

Variable	Coefficients
Age	0.02 ***
Married	0.28 ***
Black	0.35 ***
Other race	-0.32 ***
Male	0.10 **
Education	0.04 ***
Ln of Income	0.05 ***
Private health insurance	0.82 ***
Public health insurance	0.23 ***
constant	-2.59 ***
Prob>chi-square	0000
Number of obs	4929

Notes: "***", "**" and "*" indicates 1%, 5% and 10% statistical significance level respectively.
[a] The dependant variable is life insurance purchase. It is a binary variable that takes the value 1 for having life insurance and 0 for holding no life insurance.

Private health insurance purchase explains a large effect of life insurance probit index. The individuals who have private health insurance increase the probit index of having life insurance by 0.82 than those of no private health insurance. Individuals having public health insurance are more likely to hold insurance by 0.23 compare to non-holder of public health insurance. At first, my interest is to estimate the probability of having life insurance for the sample of IPUMS data using these above set of coefficient estimates. For this, I use these estimated coefficients from HRS regression with the corresponding variables from IPUMS.

The probit model allows us to predict the probability of the dependent variable using the standard normal distribution function. The predicted life insurance probability for IPUMS observations has a minimum value of 0.01 and a maximum value of 0.97 with the mean value of 0.62. Now, this predicted probability of life insurance will be used as the risk measurement variable in the next section. A value closer to 1 indicates relatively more risk aversion than a value closer to zero.

V.B. Link between Risk Aversion and Migration Decision

Table-2 represents the average risk aversion for movers and stayers stratified by a variety of demographic characteristics. It is a more informal way to gain the insight into the relationship between risk attitudes and personal characteristics and the link between risk attitudes and migration as well. I use the ttest to check the significance of the difference of relative risk aversion of stayers and movers. I find most of the differences are statistically significant. The overall findings are consistent with the hypothesis that movers are less risk averse than stayers regardless of any demographic status. It also shows that old people are more risk averse than young. Comparing different level of education, educated people turns out to be more risk averse than the people of less education. If we consider different sub groups of races, it turns out that whites are less risk averse than blacks and the races other than these two are the least risk averse group.

Table 2: Average Risk Aversion

	Average of Risk Aversion		**No. of Observation**		
	Stayers	**Movers**	**Stayers**	**Movers**	**Share of Movers**
All***	0.645	0.590	802692	15685	1.95
Between State Mig		0.591	-	12754	-
Abroad Mig		0.586	-	2931	-
Age					
27-35	0.504	0.507	138934	5576	4.01
36-45***	0.599	0.574	195019	3991	2.05
45-65***	0.707	0.677	468739	6118	1.31
Sex					
Male***	0.685	0.631	445636	9181	2.06
Female***	0.596	0.532	357056	6504	1.82
Race					
White***	0.658	0.605	651192	12215	1.88
Black***	0.680	0.637	85862	1572	1.83
Other***	0.474	0.453	65638	1898	2.89
Married					
Yes***	0.707	0.661	468522	8409	1.79
No***	0.559	0.509	334170	7276	2.18
Education					
Less than high school***	0.423	0.339	65998	929	1.41
High School***	0.600	0.508	200987	2553	1.27
Some College***	0.650	0.573	258735	4544	1.76
Graduate***	0.727	0.658	276972	7659	2.77
Citizenship					
Yes***	0 .658	0.605	755846	13542	1.79
No	0 .447	0.499	46846	2143	4.57
Place of Birth					
USA***	0.663	0.607	688399	12404	1.80
Abroad***	0.548	0.532	79116	2653	3.35

Notes: "***", "**" and "*" indicates 1%, 5% and 10% statistical significance level respectively.

In addition to this overall risk attitude by common demographic characteristics, the last column of the Table 2 depicts the migration propensity of characteristics group and most of them are consistent with our expected direction. Relatively older age with higher risk aversion is less likely to migrate. Similarly, such link between risk attitudes and propensity to migration exists in case of gender, race, marital status, citizenship status and birth place. Male headed households are more likely to migrate than female. As blacks are more risk averse than whites, I find them less likely to migrate. Based on the place of birth, I find that people who born outside of the USA are more likely to migrate having lower relative risk aversion compare to the US born households. These insights are very consistent with the outcome of Jeager et al. (2010). Nevertheless, the difference in risk attitudes between the movers and stayers is consistent regardless of the demographic group.

