Discussion Paper Series

RIEB

Kobe University

DP2025-34

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December 18, 2025

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Abstract

This study explores the impact of risk attitudes and endowment effects on migration decisions under different motivations and migration distance conditions, focusing on the variability between short- and long-distance migration. Using data from Australia, we compare two measures of risk attitudes—a continuous risk index and a categorical risk threshold approach—and further test these effects in conjunction with household-level cluster analysis. The findings suggest that the effects of risk attitudes on migration decisions are likely to operate in long-distance migration when motivation is considered. In addition, we demonstrate that the endowment effect does not play a role in long-distance but plays a key role in short-distance migration decisions. Furthermore, we introduce a clustering-based analysis to reveal the impact of variations in family background on migration decisions. We find that the differences in coefficient estimates between the clustering and main models is negligible, indicating that the results of the main model remain robust and reliable after accounting for potential group differences.

Keywords: Migration Decision; Risk Attitude; Endowment Effect; Clustering-Based Analysis; Logit Model

JEL classification: D81; J61; R23

1. Introduction

Migration is a complex and uncertain decision. Once made, it involves a change in residence while also bringing potential economic and social challenges. At the same time, migration is not only a personal choice but also has broader social and economic impacts. It can help reallocate labor resources and support the development of the labor market (Bojars 2001). Therefore, understanding the drivers of migration decisions is important for developing effective migration and economic policies.

Traditional models of migration are often based on human capital theory. These models use a cost-benefit framework, focusing primarily on the economic gains and costs of moving. For example, Sjaastad (1962) proposed that individuals evaluate whether to migrate by comparing expected returns with the costs of moving. Lee (1966) expanded this by introducing non-economic factors such as personal traits and social networks, suggesting that migration is shaped by both individual characteristics and external conditions. In addition, Borjas (1990) emphasized income and employment differences as key drivers, especially in international migration. However, these traditional economic models rarely incorporate risk and uncertainty directly, often treating them as background noise (Akgüç et al. 2016).

Since Knight's (1921) seminal work, the concepts of risk and uncertainty have become central to academic research. His distinction between measurable risk and unmeasurable uncertainty laid the foundation for subsequent studies. In migration, uncertainty often stems from limited information about both the origin and destination, as well as from unpredictable future outcomes. Migrants rarely decide blindly; as Williams and Baláž (2012) noted, they usually act based on partial but informed expectations. Jaeger et al. (2010) found that individuals with a higher risk tolerance are more likely to migrate. Using Chinese data, Akgüç et al. (2016) confirmed that migrants and non-migrants differ significantly in risk attitudes, noting the intergenerational transmission of these traits. Similarly, Bauernschuster et al. (2014) found that risk-tolerant and educated individuals are more mobile, even across culturally distant regions. Goldbach and Schlüter (2018) observed that migrants in Ghana and Indonesia are generally less risk-averse and more patient than non-migrants. Risk attitudes were particularly influential among Indonesian female migrants. These findings highlight the importance of personal risk preferences alongside education, employment, and social factors.

However, results regarding the effect of risk tolerance on migration decisions are not always consistent. Bonin et al. (2009) emphasized that risk preferences vary according to demographics and context. Balaz and Williams (2011) found no significant difference in risk attitudes between male migrants and non-migrants, suggesting that gender may influence this relationship. At the household level, Stark (1991) argued that migration may be a risk-diversification strategy. Chen, Chiang, and Leung (2003) supported this and found that families sometimes choose risk-averse members to migrate.

Meanwhile, research has begun to include other psychological insights. Prospect theory suggests that people care more about changes relative to a reference point than about absolute values (Tversky and Kahneman 1991). Clark and Lisowski (2017) applied this to migration, arguing that decisions depend on individual reference points. They showed that emotional attachment to one's current surroundings increases the psychological cost of moving. The same conclusion was confirmed by Clark, Ong ViforJ, and Phelps (2023). Based on Kahneman (2011), we consider the endowment effect—that is, emotional attachment to familiar places—as an important factor in this study. These ties can increase the psychological costs of moving, especially when social connections are strong.

Migration decisions also depend on distance and motivation. Sjaastad (1962) showed that the reasons behind short- and long-distance moves are often different. Thomas (2019) found that migration motivations vary with distance. Employment drives long-distance moves, while housing and education become more important over distance, suggesting an interaction between migration distance and motivation.

In this study, we account for the reasons behind migration and classify moves by distance to examine how risk attitudes and place attachment influence decision-making across different contexts. Specifically, we test whether risk preferences and emotional ties remain significant after controlling for various migration motives. We further aim to understand how these factors interact in short- and long-distance moves, offering a closer look at the determinants of mobility versus immobility. A key contribution of this study lies in its separate analysis of short- and long-distance migration. While the existing literature predominantly focuses on long-distance moves, we compare the drivers of both types to gain a deeper understanding of how distance shapes migration behavior.

