Residential mobility and job changes under uncertainty

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Abstract

This paper empirically investigates households’ residential mobility and job change decisions under uncertainty. We allow households’ degree of risk aversion to be a confounding factor in the joint decision of residential mobility and job changes. Using panel data to estimate a random effects multinomial probit model of households’ joint decision of residential and job mobility, our empirical results show that risk aversion discourages a household from making any changes. Moreover, when compared to single changes in either job or residential locations, risk aversion is more discouraging for joint changes to more central residential locations and less discouraging for joint changes to more distant residential locations. These effects are statistically significant, albeit small in magnitude. Our empirical results demonstrate the uncertainty does play a role in households’ job and residential mobility decisions.

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1. Introduction

This paper investigates the relationship between a household’s job changes and residential mobility joint decisions, with the household’s degree of risk aversion being a confounding factor. Uncertainty is rarely taken into consideration in most empirical studies in the housing literature. If uncertainty is an important factor in households’ mobility decision, then households with different degrees of risk aversion will show...
different tendencies for changing jobs and residence. Using data from the Panel Study of Income Dynamics and employing a multinomial probit model, our main finding is that risk aversion discourages a household from making any changes. Moreover, when compared to single changes in either the job or residential location, risk aversion is more discouraging for joint changes to a more centrally-located residence and less discouraging for joint changes to more distant residential locations. These findings substantiate our conjecture that households take into account uncertainty in their joint mobility decisions.

Residential and job mobility are intimately related (see Sjaastad [20], and Zax [24]). A job change may actually prompt an individual to move. Nevertheless, when there is a shock to commuting costs (e.g., an increase in gasoline price, or relocation of the employer), an individual may consider changing either the job or the residence in order to avoid commuting (see Zax [23]). The intricate relationship between residential mobility and job changes as such has inspired much research in the literature.

Early contributions to the literature include those by Bartel [3] and Linneman and Graves [15]. In Bartel’s [3] study job changes are classified into quits, layoffs, and transfers. Each of the joint events of migration and job changes are separately analyzed using binary logit models. While the empirical results do not provide direct evidence on the relationship between job changes and residential mobility, it is found that some variables (e.g., wages, the work status of the wife, and the length of residence) do have statistically significant impacts on the joint probabilities. Linneman and Graves [15], by contrast, divide residential mobility into intra- and inter-county moves. A multivariate logit model is used to explain the joint probabilities. Similar to those of Bartel’s [3], the results of Linneman and Graves [15] constitute indirect evidence of the association between job changes and residential mobility by demonstrating that some variables could significantly explain the joint probability of job changes and residential mobility. Although these two papers’ results do not directly pinpoint the structural relationship between residential and job mobility, they do depict a clear pattern of the relationship.

The study by Van Ommeren et al. [21] is a more recent contribution to the literature, focusing on the relationship between a job change and a residential move. The paper estimates a bivariate hazard model of residential mobility and job mobility based on cross-sectional data from the Netherlands, and it finds a positive (but statistically insignificant) correlation coefficient between the two variables. They also explain residential mobility by the predicted job change probability, but the effect is statistically insignificant. Their results are unfortunately not consistent with those obtained by other studies in the literature, perhaps because of the idiosyncratic urban structure of the Netherlands.

In the literature there are also studies that assume a job change is exogenous and use it to explain residential mobility. This line of research includes Boehm [4], Ioannides and Kan [10], Kan [11,12]. It is found here that a job change has a statistically and numerically significant effect on residential mobility. This finding provides evidence that job changes and residential mobility are positively associated.1

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1 The simultaneity between the two variables may result in an overestimation of the causal effect. This is because the two variables are likely to be affected by some common unobservable factors in the same direction, as demonstrated by the results of Bartel [3] and Linneman and Graves [15].
Empirical and analytical findings in the literature in fact suggest that job changes and residential mobility are strongly and intimately related. Nevertheless, there is an empirically untouched aspect of the joint decision—that is, its response to uncertainty. The literature does not have many studies that empirically examine a household’s job changes and residential mobility decisions under uncertainty. As demonstrated by the papers reviewed above, past studies mostly assume that an individual has perfect foresight and all statistically unexplained behavior (i.e., the disturbance term in a regression equation) is due to heterogeneity that is not observed by the econometrician. In the absence of transaction costs of residential moves or job changes, the abstraction of uncertainty does not become an issue, because individuals can make adjustments in reaction to any changes in their circumstances. However, when adjustments are costly, housing or job location decisions do have dynamic effects.

Residential mobility and job changes in reality do incur transaction costs. In the presence of transaction costs, uncertainty has profound effects on a household’s decisions to move or change jobs. This is because the transaction costs of moving prevent a household from moving or changing jobs too frequently, and the household’s residential mobility and job change decisions have to take into account any possible future situations. For example, if a household expects a sequence of future changes to occur, then it may defer any adjustments to its residential location or job since any subsequent changes may render the newly-achieved equilibrium suboptimal.

The importance of uncertainty in a household’s job and residential mobility decision implies that the household head’s degree of risk aversion is important as a determinant of the job and residential mobility joint decision. For example, facing the same kind and degree of risk aversion, a household with a higher degree of uncertainty may decide to refrain from taking any action. Conversely, one with a lower degree of risk aversion may make a more ambitious/aggressive decision.

In the empirical housing literature, there are only a few studies which take into account the effects of uncertainty on household behavior. A notable case is Andrulis [1], who analytically derives the implications of uncertainty (pertaining to income and housing price) on a household’s residential and job mobility behavior. The analytical results predict that risk aversion discourages any type of move. Nevertheless, relative to single moves (in either the job or the residence), risk aversion has a less negative impact on joint moves to more distant (from the CBD) residential locations and a greater negative impact on joint moves to residential locations closer to the CBD.

Andrulis’ [1] empirical results confirm these predictions. However, the empirical work shows several weaknesses. Firstly, the measurement of risk aversion is arbitrary: it is constructed as the sum of a set of binary variables. These binary variables include
(a) whether the household is a non-car-owner or not,
(b) whether the household’s newest car is in good condition or not,
(c) whether all cars are insured or not,
(d) whether the household head wears a seat belt only some of the time or not,
(e) whether the household head wears a seat belt all the time or not,
(f) whether the household has medical insurance or free medical care or not,
(g) whether the household head smokes less than one pack of cigarettes per day or not,
whether the household has savings of less than two months’ income or not, and
whether the household has savings of more than two months’ income or not.
A positive answer is given a score of one or two. A negative answer is given no score. It is
arguable whether some of the variables are indicators of risk aversion, and the variation in
scores given to the variables is subject to discretion.

The second problem that plagues Andrulis’ [1] empirical work is that the logistic model,
which is equivalent to the multinomial logit model, is adopted. By doing so, the cross-
equation correlation is ignored. Computational convenience is achieved at the expense of
statistical validity. It is well known (see McFadden [16]) that in using the multinomial logit
model, when the assumption of “independence of irrelevant alternatives” is invalid, then
the estimation results will be misleading.