Now I use a more formal way to capture the risk attitude effects on the migration decision. The following results of this section present the marginal effects from estimating probit models. In first, I estimate a simple regression of migration on risk and the result is given in the column 1 of Table 3. The result explains that a one-unit change in risk aversion decreases the probability that a household migrates across state by approximately 0.025. The corresponding elasticity is 0.8 which is a quite large effect. It means that, 1 % more risk aversion decreases the migration likelihood by 0.8 percent. Controlling all other variables in the model, results are presented in the column 2 of Table 3. I find the same conclusion that the more risk averse people are less likely to migrate when I consider the selective age group of 50-65 to check the robustness of the result that I mentioned earlier in section IV. However, the elasticity of risk aversion is higher (1.13%) for this selective age group. I have added a output table for this age group at the Appendix B of the paper. The squared term of age has been also included in the model. The result shows a U-shape quadratic function of age. That is, at early age, the probability of migration falls when the age of household head increases by one year but with a decreasing rate. However, after a certain age, the probability starts to increase. I find this cut-off point at the age of 55. It may reasonable in a sense that, after the age of 55, many households' head may go for early retirement and start to move.

Table 3: Probit Regression Result[b]

Variable	Column 1 Reg-1	Column 2 Reg-2	Column 3 Reg-3
Relative Risk	-0.025***	-0.026***	-0.002
Age		-0.002***	-0.001***
Age square		0.00002***	0.00002***
Male		0.004***	-0.0008
Black		0.003***	-0.0007
Other race		-0.002***	-0.002
Married		0.002***	0.005***
Citizen		-0.02***	-0.008***
Number of child		-0.004***	-0.003***
Education		0.002***	0.0007***
Foreign born		0.003***	0.006***
Mexican born		-0.02***	-0.01***
Canadian born		0.015***	0.035***
Relative Risk_Age			-0.002***
Relative Risk_Agesqr			0.00001**
Relative Risk_Male			0.008***
Relative Risk_Black			0.005**
Relative Risk_Other race			-0.001
Relative Risk_Married			-0.005***
Relative Risk_Citizen			-0.015***
Relative Risk_N_Child			-0.001***
Relative Risk_Education			0.003***
Relative Risk_Foreign born			-0.005**
Relative Risk_Mexican born			0.006
Relative Risk_Canadian born			-0.016*
Prob>chi-square	0000	0000	0000
Number of Obs	818377	818377	818377

Notes: "***", "**" and "*" indicates 1%, 5% and 10% statistical significance level respectively. [b]The dependant variable is migration. It is a binary variable that takes the value 1 for the status of migration during last year and 0 with no migration.

One year of more education increases the probability that a family moves across state by approximately 0.2 percentage point. People may move for school and education also opens up the opportunity to move through better job or other reasons. Households with relatively more children have negative marginal effect on moving decision. Such inverse relation may be reasonable in terms of settlement issue. Those who are married are more likely to migrate than not married household and the semi elasticity is 10%. This is because marriage is one of the most common reasons to move from one place to another. Similarly, I also find that male headed households are 20% more likely to move than female headed households. The probability of migration is 15% more for black headed household than whites. On the other hand, the race other than whites and blacks are less likely to move. I control another variable "citizenship status" in the regression and find a very large effect on migration. The migration probability is double for the household heads that are non-citizen compare to citizens. Depending on the place of birth, foreign born households are more likely to migrate than US born and the semi elasticity is 15%. In addition to that, I also consider the Mexican born and the Canadian born households separately as I mentioned in data analysis section. I find that the probability of moving is almost 50% less for Mexican born compared to US born households. On the other hand, Canadians are 75% more likely to migrate than US born households. Table F in Appendix B represents the same regression by excluding those who came from abroad during last year of data. The purpose of this is to control the income effect by considering state level median income of source place into the regression model. However, the result does not differ that much.