This study reveals that migration decisions are shaped by dynamic behavioral factors. Risk attitudes influence migration in a distance-dependent and time-varying manner—risk-tolerant individuals were more likely to undertake long-distance moves in 2014, but this effect disappeared by 2022, reflecting a decline in overall risk tolerance. Residential duration consistently exerts a strong negative effect, highlighting the growing inertia of long-term settlement. Meanwhile, neighborhood dissatisfaction drives short-distance mobility, whereas job-related motives remain the dominant trigger for long-distance migration. These findings suggest that migration is not a static economic choice but a behavioral process influenced by changing risk perceptions, place attachment, and contextual conditions.

The remainder of this article is structured as follows: Section 2 explains the data and variable definitions. Section 3 presents the empirical results, and Section 4 provides conclusions and future research directions.

2. Data description

This study used data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, a nationally representative longitudinal survey tracking Australian households and individuals since 2001. The initial wave included 19,914 individuals, offering a comprehensive dataset for analyzing long-term demographic and socioeconomic trends. HILDA collects data annually on a wide range of topics, including education, employment, income, health, family structure, and social relationships. Its longitudinal design allows researchers to observe changes in individual and household characteristics. Our analysis was based on data from the Responding Person file of HILDA Release 22, which includes all 22 waves of data from 2001 to 2022.

To investigate the link between migration behavior and risk preferences, we focused on the 2014 and 2022 waves. Since 2014, the Self-Completion Questionnaire (SCQ) has included a key question measuring individuals' willingness to take risks. This variable, collected every four years, enables a consistent comparison across time. Choosing the years 2014 and 2022 allowed us to examine how risk attitudes relate to migration decisions in two different social and economic contexts, offering both cross-sectional and time-comparative insights.[1]

Our sample included individuals aged 15 to 60, focusing on the working-age population.

[1] We selected 2014 and 2022 as the main comparison years to capture two distinct socioeconomic contexts: a relatively stable pre-pandemic environment and a post-pandemic period marked by heightened uncertainty and changes in mobility patterns. The year 2018 was excluded because it represented an economically stable transition phase—following the housing market correction and before the pandemic—during which migration decisions were less likely to reflect substantial shifts in risk attitudes.

We defined short-distance migration as moves between 30 and 70 kilometers, and long-distance migration as those over 70 kilometers. Based on this classification, we constructed binary dependent variables indicating whether an individual moved or remained within each distance category.

Our model allows for both horizontal (short versus long-distance migration in the same year) and vertical comparisons (changes between 2014 and 2022). This design helped reveal how migration behavior evolves over time and under different spatial scales, particularly in response to changes in individual risk preferences and external socioeconomic conditions.

2.1 Explanation of core independent variables

The first key independent variable was individual willingness to take risks, measured using the SCQ in HILDA. Respondents rated themselves on a scale from 0 ('unwilling to take risks') to 10 ('very willing to take risks'). Following Jaeger et al. (2010), we transformed this into a binary variable using the midpoint of the scale. Individuals scoring above the midpoint were categorized as risk-tolerant, and those below the midpoint were categorized as risk-averse. This simplification helps clarify the relationship between risk attitudes and migration behaviors. We hypothesized that risk-tolerant individuals are more likely to migrate, particularly over long distances, because they are more comfortable with uncertainty and potential gains. By contrast, risk-averse individuals may favor short-distance moves or choose not to migrate due to their reluctance to face unfamiliar environments.

The second key variable was the endowment effect, capturing how emotional and social ties influence migration decisions. We operationalized this concept using two measures: time at current address and the neighborhood socioeconomic status (SES).

Time at Current Address reflects the duration that an individual has lived at their current residence. To assess its impact, we grouped this variable into three categories: less than five years (reference group), five to nine years, and over nine years. This classification allowed us to evaluate whether longer residence increases place attachment and reduces the likelihood of moving. We expected that individuals living at their current address for longer periods are more reluctant to relocate due to their accumulated social connections and psychological ties. This grouping also enabled us to explore a potential threshold effect: whether the inhibiting influence of residence duration intensifies after a certain point and whether this varies between short- and long-distance moves.

Neighborhood SES represents the broader quality of one's living environment, combining indicators such as average income, education, and employment in the area. Higher SES neighborhoods typically offer better infrastructure and services, while lower SES areas may be associated with social and economic disadvantages. We included neighborhood SES to assess whether individuals in more favorable environments are less likely to migrate due to higher satisfaction with their surroundings. To allow for a more flexible analysis and improve model robustness, we avoided dividing SES into simple percentiles (e.g., quintiles). Instead, we applied two complementary treatments: a continuous variable that retains the original SES score to examine its linear influence on migration decisions, and a threshold variable that converts SES into a binary variable based on a defined cutoff, distinguishing between 'high SES' and 'low SES' groups. This dual approach balances depth and clarity. The continuous form preserves full information and captures subtle effects, whereas the threshold version simplifies the analysis, reduces multicollinearity, and avoids sensitivity to outliers.