Furthermore, the sample is void of households that made an extra-urban move. By
selecting the sample in this way, the paper fails to test the prediction fully, and the results
may be liable to sample selection bias.

The empirical findings of Andrulis [1] are not conclusive with respect to the paper’s
predictions. A firm conclusion may not be drawn as a result, because the risk aversion
variable is not statistically significant in some of the equations. The current study continues
the line of research done by Andrulis [1] by examining the effect of risk aversion on a
household’s job and residential mobility decision. Estimating a multinomial econometric
model pertaining to the joint decision of job changes and residential mobility, our analysis
is also in the same spirit as that of Bartel [3] and Linneman and Graves [15].

Our empirical work is based on data from the Panel Study of Income Dynamics (PSID).
We use a measure of risk aversion developed by Barsky et al. [2]. The measurement,
available in the PSID data, is constructed from individuals’ responses to a sequence of
questions pertaining to hypothetical situations, which avoids any arbitrariness in Andrulis’
[1] measurement of risk aversion. By not excluding households from our sample because of
their nature of residential mobility, we test the Andrulis [1] hypotheses fully and avoid any
possible sample selection bias. Moreover, we use the Beale–Ross rural–urban continuum
code, as provided by the PSID, to define whether a household’s residence is in an urban
area or not. Finally, we employ the multinomial probit model as our econometric tool.
The flexible covariance structure allows us to circumvent the shortcoming that plagues the
works of Bartel [3], Andrulis [1], and Linneman and Graves [15], who employ a logistic or
logit regression model, which has the restrictive assumption of “independence of irrelevant
alternatives” (IIA).

According to our results, a household’s degree of risk aversion has a negative impact on
all kinds of mobility. This alludes to the fact that uncertainty is an important aspect of the
job and residential mobility decisions, as suggested by Andrulis [1].

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2 The estimation proceeds as follows. A subsample with either events or observed is extracted. Based on
this subsample, a binary logit model is estimated. The coefficients represent the explanatory variables’ impacts
on event relative to event.

3 It is not clear how the author classifies a household’s new residence as being urban or not.

4 The code is available in the PSID data ever since the 1985 wave. See the 1985 Panel Study of Income
Dynamics codebook.
The organization of the study is as follows. Section 2 briefly outlines the essential features of Andrulis’ [1] model. Section 3 lays out the econometric model with which the empirical work is conducted. Section 4 describes the data used for the empirical analysis. Section 5 discusses the empirical results. Section 6 concludes the whole study.

2. Household decisions under uncertainty

In this section we briefly illustrate the effect of uncertainty on a household’s joint residential and job mobility decisions, adopting the analytical framework of Andrulis [1]. It is assumed that a household’s utility depends on the flow of housing services and non-housing goods. A household’s income and the housing price are random and location specific. In making job and residential mobility decisions, a household will consider the differences in housing prices (denoted $\Delta p$) and income (denoted $\Delta y$) between the original and new location.

The randomness of income and housing price implies that households do face uncertainty. In the presence of uncertainty, for a given decision we can derive a “cost of risk” (denoted $c$), which represents the reduction in income that an individual is willing to accept in exchange for certainty. Under Andrulis’ [1] setting, it can be shown that the cost of risk $c$ for a given decision depends positively on the variances of $\Delta p$ and $\Delta y$ (denoted $\text{var}(\Delta p)$ and $\text{var}(\Delta y)$, respectively) and the degree of risk aversion, and negatively on the covariance of $\Delta p$ and $\Delta y$ (denoted $\text{cov}(\Delta p, \Delta y)$). More specifically, the cost of risk for the four joint events are as follows:

- (a) not moving and not changing jobs: $c_0 = 0$,
- (b) moving but not changing jobs: $c_1 = b_1 \text{var}(\Delta p)$,
- (c) not moving but changing jobs: $c_2 = b_2 \text{var}(\Delta y)$,
- (d) moving and changing jobs: $c_3 = b_1 \text{var}(\Delta p) - b_3 \text{cov}(\Delta p, \Delta y) + b_2 \text{var}(\Delta y)$,

where $b_k$ ($k = 1, 2, 3$) is a positive weight, which is a positive function of a household’s risk aversion. The higher the cost of risk $c$ is, the less likely it is for a household to move or change jobs.

Based on an equilibrium model of housing price and density, Andrulis [1] indicates that when a location is sufficiently far away from the CBD, $\text{cov}(\Delta p, \Delta y)$ is positive and increases with the location’s distance from the CBD (such that $c_3 < c_1 + c_2$). However, when a location is sufficiently close to the CBD, $\text{cov}(\Delta p, \Delta y)$ may be negative (such that $c_3 > c_1 + c_2$). In other words, $c_3$ is lower when the new residential location is further away from the CBD, while $c_1$ and $c_2$ are independent of the distance from the CBD, because they do not involve $\text{cov}(\Delta p, \Delta y)$.

For a new residential location, which is sufficiently close to the CBD (so that $\text{cov}(\Delta p, \Delta y)$ is negative), we have

$$c_3 > c_1 + c_2.$$  

5 This pattern of $\text{cov}(\Delta p, \Delta y)$ is produced by the fact that an increase in the per capita income flattens the housing bid–price curve. This flattening of the bid–price curve raises the housing price for locations far away from the CBD and reduces it for locations close to the CBD. See Wheaton [22] for a similar result.
This implies that after a household has decided to move toward the CBD, the additional cost of risk for it to also change jobs becomes $c_3 - c_1$, which is higher than the cost of risk for an isolated job change $c_2$. Thus, holding the gains from changing jobs constant, then when the desired new residential location is close to the CBD, it is less likely for the household to also incur a job change and more likely to make isolated changes. Now consider a new residential location sufficiently far away from the CBD (such that $\text{cov}(\Delta p, \Delta y)$ is positive). We have

$$c_3 < c_1 + c_2,$$

suggesting that, ceteris paribus, when the desired new residential location is far away from the CBD, it is more likely for the household to also change jobs and less likely to make isolated changes.

To summarize up, risk aversion discourages all kinds of changes. Compared to risk aversion’s negative effect on single changes, risk aversion’s negative effect is stronger for joint changes involving a move to a residential location close to the CBD. Conversely, it is weaker for joint changes involving a move to a residential location far away from the CBD.

3. Econometric framework

The purpose of the current study is to empirically investigate the confounding effects of a household’s risk aversion on the relationship between housing location, residential mobility, and job changes. We rely on a random effects multinomial probit model to explain households’ housing location, residential mobility, and job change decisions. This model also takes advantage of the panel structure of the PSID data by means of a random effects specification.