My next hypothesis is to test that the impact of risk attitudes on the moving decision varies by demographic characteristics. The results are given in column 3 of Table 3. The interaction terms explain the variation of relative risk variation by demographic characteristics. A one unit increase in risk aversion will decrease the probability of migration by 0.002 when the age of the household increases by 1 year. In other words, a 1% increase in risk aversion will decrease the probability of migration by 0.06% more when the age of the household increases by 1 year. The result also shows that a one-unit increase in risk aversion will increase the probability of migration by 0.008 more for male headed households compared to female headed households. The opposite is true for married households and for US citizens. The probability of migration decreases by 0.15% for married than non-married household head with a 1% increase in relative risk aversion. I also find that a citizen household head is less likely to migrate than non-citizen when relative risk aversion increases one unit. Similarly, a one unit increase in relative risk aversion decreases the likelihood of migration by 0.005 for foreign born household head than native born. The interaction effect becomes statistically insignificant for other race and Mexican born and poorly significant for Canadian born households at 10% level. However, black headed households are more likely to move compare to non-black with one unit of more risk aversion. Risk attitudes also vary by the level of education and number of children. A one unit increase in risk aversion will increase the probability of migration by 0.003 when the education of head of household increases by one year. And a one unit increase in risk aversion will decrease the probability of migration by 0.001 with one more child.

V.C. Network Effect and Migration

This section is going to test the hypothesis that the presence of more households of the same ethnic group in the source place makes individuals less likelihood to migrate than other groups. That is, people that live in a place that has higher number of households from the same ethnic group are on average expected to be less likely to migrate. In order to test this hypothesis, I consider only internal migration. I include Asian and Hispanic and their corresponding share of the state level population. The coefficients of their interaction term can explain the network effect. As I have already mentioned in the data analysis section that due to the unavailability of a more disaggregated level data, I use state level data to estimate the network effect. To control for the income effect, I now include the state level median-household income according to the initial state. The overall results are given in column 1 of Table 4.

The marginal effect of the income coefficient in source place is statistically significant and positive. It shows that people are more likely to move from the state where the median income is higher. The result is consistent with the previous hypothesis that higher income households are more likely to move. The interaction of ethnic groups and their corresponding share shows that, if Asian share increases by one unit, the probability of migration for Asian decreases by 0.001 compare to non-Asian. Similarly, the probability of migration falls by 0.0005 compare to non-Hispanic if Hispanic share increases by one unit. The result supports the hypothesis of a network effect. The households are less likely to migrate if the size of their own ethnic group increases.

This regression result does not consider the variation of risk attitudes on migration decision neither by ethnic group nor with network effect. To capture the risk variation by ethnic group, I include the interaction term of risk aversion and the ethnic group. The results are presented in column 2 of Table 4. The result explains that a one unit increase in relative risk aversion increases the probability of migration by 0.007 for Asian compare to non-Asian. The result shows the exact same effect on migration decision for Hispanic.

Table 4: Network Effect and Migration[c]

Variable	**Column 1 Reg-1**	**Column 2 Reg-2**	**Column 3 Reg-3**
Relative Risk	-0.02**	-0.03**	-0.03***
Age	-0.002***	-0.002***	-0.002***
Age square	0.00002***	0.00002***	0.00002***
Male	0.003***	0.003***	0.003***
Black	0.002***	0.002***	0.002***
other race	-0.002***	-0.002**	-0.002**
Married	0.002***	0.002***	0.002***
Citizen	-0.004***	-0.004***	-0.004***
Number of child	-0.003***	-0.003***	-0.003***
Education	0.002***	0.002***	0.002***
Log of income (state median income)	0.005***	0.005***	0.005***
Asian	0.012***	0.005**	-0.001
Share of asian	0.0002***	0.0001***	0.0001***
Hispanic	0.012***	0.005***	-0.0007
Share of Hispanic	-0.00007***	-0.00007***	-0.00007***
Asian*Asian share	-0.001***	-0.001***	-0.0003
Hispanic*Hispanic share	-0.0005***	-0.0005***	-0.0003***
Relative Risk*Asian		0.007**	0.018***
Relative Risk*Hispanic		0.007***	0.018***
Relative Risk*Asian*Asian share			-0.002***
Relative Risk*Hispanic*Hisp share			-0.0005***
Prob>chi-square	0000	0000	
Number of obs	815385	815385	

Notes: "***", "**" and "*" indicates 1%, 5% and 10% statistical significance level respectively. [c]The dependant variable is migration. It is a binary variable that takes the value 1 for the status of migration in last year and 0 if there is no migration.

I consider the triple effect interacting ethnic group, population share and risk to test the hypothesis of variation of risk attitudes with network effect. The results are presented in column 3 of Table 4. I find the triple effect coefficients for both groups are statistically significant and negative. That is, a 1% increase in relative risk aversion decreases the likelihood of migration by 0.2% for Asian compare to non-Asian if the size of Asian in the source place increases by 1%. The similar thing happens for Hispanic too. If the size of Hispanic increases by 1%, the likelihood of migration falls by 0.05% unit for Hispanic compare to others when risk aversion increases by 1%.