We hypothesized that individuals living in high-SES neighborhoods or those with longer residential durations are less likely to migrate because their emotional and environmental satisfaction reduces their incentive to move. By contrast, those in lower-SES areas or those with shorter residences may be more mobile due to weaker community ties and lower migration costs. This aligns with insights from behavioral economics, where both environmental quality and attachment affect the perceived costs and benefits of moving.

Furthermore, while most studies on migration and risk focus on individual traits, few have directly considered migration motivation. To address this gap, we incorporated reasons for moving—specifically, housing and job-related reasons—into our model. This was motivated by Thomas (2019), who found that migration motives vary significantly with distance: long-distance migration is often job-driven, while housing factors tend to dominate short-distance moves. Including motivation allowed us to better isolate how risk preferences and endowment effects interact with the underlying reasons for migration. It also enabled a more nuanced understanding of the behavioral patterns driving both short- and long-distance relocation.

2.2 Summary of the sample

The dataset comprised four groups, categorized by migration distance (short versus long) and survey wave (2014 and 2022). Tables 1 and 2 provide the summary statistics for each group. Across all groups, movers generally exhibited a higher willingness to take risks, as reflected by their higher mean risk index relative to stayers. In 2014, this pattern was particularly pronounced when using the risk threshold measure (≥6), especially among long-distance movers. The ratio of movers reporting risk tolerance ≥6 was 0.55, compared to 0.42 among stayers, suggesting that risk tolerance may play a stronger role in long-distance migration. However, in 2022, this distinction became less marked using the same threshold (0.48 among movers versus 0.39 among stayers).

Gender distribution was stable across all groups, with females slightly outnumbering males among both movers and stayers. Education also showed a clear trend. In 2014, diploma holders comprised the largest share of both short- and long-distance movers. In 2022, diplomas remained dominant in short-distance migration, but a bachelor's degree or higher became the most common among long-distance movers, suggesting that higher education may facilitate long-distance mobility in recent years. Marital status also exhibited distance-related differences. In both years, the ratios of legally married long-distance movers were higher than those of legally married short-distance movers (0.34 and 0.32 for long-distance movers versus 0.23 and 0.28 for short-distance movers in 2014 and 2022, respectively).

Additionally, native-born individuals consistently exhibited higher mobility across both distances and years, potentially because of lower informational or cultural barriers. Household structure varied across groups. In 2014, 'lone person' households dominated short-distance moves, while 'couples without children' led long-distance. In 2022, 'couples with children' were most common among short-distance movers, while 'lone person' households again dominated long-distance moves. In terms of labor force status, employed individuals represented the majority of movers, although their proportion was slightly lower than that of stayers.

Movers generally had shorter durations at their current address, with most having lived there for less than five years, indicating lower residential stability. Movers also reported lower neighborhood satisfaction, particularly among short-distance movers. This may suggest that dissatisfaction with the immediate environment is a key driver of short-distance relocation. With respect to migration reasons, long-distance movers were more likely to move for work than their short-distance counterparts (0.44 and 0.37 for long-distance movers versus 0.25 and 0.24 for short-distance movers in 2014 and 2022, respectively), while short-distance movers tended to be more driven by housing needs than long-distance movers (0.25 and 0.23 for short-distance movers versus 0.09 and 0.17 for long-distance movers in 2014 and 2022, respectively).

[Table 1]

[Table 2]

3. Empirical results

3.1 The 2014 wave

Table 3 presents the logit estimation results for short-distance and long-distance migrations in the 2014 wave. In the short-distance model, both *Risk_index* and *Risk_threshold* were not significant, suggesting that short-distance moves may not be strongly influenced by risk attitudes. Among demographic variables, with legally married individuals as the reference category, cohabiting (unmarried but living together) or separated (legally married but living apart) individuals showed different migration probabilities. Specifically, being separated was associated with a significantly lower likelihood of migration, possibly due to increased family responsibilities. In contrast, lone-person households were significantly more likely to move, probably due to fewer social constraints and greater flexibility. Additionally, change of address since the last wave strongly predicted current migration, indicating persistence in migratory behavior.

The endowment effect was clearly present: individuals who had lived at their current address for more than nine years were significantly less likely to migrate compared to those who had lived there for fewer than five years, reflecting the influence of long-term community attachment. Neighborhood SES, estimated by either *Neighborhood_SES* or *Neighborhood_threshold,* also showed a significant negative effect, suggesting that individuals in high-SES areas were less likely to relocate, likely due to higher satisfaction with their environment. Additionally, migration motives played a substantial role. Both job-related and housing-related reasons were significant predictors of migration, with job motivation showing a positive effect, consistent with localized employment-driven mobility.

Distinct patterns emerged in the long-distance model. The risk index had a positive effect, confirming that risk-tolerant individuals are more likely to engage in long-distance migration, where uncertainty is higher. Age played a nonlinear role: age had a positive effect, while *Age_sq* was negative, indicating an inverted U-shaped relationship between age and the probability of long-distance migration—in other words, the likelihood of migrating increases with age, reaches a peak, and then declines.