Since the random effects multinomial probit model is not commonly used and its specification is rarely illustrated in the housing literature, in the following we explain the model’s specification in detail. We define $m_{it}$ to be an indicator variable with $m_{it} = j$, $j = 0, \ldots, 4$, such that

- $m_{it} = 0$ if $i$ makes no changes,
- $m_{it} = 1$ if $i$ changes jobs only,
- $m_{it} = 2$ if $i$ changes residence only,
- $m_{it} = 3$ if $i$ changes jobs and moves to the CBD,
- $m_{it} = 4$ if $i$ changes jobs and moves to a non-CBD location,

where $i$ is the index for households. The variable $m_{it}$ is determined as follows:

\[ m_{it} = \text{arg max}_k (m_{it}^*), \quad m_{it}^* = \delta_k z_{it} + v_{ki} + \epsilon_{kit}, \quad (1) \]

where $m_{it}^*$ is a latent variable indicating the utility associated with choice $k$, and an option is taken if it provides the highest level of utility to household $i$, such that

\[ \text{Prob}(m_{it} = j) = \text{Prob}(m_{jt}^* \geq m_{kit}^*), \quad \forall j, k \in \{0, \ldots, 4\}, \quad (2) \]

\[ = \text{Prob}(m_{jt}^* - m_{kit}^* \geq 0). \quad (3) \]
The latent (i.e., unobserved) variable \( m_{jit}^* \) is assumed to be a linear function of a vector of demographic variables \( z_i \), \( \delta_j \) denotes a vector of parameters to be estimated, and \( \epsilon_{jit} \) and \( v_{ji} \) are mean-zero, normally-distributed random variables, which are unobservable to the econometrician. The variable \( v_{ji} \) controls heterogeneity, and it is independent of \( \epsilon_{jit} \) and is invariant across time for a given individual. We allow for a contemporaneous correlation between \( \epsilon_{jit} \) and \( \epsilon_{kit} \), and a correlation between \( v_{ji} \) and \( v_{ki} \), \( \forall i, k \in \{0, \ldots, 4\} \).

Since not all parameters could be identified, normalization is necessary. First of all, we set \( m_{i0}^* \) to be equal to zero. This implies that \( \delta_0, \text{var}(\epsilon_{0it}), \text{cov}(\epsilon_{0it}, \epsilon_{jit}), \text{var}(\nu_{i0}), \text{and} \text{cov}(\nu_{0i}, \nu_{ji}) \) are all equal to zero. In addition, the identification of some elements in the covariance matrix of \( \epsilon_{it} \equiv \{\epsilon_{1it}, \ldots, \epsilon_{4it}\} \) could be numerically difficult (see Keane [14]).

To ensure numerical stability and identification, we set \( \text{var}(\epsilon_{jit}) = 1 \) and \( \text{var}(\nu_{ji}) = 1 \) for \( j = 1, \ldots, 4 \). The covariance matrices of \( \epsilon_{it} \) and \( \nu_i \equiv \{\nu_{i1}, \nu_{i2}, \nu_{i3}, \nu_{i4}\} \) are to be defined below.

For a given period \( t \), the covariance matrix of the vector \( \epsilon_{it} \) has the form

\[
\Sigma_{\epsilon} = \begin{bmatrix}
1 & \sigma_{\epsilon,12} & \sigma_{\epsilon,13} & \sigma_{\epsilon,14} \\
\sigma_{\epsilon,12} & 1 & \sigma_{\epsilon,23} & \sigma_{\epsilon,24} \\
\sigma_{\epsilon,13} & \sigma_{\epsilon,23} & 1 & \sigma_{\epsilon,34} \\
\sigma_{\epsilon,14} & \sigma_{\epsilon,24} & \sigma_{\epsilon,34} & 1
\end{bmatrix},
\]

(4)

where \( \sigma_{\epsilon,jk} \) denotes the covariance of \( \epsilon_{jit} \) and \( \epsilon_{kit} \). We further denote the covariance matrix of \( u_{it} \equiv \{\nu_{i1} + \epsilon_{i1t}, \ldots, \nu_{i1} + \epsilon_{iT_i}\} \), where \( T_i \) is the number of periods that household \( i \) is in the sample, could be constructed based on \( \Sigma_{\epsilon} \) and \( \Sigma_{\nu} \) as follows:

\[
\Sigma_{u} = \begin{bmatrix}
\Sigma_{\epsilon} + \Sigma_{\nu} & \Sigma_{\nu} & \cdots & \Sigma_{\nu} \\
\Sigma_{\nu} & \Sigma_{\epsilon} + \Sigma_{\nu} & \cdots & \Sigma_{\nu} \\
\vdots & \vdots & \ddots & \vdots \\
\Sigma_{\nu} & \Sigma_{\nu} & \Sigma_{\nu} & \Sigma_{\epsilon} + \Sigma_{\nu}
\end{bmatrix}.
\]

(6)

To demonstrate the model’s computational aspect, we construct the likelihood function below. We define a \( J \times J \) matrix \( \Delta_{jit} \), where \( J \) equals the number of options minus one and for our model \( J = 4 \). The matrix \( \Delta_{jit} \) depends on \( m_{it} \), such that its diagonal equals \(-1\), the \( j \)th row equals \( 1 \), and all other elements equal zero for \( j = 1, \ldots, J \) (see Daganzo [5]), i.e.,

\[
\Delta_{jit} = \begin{bmatrix}
-1 & 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & 0 \\
0 & -1 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & 0 \\
0 & 0 & -1 & \cdots & 0 & 0 & 0 & \cdots & 0 & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
1 & 1 & 1 & \cdots & 1 & 1 & 1 & \cdots & 1 & 1 \\
0 & 0 & 0 & \cdots & -1 & 0 & 0 & \cdots & 0 & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
\end{bmatrix}^{\text{ji}}.
\]

(7)
For example, in our model when option 3 is chosen, we have

\[
\Delta_{3it} = \begin{bmatrix}
-1 & 0 & 0 & 0 \\
0 & -1 & 0 & 0 \\
1 & 1 & 1 & 1 \\
0 & 0 & 0 & -1
\end{bmatrix}.
\] (8)

For the case \( j = 0 \), the matrix \( \Delta_{j|it} \) is a diagonal matrix and it does not have a row of 1. With \( \Delta_{j|it} \), we can rewrite (3) to express the probability of \( m_{it} = j \) as

\[
\text{Prob}(m_{it} = j) = \text{Prob}(\Delta'_{j|it} m^*_it \geq 0), \quad j \neq k,
\]

where \( m^*_it = [m^*_it1, \ldots, m^*_it4] \) and 0 stands for a 4 \( \times \) 1 vector of zeros, and the normalization \( m^*_{0it} = 0 \) is noted.