VI. Conclusion

In this paper, I use the 'Two Sample Two-Stage Instrumental Variable' technique to measure the relative risk aversion using the information of life insurance purchase. The overall result leads us to four main conclusions. Firstly, risk attitude has a significantly large impact on migration decision. A one percent increase in risk aversion decreases the probability of migration by 0.8 percent. This is quiet a large effect. Secondly, the impact of risk attitude on migration varies by other demographic characteristics. Thirdly, people with higher concentration of same ethnic households living in a particular place are expected to migrate less from their current place. Such effect has been tested using two ethnic groups; Asian and Hispanic. Contingent upon the availability of data, further research can be done to see whether there is a strong effect of this network in case of choosing the destination place also. Fourthly, the risk attitudes on migration vary by ethnic groups. Lastly, the result finds the link between risk aversion and network effect. That is, risk attitudes on migration decision vary with network effect.

Migration study has always been an important topic for economists and policy makers. Analysis of Risk factor in migration decision has now emerged as another central area of research. It becomes even more important for the migration analysis of developing countries. The rural-urban migration due to uncertain income can largely be explained by risk behavior. The rural area in developing country where financial market is malfunctioning, risk behavior may explain migration decision in a different way than developed countries like the US. Individual and household level risk preference play important roles to determine the motives and pattern of migration. As the efficient outcome of labor market is largely expected to be influenced by migration, the link between risk attitudes and migration should have got more importance especially in empirical studies. The empirical findings of the relationship between risk attitudes and migration for developing country can be proved significant to reduce the huge pressure of rural-urban migration. The findings that I have in this paper relating risk attitude, migration decision and network effect can act as a strong base to find out the direction and magnitudes of these relationships within developing country settings and facilitate my future research endeavor.

Appendix A: First Stage of TS2SIV

Table A: Definition of Variables (HRS)

Variable Name	Description	Minimum	Maximum
Age	Age of respondent Age limit: 27-65	27	65
Marital Status	1, married/partnered 0, otherwise (never married, separated, widow, divorce)	0	1
Race	Base Variable: White		
Black	1, if Black 0, otherwise	0	1
Other Race	1, other (American Indian, Alaskan Native, Asian, Native Hawaiian, Pacific Islander) 0, otherwise	0	1
Gender	1, Male 0, Female	0	1
Education	Year of education attainment	0	17
Health Insurance	It indicates whether persons had private/public/any health insurance coverage at the time of interview 0, without coverage 1, with coverage	0	1
Earnings	Log of earnings Each respondent's total pre-tax personal income or losses from all sources for the previous year. Amounts are expressed in contemporary dollars.	0	14.15
Life Insurance	It indicates whether persons had private/public/any health insurance coverage at the time of interview 0, without life insurance 1, with life insurance	0	1
Observation	4929 (HRS)		
Year of Data	Year 2010		
Source	HRS		

Table B: Summary Statistics (HRS Data)

	Share (in total observation)		Share (in terms of Insurance holding)	
Dummy Variables	**No. of Observation**	**Share**	**No. of Observation who have Life Insurance**	**Share**
Life Insurance	3162	64.15	-	-
Married	3711	75.30	2474	66.67
Race				
Black	773	15.68	504	65.20
White	3780	76.70	2460	65.10
Other race	463	9.40	198	42.80
Gender				
Male	1919	39	1277	66.55
Female	3010	61	1885	60.90
Health Insurance				
Private insurance	3428	69.55	2561	74.71
Public insurance	1153	23.40	581	50.40
Total Observation	4929	-	3162	64.15

Continuous Variables	**10%**	**20%**	**30%**	**40%**	**50%**
Earning (percentile)	3.33	8.31	8.85	10.60	11.22

Table-C: Summary Statistics (IPUMS Data)

	Share (in total observation)	
Dummy Variables	**No. of Observation**	**Share**
Married	984452	64.61
Race		
Black	156672	10.28
White	1223384	80.30
Other race	143633	9.43
Gender (Male)	738631	48.48
Health Insurance		
Private insurance	1123257	73.72
Public insurance	222886	14.63
Total Observation	1523689	-

Continuous Variables	**10%**	**20%**	**30%**	**40%**	**50%**
Earning (percentile)	5.86	9.40	10.30	10.92	11.41