Among household factors, cohabiting reduced the likelihood of migration, while lone-person households again showed a strong positive effect. Gender differences were also notable: females were significantly more likely to undertake long-distance moves, possibly reflecting growing autonomy and evolving gender roles. Place of birth also matters. Individuals born in Australia or other English-speaking countries were significantly more likely to migrate long distances, likely due to lower informational or cultural barriers. Labor force status also showed clear effects. Both the unemployed and those not in the labor force were more likely to migrate than the employed, with a stronger effect among those not in the labor force.

Regarding the endowment effect in the long-distance model, as in the short-distance model, a longer duration of residence was associated with a lower probability of migration, thus confirming the presence of the endowment effect. However, neighborhood SES did not significantly influence long-distance migration, possibly because job or housing motives override local satisfaction at greater distances.

Finally, motivation to move remained significant. Interestingly, while job-related motives remained important, housing-related motives showed a stronger effect in the long-distance group—suggesting that as migration distance increases, both motivations exert a stronger influence.

[Table 3]

3.2 The 2022 wave

The logit estimation results for short-distance and long-distance migrations in the 2022 wave are presented in Table 4. In the short-distance migration model, the risk index did not show a significant effect, indicating that risk preferences do not play a key role in short-range mobility during this period. Cohabiting status had a significant negative effect, suggesting that shared household responsibilities may limit flexibility in short-distance moves. Individuals not in the labor force showed a slightly positive effect on migration probability, indicating that this group may have fewer constraints and a greater willingness to relocate. The variable *Change Address since Last Wave* remained a strong predictor, showing a highly significant positive association with current migration and reinforcing the persistence of past migration behavior.

Regarding residential duration, both the five-to-nine-years and over-nine-years groups showed a significantly lower migration probability compared to those residing for less than five years. Notably, the five to nine year group showed a relatively stronger effect, implying a possible tipping point in community attachment. Additionally, neighborhood SES had a significantly negative impact on the likelihood of moving, suggesting that individuals in high-SES environments are more likely to stay due to higher satisfaction or community cohesion. Similar to the results in the 2014 wave, both job- and housing-related reasons were significant, but job motivation exerted a stronger influence on short-distance migration.

Different patterns were observed in the long-distance model. *Age* showed a negative effect, while *Age_sq* was positive, indicating a U-shaped relationship: the likelihood of migrating declines with age, reaches a minimum point, and then increases. This result is the exact opposite of the findings in the 2014 wave. To examine the robustness of this finding, additional cluster-based estimations were conducted, and the U-shaped pattern remained consistent. This suggests that the difference is not driven by sample composition or clustering methods but likely reflects a substantive change in migration behavior. A plausible explanation is that in recent years, older cohorts have become increasingly inclined to undertake long-distance moves, possibly due to retirement relocation, access to healthcare, or family reunification. This finding highlights that migration incentives are not fixed over the life course but can vary significantly across periods depending on the broader socioeconomic context.

Education plays a marginal role; at the 10% level, individuals with a high school diploma or certificate are significantly more likely to migrate than those with lower education levels. In terms of marital status, cohabiting, separated, and never married/non-cohabiting individuals are less likely to migrate, likely due to relationship-related constraints or a lack of support systems. Native-born individuals are significantly more mobile than foreign-born individuals, likely because they possess greater knowledge of available opportunities and face fewer cultural barriers. Regarding household structure, couples without children and lone-person households showed a significantly higher likelihood of migration.

As in the short-distance model, previous address change strongly predicts current migration, with a larger effect on long-distance moves. Similarly, longer residence significantly reduces the probability of moving, with the over-nine-years group showing the strongest negative effect. Unlike the 2014 wave, neighborhood SES was also significant in the long-distance model in 2022, indicating that broader environmental satisfaction may discourage long-range moves. Finally, motivation patterns shift with distance: job-related motives increase in strength, whereas the effect of housing-related motives declines.

[Table 4]

3.3 Robustness check

To assess the robustness of the results, we compared the main model with a cluster-robust version that adjusted standard errors at the household level. A robustness check is essential in empirical research to ensure that the findings are not driven by specific model assumptions. The results, based on clustering standard errors, indicated that the marginal effect estimates remained unchanged across both models, with only minor differences in the standard errors that did not affect their statistical significance.[2] This consistency suggests that the marginal effects and explanatory power of key variables were not sensitive to clustering adjustments, enhancing the credibility and generalizability of the results.

The clustering correction provided more conservative standard errors by accounting for potential intra-group correlation. This indicated that the original model may underestimated random errors, and clustering offered a more reliable criterion for inference, thus reducing the risk of type I errors or over-interpretation of marginally significant results. Importantly, even after correcting for within-group correlation, the direction and strength of the variable effects remained stable. This finding supports the validity of the model specifications and the variable selection used in this study. It also suggests that the model is robust to potential misspecifications in the error structure.