Due to the data’s panel structure, we define the matrix \( \Delta_i \) based on \( \Delta_{j|it} \),

\[
\Delta_i = \begin{bmatrix}
\Delta_{k1i} & 0 & \cdots & \cdots \\
0 & \Delta_{k2i} & \cdots & \cdots \\
\cdots & \cdots & \cdots & \cdots \\
0 & 0 & \cdots & \Delta_{kTi_i}
\end{bmatrix},
\] (9)

where 0 is a matrix of zeros and \( k \) is an index indicating the option actually chosen in a given period by household \( i \), as is observed in the data. That is, the matrix \( \Delta_i \) is a block diagonal matrix, with the diagonal blocks all equal to \( \Delta_{k|it} \). The likelihood function \( L_i \) could be defined as follows:

\[
L_i = \int_{-\infty}^\infty f(\Delta'_{i|ui}, \Delta'_{i|ui} \Sigma_i) \, d\Delta'_{i|ui},
\] (10)

where \( \mu_i = [\mu_{i1}, \ldots, \mu_{iT_i}] \), \( \mu_{iT_i} \equiv [\delta_{i1}z_{it}, \ldots, \delta_{iT_i}z_{it}] \), and \( f(\cdot) \) is the multivariate normal density function.

The parameters are estimated by maximizing the log likelihood,

\[
\log L = \sum_i \log L_i.
\] (11)

Likelihood function (10) shows that the model’s estimation requires high-dimensional numerical integrations. The number of integrations for a given household is \( 4 \times T_i \), where \( T_i \) is the number of periods that a household is present in the sample. To deal with multiple integrations, a simulation method is used. The GHK simulator is employed to evaluate multiple integrations numerically,\(^6\) and the number of replications for the simulation here is 30.\(^7\)

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\(^6\) GHK is an acronym for Geweke, Hajivassiliou, and Keane, whose related (but independent) works give birth to such an algorithm. See Geweke [6], Hajivassiliou and McFadden [8], and Keane [14].

\(^7\) It is shown by Hajivassiliou [7] that the algorithm is quite accurate with even only 5 replications.
4. Data

The data employed for the estimation is the Panel Study of Income Dynamics from the Survey Research Center of the University of Michigan. In this section the sample selection rules in extracting data from the full PSID data and the variables that are used to explain household residential and job mobility behavior are illustrated. A brief description of each of the variables is listed in Table 1. Moreover, characteristics of the sample used for the estimation are briefly described below.

The estimations are based on a sample consisting of a three-year balanced panel of 3288 households over the years 1991–1993. There are a total of 9864 observations. Based on the officially-distributed (final release) data, we select all individuals who have ever been interviewed in any year during 1988–1993. To explain the survey year $t$ dependent variable, we use explanatory variables that involve survey years $t-3$ to $t$ in their construction. Thus, our dependent variables pertain to survey information from the years 1991–1993, while our explanatory variables pertain to household characteristics of the 1988–1993 survey years.

Our dependent variable, denoted $MJ_t$, is constructed from the variables pertaining to residential mobility and job changes. Variable $MJ_t$ indicates whether a household made no changes ($MJ_t = 0$), changed jobs only ($MJ_t = 1$), changed residence only ($MJ_t = 2$), changed jobs and moved to an urban district ($MJ_t = 3$), or changed jobs and moved to a non-urban district ($MJ_t = 4$) in year $t$. The exact definition and sample frequency distribution of $MJ_t$ are presented in Table 1. The figures in Table 1 show that most (70.58%) of the households did not made any changes, and more households make single moves (10.15% for isolated job changes and 13.10% for isolated residential moves) than joint moves (4.18% and 2.00% for joint moves to a CBD residence and to a non-CBD residence, respectively).

The construction of $MJ_t$ requires the classification of whether a household’s residence is urban or not. We use the Beale–Ross rural–urban continuum code for this purpose, with the code ranging from 1 to 10. Taking a value 1 indicates central counties of metropolitan areas with a population of 1 million or more; while a value 10 indicates a completely rural area, which is not adjacent to a metropolitan area. We assume that a district is urban if it belongs to metropolitan areas with a population of 250,000 or more, i.e., the Beale–Ross rural–urban continuum code is 1–3. The exact definition and the sample frequency distribution of the code are presented in Table 2.

The main objective of our empirical work is to find out the effect of risk aversion on the joint decision of residential and job mobility. Thus, in the empirical work we use a household’s degree of risk aversion to explain this joint decision. Information on households’ risk aversion is collected in the 1996 PSID survey as a supplement. The PSID solicited respondents’ risk aversion based on a sequence of five questions, asking about the respondent’s willingness to take jobs with different prospects in the 1996 wave of the survey. Each question proposes whether a respondent is willing to accept a new job with a 50–50 chance to double one’s income or to cut the income in different proportions. These questions were asked if a respondent in fact has a job, and because these questions were