Appendix B: Second Stage of TS2SIV

Table D: Definition of Variable (IPUMS data)

Variable Name	Description	Minimum	Maximum
Total Observation	818377		
Migration	Migration status in last year (in between 2009-2010). Migration includes moving between states or moving to USA from abroad 1, if moves in last year 0, if not	0	1
Age	Age of respondant Age restriction: 27-65	27	65
Marital Status	1, married/partnered 0, otherwise (never married, separated, widow, divorce)	0	1
Race			
Black	1, if Black 0, otherwise	0	1
Other Race	1, other race (American Indian, Alaskan Native, Asian, Native Hawaiian, Pacific Islander) 0, otherwise	0	1
Gender	1, Male 0, Female	0	1
Education	Year of education attainment	0	17
Life Insurance	Predicted likelihood of risk indicator. Higher probability indicates more risk aversion	0.01	0.97
Citizenship status	1, if US citizen 0, otherwise	0	1
Children	Number of child in household	0	9
Place of Birth			
(abroad)	1, if born in rest of the world 0, otherwise	0	1
(Canada)	1, if born in Canada 0, otherwise	0	1
(Mexico)	1, if born in Mexico 0, otherwise	0	1
Year of Data	Year 2010		
Source	IPUMS		

Network Effect			
Observations	815385		
Asian	1, if ethnicity is Asian (of any race) 0, otherwise	1	0
Hispanic	1, if ethnicity is Hispanic (of any race) 0, otherwise Hispanic ethnicity also include Mexican, Puerto Rican and Cuban	1	0
Population Share of Asian	Share of Asian living in each State. This share has been taken as the average of Asian Share in between 2007-2009	0.6	38.6
Population Share of Hispanic	Share of Hispanic living in each State. This share has been taken as the average of Asian Share in between 2007-2009	1.2	46.3
Household Median Income	Median household income by each state (log of income). This is the average level of income in 2007-2009. Source: American Community Survey	10.51 ($36796)	11.17 ($71037)
Year of Data	Year 2010		
Source	IPUMS		

Table E: Summary Statistics (Household Level IPUMS Data)

	Share (in total observation)	
Name of Variables	**No. of Observation**	**Share (%)**
Migration	15685	2.00
Married	476931	58.30
Race		
Black	87434	10.70
White	663407	81.00
Other race	67536	8.00
Gender (Male)	454817	55.60
Place of birth		
USA	700803	85.63
Abroad	81769	10.00
Mexico	28261	3.45
Canada	3101	0.38
Total Observation	818377	-
Network Effect		
Asian	34781	4.27
Hispanic	84241	10.33
Total Observations	815385	-

Table F:

Variable	**Coefficients**
Relative Risk	-0.025***
Age	-0.002***
Age square	0.00002***
Male	0.003***
Black	0.002***
Other race	-0.002***
Married	0.002***
Citizen	-0.01***
Number of child	-0.003***
Education	0.002***
Foreign born	-0.001***
Mexican born	-0.01***
Canadian born	0.004*
Income	0.004***
Prob>chi-square	0000
Number of Obs	815385

Notes: "***", "**" and "*" indicates 1%, 5% and 10% statistical significance level respectively. [c]The dependant variable is migration. It is a binary variable that takes the value 1 for the status of migration in last year and 0 if there is no migration.

Table G:

Variable	**Column 1 Age 27-65**	**Column 2 Age 50-65**	**Column 3 Age 27-65**	**Column 4 Age 50-65**
Relative Risk	-0.025***	-0.012***	-0.026***	-0.021***
Age			-0.002***	-0.005***
Age square			0.00002***	0.00004***
Male			0.004***	0.002***
Black			0.003***	0.002***
Other race			-0.002***	-0.0006
Married			0.002***	0.00004
Citizen			-0.02***	-0.017***
Number of child			-0.004***	-0.005***
Education			0.002***	0.001***
Foreign born			0.003***	0.001
Mexican born			-0.02***	-0.005***
Canadian born			0.015***	0.015***
Prob>chi-square	0000	0000	0000	0000
Number of Obs	818377	378649	818377	378649

Notes: "***", "**" and "*" indicates 1%, 5% and 10% statistical significance level respectively. [c]The dependant variable is migration. It is a binary variable that takes the value 1 for the status of migration in last year and 0 if there is no migration.

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