However, the slight changes in the estimated standard errors implied that between-group heterogeneity may still be present. If such heterogeneity is substantial, future studies could consider group-specific regressions or multilevel (hierarchical) models to capture more complex structures in the data. Additionally, verifying model assumptions such as error independence and exploring dual-clustering approaches may further improve reliability.

4. Conclusion

This study finds that risk attitude (measured by either *Risk_index* or *Risk_threshold*) plays a distance-dependent role in migration behavior. In 2014, higher risk tolerance significantly increased the likelihood of long-distance migration, whereas no such effect was observed for short-distance moves. However, by 2022, risk attitude did not significantly affect either type

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[2] The results with standard errors clustered at household level are not reported, but are available upon request.

of migration. This may reflect a general decline in risk tolerance between the two periods. As shown in the descriptive statistics, both the overall sample and the mover subsample exhibited lower risk scores in 2022, possibly due to broader socioeconomic uncertainty and policy changes, making individuals more conservative. These findings highlight that risk preferences are dynamic and their influence on migration may vary across contexts and over time.

The endowment effect, as measured by residential duration, showed a stable and significant negative impact on migration in both years. Individuals residing at the same address for over nine years were consistently less likely to move, indicating that emotional attachment and community embeddedness significantly reduce the likelihood of migration. This effect was more pronounced in 2022, suggesting an increase in inertia associated with long-term residence. Neighborhood SES also showed a negative effect, particularly in short-distance migration, where dissatisfaction with local surroundings may motivate migration. The effect in long-distance cases was less consistent, possibly due to greater heterogeneity or a smaller subsample size.

Migration motivation remains a robust predictor across models. Job-related motives were consistently associated with a higher migration probability, especially for long-distance migration, supporting the existing literature that emphasizes employment as a key driver (Clark and Maas 2015; Niedomysl 2011; Thomas 2019). In contrast, housing-related motives tended to reduce the probability of long-distance migration, possibly reflecting individuals' preference for stability and environmental continuity when housing is the main concern.

To ensure robustness, we applied both continuous and threshold estimation methods to the core variables. The consistency of results across these specifications confirmed the validity of our findings. Household-level clustering yielded comparable results, thereby strengthening the reliability of the analysis.

The results of this study have several implications. Targeted support for risk-averse individuals, including access to information, housing options, and social integration programs, can enhance long-distance migration. For short-distance movers, improving neighborhood conditions and housing affordability is key. Moreover, policies tailored to cohabiting individuals or those outside the labor market could help reduce barriers to mobility and increase participation.

Finally, it should be noted that this study is based on cross-sectional data; therefore, the ability to draw causal inferences is limited. While we assume that risk preferences influence migration, it is also plausible that migration experiences reshape risk attitudes, leading to possible reverse causality (Goldbach and Schlüter 2018). Individuals who move may adjust their risk preferences based on new environments that are not observable at a single point in time. Future research should use panel data to track individuals over time and identify causal links (Yue et al. 2013). Furthermore, risk preferences are not static. They may change with life stage, career progress, or family responsibilities. Migration decisions often involve intertemporal trade-offs in which individuals weigh short-term uncertainty against long-term gains. Future models should incorporate lagged risk variables and dynamic specifications to better capture how changing risk tolerance influences migration over time.

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Table 1. Summary of the sample in the 2014 wave