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8 The exact wording of the questions can be found on the PSID website at http://www.isr.umich.edu/src/psid/.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean (Std. dev.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MJ_{it}</td>
<td>Whether a household changes residence and/or job between ( t ) and ( t-1 ).</td>
<td>0.7058 (0.4557)</td>
</tr>
<tr>
<td>MJ_{it}</td>
<td>( MJ_{it} = 0 ), if the household made no changes;</td>
<td></td>
</tr>
<tr>
<td>MJ_{it}</td>
<td>( MJ_{it} = 1 ), if the household changed jobs only;</td>
<td>0.1015 (0.3020)</td>
</tr>
<tr>
<td>MJ_{it}</td>
<td>( MJ_{it} = 2 ), if the household changed residence only;</td>
<td>0.1310 (0.3374)</td>
</tr>
<tr>
<td>MJ_{it}</td>
<td>( MJ_{it} = 3 ), if the household changed jobs and moved to an urban district;</td>
<td>0.0418 (0.2001)</td>
</tr>
<tr>
<td>MJ_{it}</td>
<td>( MJ_{it} = 4 ), if the household changed jobs and moved to a non-urban district.</td>
<td>0.0200 (0.1399)</td>
</tr>
<tr>
<td>HAGE_{it}</td>
<td>Age of household head in year ( t ) divided by 100.</td>
<td>13.1812 (2.4127)</td>
</tr>
<tr>
<td>HAGE_{it}^{2}</td>
<td>Square of age of the household head in year ( t ) divided by 1000.</td>
<td></td>
</tr>
<tr>
<td>OWN_{it}</td>
<td>Whether or not one is a home-owner. ( OWN_{it} = 1 ), if yes; ( OWN_{it} = 0 ), otherwise.</td>
<td>0.6095 (0.4879)</td>
</tr>
<tr>
<td>HEDUC_{it}</td>
<td>Years of education of the household head.</td>
<td></td>
</tr>
<tr>
<td>AA</td>
<td>Whether the household head is African American. ( AA = 1 ), if yes; ( AA = 0 ), otherwise.</td>
<td>0.3020 (0.4592)</td>
</tr>
<tr>
<td>MS_{it}</td>
<td>Household head’s marital status in year ( t ).</td>
<td>0.6494 (0.4772)</td>
</tr>
<tr>
<td>MS_{it}</td>
<td>( MS_{it} = 1 ), if married or co-habiting; ( MS_{it} = 0 ), otherwise.</td>
<td></td>
</tr>
<tr>
<td>DMS_{it}</td>
<td>Changes in household head’s marital status between years ( t-2 ) and ( t ).</td>
<td>0.1231 (0.3816)</td>
</tr>
<tr>
<td>DMS_{it}</td>
<td>( DMS_{it} = 1 ), if any changes; ( DMS_{it} = 0 ), otherwise.</td>
<td></td>
</tr>
<tr>
<td>INCKID_{it}</td>
<td>Number of children in year ( t ).</td>
<td>1.3139 (0.9786)</td>
</tr>
<tr>
<td>INCKID_{it}</td>
<td>( INCKID_{it} = \text{KID}<em>{it} - \text{KID}</em>{it-1} ), if it is positive; ( INCKID_{it} = 0 ), otherwise.</td>
<td>0.1729 (0.4721)</td>
</tr>
<tr>
<td>DECKID_{it}</td>
<td>Decrease in the number of children between years ( t-2 ) and ( t ).</td>
<td>0.2141 (0.6343)</td>
</tr>
<tr>
<td>DECKID_{it}</td>
<td>( DECKID_{it} = (\text{KID}<em>{it} - \text{KID}</em>{it-2}) \times (-1) ), if it is positive; ( DECKID_{it} = 0 ), otherwise.</td>
<td></td>
</tr>
<tr>
<td>FINC_{it}</td>
<td>Real family income divided by 10,000 in year ( t ). ( FINC_{it} = \frac{\text{family income}_{it}}{10,000} ).</td>
<td>3.7866 (3.5061)</td>
</tr>
<tr>
<td>FINC_{it}</td>
<td>where CPI_{t} is the consumer price index obtained from the Bureau of Labor Statistics; the base year is 1989.</td>
<td></td>
</tr>
<tr>
<td>INCFINC_{it}</td>
<td>Increase in family income between years ( t-2 ) and ( t ).</td>
<td>0.5988 (1.6345)</td>
</tr>
<tr>
<td>INCFINC_{it}</td>
<td>( INCFINC_{it} = \text{FINC}<em>{it} - \text{FINC}</em>{it-2} ), if it is positive; ( INCFINC_{it} = 0 ), otherwise.</td>
<td></td>
</tr>
<tr>
<td>DECFINC_{it}</td>
<td>Decrease in family income between years ( t-2 ) and ( t ).</td>
<td>0.5552 (1.7424)</td>
</tr>
<tr>
<td>DECFINC_{it}</td>
<td>( DECFINC_{it} = (\text{FINC}<em>{it} - \text{FINC}</em>{it-2}) \times (-1) ), if it is positive; ( DECFINC_{it} = 0 ), otherwise.</td>
<td></td>
</tr>
<tr>
<td>JOBTEN_{it}</td>
<td>Job tenure of the household head.</td>
<td>6.5769 (7.6740)</td>
</tr>
<tr>
<td>JOBTEN_{it}^{2}</td>
<td>Square of ( JOBTEN_{it} ) divided by 100.</td>
<td>1.0214 (1.9399)</td>
</tr>
</tbody>
</table>
Table 2
Beale–Ross rural–urban continuum code

<table>
<thead>
<tr>
<th>Code value</th>
<th>Definition</th>
<th>Proportion&lt;sup&gt;a&lt;/sup&gt; (Std. dev.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>Central counties of metropolitan areas with 1 million people or more</td>
<td>0.2996 (0.4581)</td>
</tr>
<tr>
<td>02</td>
<td>Fringe counties of metropolitan areas with 1 million people or more</td>
<td>0.1546 (0.3615)</td>
</tr>
<tr>
<td>03</td>
<td>Counties in metropolitan areas with 250,000 to 1 million people</td>
<td>0.2348 (0.4239)</td>
</tr>
<tr>
<td>04</td>
<td>Counties in metropolitan areas with less than 250,000 people</td>
<td>0.0694 (0.2542)</td>
</tr>
<tr>
<td>05</td>
<td>Urban population of 20,000 or more, adjacent to a metropolitan area</td>
<td>0.0253 (0.1572)</td>
</tr>
<tr>
<td>06</td>
<td>Urban population of 20,000 or more, not adjacent to a metropolitan area</td>
<td>0.0261 (0.1593)</td>
</tr>
<tr>
<td>07</td>
<td>Urban population of less than 20,000, adjacent to a metropolitan area</td>
<td>0.0671 (0.2502)</td>
</tr>
<tr>
<td>08</td>
<td>Urban population of less than 20,000, not adjacent to a metropolitan area</td>
<td>0.0893 (0.2852)</td>
</tr>
<tr>
<td>09</td>
<td>Completely rural, adjacent to a metropolitan area</td>
<td>0.0111 (0.1045)</td>
</tr>
<tr>
<td>10</td>
<td>Completely rural, not adjacent to a metropolitan area</td>
<td>0.0178 (0.1324)</td>
</tr>
</tbody>
</table>

<sup>a</sup> The proportions of sample respondents who resided in a location of a given code value.

asked of household heads with a job, our sample excludes those respondents who were not working in 1996.

Assuming that the utility function takes the form

\[ U(c) = \frac{1}{1 - \frac{1}{\theta}} e^{1-1/\theta}, \] (12)

answers to these questions allow for an estimation of the parameter \( \theta \) (the risk tolerance parameter), and the risk aversion is derived as \( 1/\theta \).<sup>9</sup> Two estimates of \( \theta \) are provided by the PSID. One is not corrected for measurement errors and the other one is corrected for measurement errors. We use the estimate that is corrected for measurement errors and use the inverse of \( \theta \) as a measurement of risk aversion.<sup>10</sup>

Information on households’ risk aversion is collected in the 1996 survey, but our dependent variable actually pertains to the sample households’ decisions in the 1991–1993 survey years. By doing this, we implicitly assume that the degree of risk aversion is time-invariant. Moreover, we require that households in our sample be also present in

<sup>9</sup> See Barsky et al. [2].

<sup>10</sup> We note a caveat in the use of the risk aversion measure in the current study. While a specific utility function is assumed to derive the measure, our econometric model implies yet another utility function. Ideally, the econometric model should be specified such that it is consistent with the utility function (12), and \( \theta \) and other parameters are estimated simultaneously. However, such structural approach will lead to an intractable econometric model.
the 1996 survey. The reason why we do not use data around 1996 (e.g., 1995–1997) is that post-1993 PSID data are still in the pre-release stage. This implies that the data are not thoroughly cleaned, and more importantly, a lot of important information is not available in the pre-release version of the data, including the Beale–Ross rural–urban continuum code and family income.

To explain a household’s residential and job mobility behavior in year $t$, household socioeconomic characteristics and changes in some of those characteristics are used, in addition to the household head’s degree of risk aversion. The household characteristics that are used to explain household behavior include: age of the household head ($HAGE_t$) and its square ($HAGE_t^2$); the number of children ($KID_t$) and its increase ($INCKID_t$) and decrease ($DECKID_t$); the household head’s marital status ($MS_t$) and its change ($DMS_t$); the previous years’ real family income ($FINC_{t-1}$, created by dividing total family income by the CPI) and its increase ($INCFINC_{t-1}$) and decrease ($DECFINC_{t-1}$); previous housing tenure status ($OWN_t$, i.e., whether owning or renting); years of education received by the head ($HEDUC$); whether the household head is an African American ($AA$); and the household head’s job tenure ($JOBTEN_t$) and its square ($JOBTEN_t^2$). A detailed illustration of these variables and their descriptive statistics are provided in Table 1.

5. Results

In this section we discuss our estimation results. The estimation results are presented in Tables 3 and 4. Since our specification of the covariance structure is very flexible, it may be liable to over-parametrization. As a rough specification diagnosis, we examine the coefficient estimates of the covariance matrix in Table 4. For $\epsilon_{it}$, there is only one statistically significant covariance term, i.e., $\text{cov}(\epsilon_{1it}, \epsilon_{1it})$, with a significance level only at 10%. There are more statistically significant covariance terms for $\nu_i$, indicating over-parametrization for the covariance structure. To get rid of the over-parametrization problem, we restrict the covariances among $\epsilon_{it}$ to zero, i.e., they are assumed to be independent of each other.

There are two reasons why we choose to impose the independence restriction on $\epsilon_{it}$ rather than $\nu_i$. Firstly, $\nu_i$ has a larger number of statistically significant covariances than $\epsilon_{it}$. Secondly, it is more reasonable for the cross-equation correlation to arise from household heterogeneity in a household’s propensity to move or change jobs (i.e., $\nu_i$). For example, a mobility-prone (mobility-averse) household is likely to have a higher (lower) propensity to have all kinds of mobility, implying that there exist positive correlations among $\nu_i$. On the other hand, a household’s job change decision and residential mobility decisions are likely to be affected by very different time-varying factors (i.e., $\epsilon_{it}$). This is because the job change decision is part of the labor supply behavior, while the residential mobility decision is part of the housing consumption behavior, and their connections are only through commuting costs.

11 This requirement does not distort our sample very much though, because of the low attrition rate of the PSID survey.
<table>
<thead>
<tr>
<th></th>
<th>$M_I = 1$</th>
<th>$M_I = 2$</th>
<th>$M_I = 3$</th>
<th>$M_I = 4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/$\theta$</td>
<td>-0.0369**</td>
<td>-0.0316**</td>
<td>-0.0693**</td>
<td>-0.0341</td>
</tr>
<tr>
<td>($-2.2598$)</td>
<td>($-2.0005$)</td>
<td>($-3.3718$)</td>
<td>($-1.3058$)</td>
<td></td>
</tr>
<tr>
<td>$HAGE_t$</td>
<td>-2.3979**</td>
<td>-12.3750**</td>
<td>-8.1638**</td>
<td>-6.8125**</td>
</tr>
<tr>
<td>($-1.2523$)</td>
<td>($-6.7068$)</td>
<td>($-3.4206$)</td>
<td>($-1.9961$)</td>
<td></td>
</tr>
<tr>
<td>$HAGE_t^2$</td>
<td>0.0961</td>
<td>1.1885**</td>
<td>0.7608**</td>
<td>0.7240*</td>
</tr>
<tr>
<td>($0.4376$)</td>
<td>($5.4551$)</td>
<td>($2.7047$)</td>
<td>($1.7549$)</td>
<td></td>
</tr>
<tr>
<td>$OWN_t$</td>
<td>-0.1508**</td>
<td>-1.0597**</td>
<td>-1.1110**</td>
<td>-0.8644**</td>
</tr>
<tr>
<td>($-1.8187$)</td>
<td>($-16.6500$)</td>
<td>($-11.2185$)</td>
<td>($-6.1278$)</td>
<td></td>
</tr>
<tr>
<td>$HEduC$</td>
<td>-0.0306**</td>
<td>0.0521**</td>
<td>0.1203**</td>
<td>0.0556**</td>
</tr>
<tr>
<td>($-1.9343$)</td>
<td>($3.1757$)</td>
<td>($5.4186$)</td>
<td>($2.4324$)</td>
<td></td>
</tr>
<tr>
<td>$AAt$</td>
<td>-0.1506**</td>
<td>-0.1733**</td>
<td>-0.2784**</td>
<td>-1.0724**</td>
</tr>
<tr>
<td>($-1.8626$)</td>
<td>($-2.1885$)</td>
<td>($-2.6571$)</td>
<td>($-4.8913$)</td>
<td></td>
</tr>
<tr>
<td>$MS_{t-1}$</td>
<td>0.0809</td>
<td>-0.1249*</td>
<td>-0.0283</td>
<td>0.1726</td>
</tr>
<tr>
<td>($1.0175$)</td>
<td>($-1.7481$)</td>
<td>($-0.2598$)</td>
<td>($1.2602$)</td>
<td></td>
</tr>
<tr>
<td>$DMS_t$</td>
<td>0.0759</td>
<td>0.3854**</td>
<td>0.2091**</td>
<td>0.4021**</td>
</tr>
<tr>
<td>($1.0746$)</td>
<td>($6.9577$)</td>
<td>($2.5128$)</td>
<td>($3.8473$)</td>
<td></td>
</tr>
<tr>
<td>$KID_{t-1}$</td>
<td>-0.0109</td>
<td>0.0115</td>
<td>-0.0584</td>
<td>0.0232</td>
</tr>
<tr>
<td>($-0.4341$)</td>
<td>($0.4966$)</td>
<td>($-1.5895$)</td>
<td>($0.5327$)</td>
<td></td>
</tr>
<tr>
<td>$INCKID_t$</td>
<td>0.0387</td>
<td>0.1551**</td>
<td>0.2080**</td>
<td>0.1686**</td>
</tr>
<tr>
<td>($0.7689$)</td>
<td>($3.4079$)</td>
<td>($3.6589$)</td>
<td>($1.9582$)</td>
<td></td>
</tr>
<tr>
<td>$DECKID_t$</td>
<td>0.1151**</td>
<td>0.2284**</td>
<td>0.2959**</td>
<td>0.3193**</td>
</tr>
<tr>
<td>($2.7850$)</td>
<td>($7.4806$)</td>
<td>($6.3872$)</td>
<td>($5.2413$)</td>
<td></td>
</tr>
<tr>
<td>$FINC_{t-1}$</td>
<td>-0.0595**</td>
<td>-0.0004</td>
<td>-0.0525**</td>
<td>-0.1392**</td>
</tr>
<tr>
<td>($-4.4752$)</td>
<td>($-0.0245$)</td>
<td>($-2.5835$)</td>
<td>($-4.8476$)</td>
<td></td>
</tr>
<tr>
<td>$INCFINC_{t-1}$</td>
<td>-0.0058</td>
<td>0.0005</td>
<td>-0.0073</td>
<td>0.0436</td>
</tr>
<tr>
<td>($-0.2154$)</td>
<td>($0.0298$)</td>
<td>($-0.1897$)</td>
<td>($1.1274$)</td>
<td></td>
</tr>
<tr>
<td>$DECFINC_{t-1}$</td>
<td>-0.0366**</td>
<td>-0.0242</td>
<td>-0.0011</td>
<td>-0.0084</td>
</tr>
<tr>
<td>($-2.3326$)</td>
<td>($-1.3740$)</td>
<td>($-0.0451$)</td>
<td>($-0.2132$)</td>
<td></td>
</tr>
<tr>
<td>$JOBTen_{t-2}$</td>
<td>-0.1107**</td>
<td>0.0027</td>
<td>-0.1209**</td>
<td>-0.0791**</td>
</tr>
<tr>
<td>($-10.7391$)</td>
<td>($0.2461$)</td>
<td>($-6.7931$)</td>
<td>($-3.2723$)</td>
<td></td>
</tr>
<tr>
<td>$JOBTEN_{t-2}^2$</td>
<td>0.2879**</td>
<td>-0.0060</td>
<td>0.3219**</td>
<td>0.2127**</td>
</tr>
<tr>
<td>($6.9823$)</td>
<td>($-0.1438$)</td>
<td>($3.5410$)</td>
<td>($1.9124$)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.4205</td>
<td>1.3800**</td>
<td>-0.4221</td>
<td>-0.7883</td>
</tr>
<tr>
<td>($0.9744$)</td>
<td>($3.3005$)</td>
<td>($-0.7271$)</td>
<td>($-1.1020$)</td>
<td></td>
</tr>
</tbody>
</table>