Variables	Short Distance			Long Distance		
	All n=10537	Movers n=146	Stayers n=10391	All n=10906	Movers n=370	Stayers n=10536
Risk Threshold						
- 5 or below	6135 (0.58)	72 (0.49)	6063 (0.58)	6300 (0.58)	165 (0.45)	6135 (0.58)
- 6 or above	4402 (0.42)	74 (0.51)	4328 (0.42)	4606 (0.42)	205 (0.55)	4401 (0.42)
Sex						
- Male	4950 (0.47)	73 (0.50)	4877 (0.47)	5110 (0.47)	160 (0.43)	4950 (0.47)
- Female	5587 (0.53)	73 (0.50)	5514 (0.53)	5796 (0.53)	210 (0.57)	5586 (0.53)
Highest Education						
- Less than high school	2249 (0.21)	29 (0.20)	2220 (0.21)	2300 (0.21)	51 (0.13)	2249 (0.21)
- Bachelor’s degree and more	2960 (0.28)	34 (0.23)	2926 (0.28)	3074 (0.28)	115 (0.31)	2959 (0.28)
- Diploma	3477 (0.33)	45 (0.31)	3432 (0.33)	3601 (0.33)	124 (0.34)	3477 (0.33)
- High school or certificate	1851 (0.18)	38 (0.26)	1813 (0.17)	1931 (0.18)	80 (0.21)	1851 (0.18)
Marital Status						
- Legally married	4952 (0.47)	34 (0.23)	4918 (0.47)	5076 (0.47)	124 (0.34)	4952 (0.47)
- Cohabiting	1876 (0.18)	44 (0.30)	1832 (0.18)	1958 (0.18)	82 (0.22)	1876 (0.18)
- Separated	280 (0.03)	2 (0.01)	278 (0.03)	292 (0.03)	12 (0.03)	280 (0.03)
- Divorced	519 (0.05)	12 (0.08)	507 (0.05)	536 (0.05)	17 (0.05)	519 (0.05)
- Never married and not	2910 (0.28)	54 (0.37)	2856 (0.27)	3044 (0.27)	135 (0.36)	2909 (0.28)
Country of Birth						
- Others	1150 (0.11)	14 (0.10)	1136 (0.11)	1172 (0.11)	22 (0.06)	1150 (0.11)
- Native-born	8526 (0.81)	117 (0.80)	8409 (0.81)	8846 (0.81)	321 (0.87)	8525 (0.81)
- English-speaking Country	861 (0.08)	15 (0.10)	846 (0.08)	888 (0.08)	27 (0.07)	861 (0.08)
Family Status						
- Others	1947 (0.18)	16 (0.11)	1931 (0.19)	1985 (0.18)	38 (0.10)	1947 (0.18)
- With Children	4937 (0.47)	45 (0.31)	4892 (0.47)	5036 (0.46)	99 (0.27)	4937 (0.47)
- Without Children	2434 (0.23)	38 (0.26)	2396 (0.23)	2552 (0.23)	118 (0.32)	2434 (0.23)
- Lone person	1219 (0.12)	47 (0.32)	1172 (0.11)	1333 (0.12)	115 (0.31)	1218 (0.12)
Labor Force Status						
- Employed	8134 (0.77)	108 (0.74)	8026 (0.77)	8382 (0.77)	249 (0.67)	8133 (0.77)
- Unemployed	475 (0.05)	9 (0.07)	466 (0.04)	502 (0.05)	27 (0.07)	475 (0.05)
- Not in the labor force status	1928 (0.18)	29 (0.20)	1899 (0.18)	2022 (0.19)	94 (0.25)	1928 (0.18)
Change Address Since Last Wave						
- No	8972 (0.85)	9 (0.06)	8963 (0.86)	8990 (0.82)	18 (0.05)	8972 (0.85)
- Yes	1565 (0.15)	137 (0.94)	1428 (0.14)	1916 (0.18)	352 (0.95)	1564 (0.15)
Time at Current Address						
- Under 5 years	5322 (0.51)	143 (0.98)	5179 (0.50)	5685 (0.52)	364 (0.98)	5321 (0.51)

-5–9 years	1718 (0.16)	2 (0.01)	1716 (0.17)	1721 (0.16)	3 (0.01)	1718 (0.16)
-10+ years	3497 (0.33)	1 (0.01)	3469 (0.33)	3500 (0.32)	3 (0.01)	3497 (0.33)
Neighborhood Threshold						
- Below 6	5036 (0.48)	88 (0.60)	4948 (0.48)	5218 (0.48)	182 (0.49)	5036 (0.48)
- Over 5	5501 (0.52)	58 (0.40)	5443 (0.52)	5688 (0.52)	188 (0.51)	5500 (0.52)
Move for Housing						
- No	9737 (0.92)	109 (0.75)	9628 (0.93)	10072 (0.92)	336 (0.91)	9736 (0.92)
- Yes	800 (0.08)	37 (0.25)	763 (0.07)	834 (0.92)	34 (0.09)	800 (0.08)
Move for Job						
- No	10372 (0.98)	110 (0.75)	10262(0.99)	10579 (0.97)	207 (0.56)	10372(0.98)
- Yes	165 (0.02)	36 (0.25)	129 (0.01)	327 (0.03)	163 (0.44)	164 (0.02)
Continuous Variables, Mean						
Age	38.08	31.92	38.17	37.92	33.18	38.08
Risk Index	4.93	5.34	4.93	4.96	5.65	4.93
SES Score	2.02	1.66	2.02	2.02	2.00	2.02

Note: Ratios of the number of respondents in each category to those of the corresponding samples are shown in parentheses