Log likelihood: $-8171.7120$

No. of obs.: 9864

Note. The covariances among $\epsilon_{it}$ are unrestricted.

* $t$-statistics significant at 5%.

** $t$-statistics significant at 10%.

The estimation results with the independence restriction imposed on $\epsilon_{it}$ are presented in Tables 5 and 6. We test whether the restriction is valid by means of the likelihood ratio test. The test statistic, being 4.5692, suggests that the restriction is statistically valid. The test statistic is $\chi^2$ distributed with six degrees of freedom. The $p$-value of our test statistic is 0.6001, implying that the test statistic is statistically insignificant and we cannot reject the null hypothesis that $\text{corr}(\epsilon_{ij1}, \epsilon_{ij2}) = 0$, where $j, k = 1, 2, 3, 4$, and $j \neq k$. 

---

12 The test statistic is $\chi^2$ distributed with six degrees of freedom. The $p$-value of our test statistic is 0.6001, implying that the test statistic is statistically insignificant and we cannot reject the null hypothesis that $\text{corr}(\epsilon_{ij1}, \epsilon_{ij2}) = 0$, where $j, k = 1, 2, 3, 4$, and $j \neq k$. 

---
Table 4
Covariance matrixa of \( u_i \): Specification I

<table>
<thead>
<tr>
<th>Covariances among ( {\epsilon_{1it}, \epsilon_{2it}, \epsilon_{3it}, \epsilon_{4it}} )</th>
<th>Covariances among ( {\nu_{1i}, \nu_{2i}, \nu_{3i}, \nu_{4i}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0.1464*</td>
<td>0.1334**</td>
</tr>
<tr>
<td>(1.8057)</td>
<td>(2.6071)</td>
</tr>
<tr>
<td>0.1110</td>
<td>0.3784*</td>
</tr>
<tr>
<td>(1.2944)</td>
<td>(1.7013)</td>
</tr>
<tr>
<td>0.0241</td>
<td>0.3636*</td>
</tr>
<tr>
<td>(1.1778)</td>
<td>(1.7128)</td>
</tr>
<tr>
<td>0.2076</td>
<td>0.2191</td>
</tr>
<tr>
<td>(1.8057)</td>
<td>(1.5302)</td>
</tr>
<tr>
<td>0.0986</td>
<td>0.2538</td>
</tr>
<tr>
<td>(0.9957)</td>
<td>(1.2606)</td>
</tr>
<tr>
<td>0.2001</td>
<td>1</td>
</tr>
<tr>
<td>(0.7052)</td>
<td></td>
</tr>
</tbody>
</table>

a Asymptotic t-statistics are in parentheses.

* t-statistics significant at 5%.

** t-statistics significant at 10%.

Table 5
Covariance matrixa of \( u_i \): Specification II

<table>
<thead>
<tr>
<th>Covariances among ( {\epsilon_{1it}, \epsilon_{2it}, \epsilon_{3it}, \epsilon_{4it}} )</th>
<th>Covariances among ( {\nu_{1i}, \nu_{2i}, \nu_{3i}, \nu_{4i}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>0.0996**</td>
</tr>
<tr>
<td>(3.5935)</td>
<td>(2.2656)</td>
</tr>
<tr>
<td>1</td>
<td>0.3931**</td>
</tr>
<tr>
<td>(2.2656)</td>
<td>(2.4904)</td>
</tr>
<tr>
<td>0.3354**</td>
<td>0.2285**</td>
</tr>
<tr>
<td>(2.2656)</td>
<td>(2.4904)</td>
</tr>
<tr>
<td>0.2373*</td>
<td>1</td>
</tr>
<tr>
<td>(2.0728)</td>
<td>(1.7713)</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0.3952**</td>
</tr>
<tr>
<td>(2.0728)</td>
<td>(1.7713)</td>
</tr>
<tr>
<td>0</td>
<td>0.2076</td>
</tr>
<tr>
<td>(2.0728)</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.2285**</td>
</tr>
<tr>
<td>(2.4904)</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.3354**</td>
</tr>
<tr>
<td>(2.4904)</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.3931**</td>
</tr>
<tr>
<td>(2.4904)</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.3952**</td>
</tr>
<tr>
<td>(2.4904)</td>
<td></td>
</tr>
</tbody>
</table>

a Asymptotic t-statistics are in parentheses.

* t-statistics significant at 5%.

** t-statistics significant at 10%.

are some differences between the two sets of results, with and without the independence restriction for \( \epsilon_{it} \). The most obvious differences are as follows.

1. Both the magnitude and t-statistic of \( DECFINC_{t-1} \)'s coefficient in the \( MJ_1 = 1 \) equation decrease slightly with the independence restriction, and the slight decrease in the t-statistics makes the coefficient become statistically less significant. It is significant at the 5% level without the independence restriction and it becomes significant only at the 10% level with the restriction.