Table 2. Summary of the sample in the 2022 wave

Variables	Short Distance			Long Distance		
	All n=9508	Movers n=112	Stayers n=9396	All n=9801	Movers n=294	Stayers n=9507
Risk Threshold						
- 5 or below	5761 (0.61)	61 (0.54)	5700 (0.61)	5912 (0.60)	152 (0.52)	5760 (0.61)
- 6 or above	3747 (0.39)	51 (0.46)	3696 (0.39)	3889 (0.40)	142 (0.48)	3747 (0.39)
Sex						
- Male	4411 (0.46)	49 (0.44)	4362 (0.46)	4546 (0.46)	135 (0.46)	4411 (0.46)
- Female	5097 (0.54)	63 (0.56)	5034 (0.54)	5255 (0.54)	159 (0.54)	5096 (0.54)
Highest Education						
- Less than high school	1497 (0.16)	25 (0.22)	1472 (0.16)	1534 (0.16)	38 (0.13)	1496 (0.16)
- Bachelor's degree and more	3222 (0.34)	30 (0.28)	3192 (0.34)	3321 (0.34)	99 (0.34)	3222 (0.34)
- Diploma	3140 (0.33)	37 (0.33)	3103 (0.33)	3224 (0.33)	84 (0.29)	3140 (0.33)
- High school or certificate	1649 (0.17)	20 (0.18)	1629 (0.17)	1722 (0.18)	73 (0.25)	1649 (0.17)
Marital Status						
- Legally married	4212 (0.44)	31 (0.28)	4181 (0.44)	4307 (0.44)	95 (0.32)	4212 (0.44)
- Cohabiting	2006 (0.21)	28 (0.25)	1978 (0.21)	2075 (0.21)	69 (0.23)	2006 (0.21)
- Separated	254 (0.03)	6 (0.05)	248 (0.03)	260 (0.03)	6 (0.02)	254 (0.03)
- Divorced	417 (0.04)	5 (0.04)	412 (0.04)	433 (0.04)	16 (0.05)	417 (0.04)
- Never married and not	2619 (0.28)	42 (0.38)	2577 (0.27)	2726 (0.28)	108 (0.37)	2618 (0.28)
Country of Birth						
- Others	946 (0.10)	11 (0.10)	935 (0.10)	961 (0.10)	15 (0.05)	946 (0.10)
- Native-born	7830 (0.82)	96 (0.86)	7830 (0.83)	8191 (0.84)	266 (0.90)	7925 (0.83)
- English-speaking Country	631 (0.07)	5 (0.04)	631 (0.07)	649 (0.07)	13 (0.04)	636 (0.07)
Family Status						
- Others	1647 (0.17)	20 (0.18)	1627 (0.17)	1668 (0.17)	21 (0.07)	1647 (0.17)
- With Children	4634 (.49)	35 (0.31)	4599 (0.49)	4722 (0.48)	88 (0.30)	4634 (0.49)
- Without Children	2121 (0.22)	29 (0.26)	2092 (0.22)	2205 (0.22)	84 (0.29)	2121 (0.22)
- Lone person	1106 (0.12)	28 (0.25)	1078 (0.11)	1206 (0.12)	101 (0.34)	1105 (0.12)
Labor Force Status						
- Employed	7840 (0.82)	78 (0.70)	7762 (0.83)	8076 (0.82)	228 (0.78)	7839 (0.82)
- Unemployed	289 (0.03)	10 (0.09)	279 (0.03)	307 (0.03)	18 (0.06)	289 (0.03)
- Not in the labor force status	1379 (0.15)	24 (0.21)	1355 (0.14)	1427 (0.15)	48 (0.16)	1379 (0.15)
Change Address Since Last Wave						
- No	8087 (0.85)	13 (0.12)	8074 (0.86)	8105 (0.83)	18 (0.06)	8087 (0.85)
- Yes	1421 (0.15)	99 (0.88)	1322 (0.14)	1696 (0.17)	276 (0.94)	1420 (0.15)
Time at Current Address						
- Under 5 years	4793 (0.50)	109 (0.97)	4684 (0.50)	5081 (0.52)	289 (0.98)	4792 (0.50)

-5–9 years	1694 (0.18)	1 (0.001)	1693 (0.18)	1696 (0.17)	2 (0.01)	1694 (0.18)
-10+ years	3021 (0.32)	2 (0.002)	3019 (0.32)	3024 (0.31)	3 (0.01)	3021 (0.32)
Neighborhood Threshold						
- Below 6	4805 (0.51)	77 (0.69)	4728 (0.50)	4965 (0.51)	161 (0.55)	4804 (0.51)
- Over 5	4703 (0.49)	35 (0.31)	4668 (0.50)	4836 (0.49)	133 (0.45)	4703 (0.49)
Move for Housing						
- No	8795 (0.93)	86 (0.77)	8709 (0.93)	9038 (0.92)	244 (0.83)	8794 (0.93)
- Yes	713 (0.07)	26 (0.23)	687 (0.07)	763 (0.08)	50 (0.17)	713 (0.07)
Move for Job						
- No	9413 (0.99)	85 (0.76)	9328 (0.99)	9597 (0.98)	184 (0.63)	9413 (0.99)
- Yes	95 (0.01)	27 (0.24)	68 (0.01)	204 (0.02)	110 (0.37)	94 (0.01)
Continuous Variables, Mean						
Age	38.46	32.71	38.53	38.31	33.35	38.45
Risk Index	4.83	5.29	4.83	4.85	5.3	4.83
SES Score	1.95	1.55	1.96	1.95	1.81	1.95

Note: Ratios of the number of respondents in each category to those of the corresponding samples are shown in parentheses.

Table 3. Empirical results for short-distance and long-distance migration in 2014

Year 2014	Short Distance		Long Distance	
	Model 1	Model 2	Model 1	Model 2
Risk_index	-0.00016		0.00164**	
Risk_threshold		0.00160		0.00846***
Age	0.00071	0.00069	0.00224**	0.00223**
Age_sq	-0.00001	-0.00001	-0.00003**	-0.00003**
Female	-0.00004	0.00034	0.00679**	0.00694**
Highest Education (reference: less than high school)				
Bachelor and more	-0.00299	-0.00315	0.00756	0.00723
Diploma	-0.00392	-0.00398	0.00441	0.00454
High school and Certificate	0.00188	0.00181	0.00338	0.00338
Income	0.00000	0.00000	0.00000	0.00000
Income_sq	-0.00000	-0.00000	-0.00000	-0.00000
Marital Status (reference: Legally Married)				
Cohabiting	0.00193	0.00153	-0.01099**	-0.01129***
Separated	-0.00952**	-0.01008**	-0.01328	-0.01296
Divorced	0.00849	0.00832	-0.01080	-0.01038
Never Married and not Cohabiting	-0.00213	-0.00252	-0.01062	-0.01065
Country of Birth (reference: Others)				
Native-born	-0.00053	-0.00010	0.01499***	0.01528***
English-speaking Country	0.00545	0.00598	0.01188*	0.01213**
Family Status (references: Others)				
with Children	-0.00219	-0.00157	-0.00761	-0.00714
without Children	0.00017	0.00003	0.00838	0.00871
Lone Person	0.00782*	0.00810*	0.01152**	0.01149**
Labor Force Status (reference: Employed)				
Unemployed	-0.00068	-0.00062	0.01268*	0.01286*
Not in the Labor Force Status	0.00475	0.00516	0.02106***	0.02095***
Change Address since Last Wave	0.04180***	0.04181***	0.07991***	0.07984***
Time at current address (reference: less than 5 year)				
5-9 year	-0.00114	-0.00083	-0.00719	-0.00732
>9 year	-0.00744*	-0.00731*	-0.01277**	-0.01311**
Neighborhood_SES	-0.00256***		-0.00148	
Neighborhood_threshold		-0.00632***		-0.00376
Move_for_housing	-0.01153***	-0.01188***	-0.04133***	-0.04161***
Move_for_job	0.01441***	0.01430***	0.03975***	0.03983***
Log-likelihood	-487.03014	-488.42252	-825.28767	-824.63366
N	10537	10537	10906	10906

Note: * p<0.1, ** p<0.05, *** p<0.01. The results are reported as marginal effects. Standard errors and z-values are omitted to save space.

Table 4. Empirical results for short-distance and long-distance migration in 2022

Year 2022	Short Distance		Long Distance	
	Model 1	Model 2	Model 1	Model 2
Risk_index	0.00069		0.00086	
Risk_threshold		0.00208		0.00356
Age	0.00088	0.00079	-0.00225**	-0.00234**
Age_sq	-0.00001	-0.00001	0.00003**	0.00003**
Female	0.00097	0.00102	0.00108	0.00109
Highest Education (reference: less than high school)				
Bachelor and more	-0.00246	-0.00233	0.00695	0.00704
Diploma	-0.00209	-0.00165	-0.00043	-0.00004
High school and Certificate	-0.00270	-0.00281	0.00909*	0.00887*
Income	0.00000	0.00000	0.00000	0.00000
Income_sq	-0.00000	-0.00000	-0.00000	-0.00000
Marital Status (reference: Legally Married)				
Cohabiting	-0.00651*	-0.00632*	-0.01535***	-0.01501***
Separated	-0.00167	-0.00210	-0.02686***	-0.02645***
Divorced	0.00086	0.00104	-0.00518	-0.00504
Never Married and not Cohabiting	-0.00712	-0.00773	-0.01849**	-0.01846**
Country of Birth (reference: Others)				
Native-born	-0.00396	-0.00373	0.01135**	0.01143**
English-speaking Country	-0.00551	-0.00595	0.00130	0.00127
Family Status (references: Others)				
with Children	-0.00857	-0.00907	0.00819	0.00790
without Children	-0.00111	-0.00185	0.01752**	0.01720**
Lone Person	0.00219	0.00290	0.03408***	0.03403***
Labor Force Status (reference: Employed)				
Unemployed	0.00933	0.00830	0.00995	0.01014
Not in the Labor Force Status	0.00844*	0.00752*	0.00997*	0.00951*
Change Address since Last Wave	0.02927***	0.02918***	0.06891***	0.06878***
Time at current address (reference: less than 5 year)				
5-9 year	-0.00813**	-0.00798**	-0.01337**	-0.01335*
>9 year	-0.00703**	-0.00668**	-0.01596***	-0.01579***
Neighborhood_SES	-0.00273***		-0.00324***	
Neighborhood_threshold		-0.00817***		-0.00774**
Move_for_housing	-0.00951***	-0.00949***	-0.02705***	-0.02690***
Move_for_job	0.02198***	0.02186***	0.04380***	0.04396***
Log-likelihood	-400.83559	-400.90979	-713.12391	-714.67785
N	9508	9508	9801	9801

Note: * p<0.1, ** p<0.05, *** p<0.01. The results are reported as marginal effects. Standard errors and z-values are omitted to save space.