2. The opposite happens to \( INCKID_1 \)'s coefficient in the \( MJ_1 = 4 \) equation. It is statistically significant at the 10% level without the restriction and become statistically insignificant with the independence restriction.

3. All the covariances among \( \nu_i \) are statistically significant when independence for \( \epsilon_{it} \) is imposed, while only three of them are statistically significant when the restriction is not imposed.

These differences imply that the correct specification of the covariance matrix (i.e., the error structure) is important.

Since the model with the independence restriction imposed seems to be more valid, our discussion below is based on the second set of results, as reported in Tables 5.
The focus of the paper. The estimation results show that the degree of risk aversion and the marginal effects of the explanatory variables are reported in Table 7. We note that the covariances among the error terms are set to zero.

**Note.** The covariances among $\epsilon_{it}$ are set to zero.

* $t$-statistics significant at 5%.

** $t$-statistics significant at 10%.

and 6. The marginal effects of the explanatory variables are reported in Table 7. We first look at the effects of risk aversion on households’ joint mobility decision, which is the focus of the paper. The estimation results show that the degree of risk aversion (denoted $1/\theta$) discourages all kinds of mobility, both for single or joint changes in jobs and residential locations. However, the coefficient is small in magnitude for single changes, being $-0.0350$ for an isolated job change ($M_{J_t} = 1$) and $-0.0404$ for an isolated
residential move ($MJ_t = 2$). Compared to the coefficients for single moves, that for a joint move to a CBD residence ($MJ_t = 3$), which is $-0.0754$, is much larger in magnitude, while that for a joint move to a non-CBD residence ($MJ_t = 4$), being $-0.0178$, is much smaller in magnitude. In other words, relative to single changes, the degree of risk aversion is more discouraging for joint changes to a CBD residence and less discouraging to a non-CBD residence. This is consistent with Andrulis’ [1] predictions.

The marginal effects of $1/\theta$ on the probabilities of events $MJ_t = 1, 2, 3, 4$ are $-0.0043$, $-0.0052$, $-0.0028$, and $-0.0003$, respectively. Compared with the marginal effects of other explanatory variables, those of $1/\theta$ are not large. This suggests that even though households’ risk aversion is a manifest factor affecting their mobility decisions (as suggested by the statistical significance of its coefficients for the events $MJ_t = 1, 2, 3$), its effects are not substantial in magnitude.

The general implication for the statistical significance of a household’s degree of risk aversion in determining the joint mobility decisions is that uncertainty does have an impact

13 The $t$-test of the null hypothesis that the $1/\theta$ coefficient for $MJ_t = 1$ is greater than that for $MJ_t = 3$ yields a p-value of 0.0594. The $p$-value, corresponding to the $t$-statistic of the null hypothesis that the $1/\theta$ coefficient for $MJ_t = 2$ is greater than that for ($MJ_t = 3$), is 0.0768. That is, the differences are statistically significant. Even though the coefficient estimate of $1/\theta$ for $MJ_t = 4$ is statistically insignificant and numerically small, the standard deviation of the $1/\theta$ coefficient for $MJ_t = 4$ is too large, such that the $t$-statistic, of the null hypothesis that it is smaller than any other coefficient estimates of $1/\theta$, is statistically insignificant. In this aspect our empirical results are similar to Andrulis’ [1].

14 It is stressed that Andrulis’ [1] predictions on the impacts of risk aversion are in terms of the “inducement” to mobility, i.e., the latent variable $m^*_{j,t}$, as defined in (1).
on one’s consideration of whether to change jobs or residential locations, although the size of this impact is not substantial. The consistency between our results and Andrulis’ [1] predictions indicates that the paper’s setup (mainly the source of uncertainty and the urban structure) conforms with the reality.\textsuperscript{15}

The rest of the results is mostly in line qualitatively with those obtained by Bartel [3], Andrulis [1], and Linneman and Grave [15]. The coefficient of the household head’s age (denoted $HAGE_t$) is \textit{negative} for all moves, being statistically significant for all changes, except for an isolated job change ($MI_t = 1$). This seems to demonstrate that a household who is older will not be less likely to change jobs, but rather would avoid changing residence.

Homeownership (i.e., $OWN_t = 1$) retards a household’s tendency to undergo any kind of mobility, especially those involving a change in residential location. The magnitudes of the marginal effects of $OWN_t = 1$ are large relative to those of other explanatory variables, especially for those involving residential mobility. As suggested by the magnitudes of the marginal effects of $OWN_t$, the housing tenure status is a very important factor in affecting a household’s mobility decisions.

The coefficient of the number children (denoted $KID_t$) is statistically insignificant for all changes. The magnitudes of its marginal effects are not large either. The coefficient is negative and almost statistically significant at the 10\% level for a joint change to an urban residence ($MI_t = 3$) though. This weakly indicates that a household with a larger number of children does not totally refrain from moving; it just avoids moving to an urban residence together with a job change.

The marital status (denoted $MS_t$) of the household head is found to discourage an isolated residential move ($MI_t = 2$). Its effects are not statistically significant on the decisions to make other changes. These results are consistent with those of Linneman and Grave [15].\textsuperscript{16}

The household head’s years of education ($HEDUC$) boost the likelihood for a household to make a residential move ($MI_t = 2, 3, 4$). They also have a negative effect on an isolated job change ($MI_t = 1$). This suggests that the positive effect of education on the likelihood of residential mobility is not through education’s effect on job changes as suggested by some previous studies, e.g., Schwartz [19] and Schaeffer [18].

A household head who is African American (i.e., $AA = 1$) is unlikely to make any changes. In terms of the magnitude of the coefficients, this is especially true with respect to a move to a suburban area (i.e., $MI_t = 4$), and it is consistent with the phenomenon portrayed by the spatial mismatch hypothesis. That is, African Americans are more likely to congregate in central urban areas. See, e.g., Holzer [9] for a survey and Rogers [17] for a recent contribution. However, in terms of the marginal effects, $AA$’s impact on $MI_{t,t} = 4$ is only comparable to, but not larger than, its impacts on $MI_{t,t} = 1$ and $MI_{t,t} = 2$.

\textsuperscript{15} It is noted that Andrulis’ [1] empirical results are ambiguous with respect to the paper’s analytical predictions. Andrulis attributes this to a large covariance between housing price and income. Based on our empirical results, we suspect that the inconclusiveness of Andrulis’ [1] empirical results is due to either the small size of the sample or the arbitrariness of the definition of risk aversion.\textsuperscript{16} Linneman and Grave [15] do not provide standard errors for their coefficient estimates, making any inference on the basis of their results difficult.
A household’s family income \((FINC_{t-1})\) has a negative effect on all kinds of moves, except for an isolated residential move \((MJ_t = 2)\). Its effects on an isolated job change and the joint event of a job change and a residential relocation toward the suburbs are statistically significant at the 5% level, while that on the joint event of a job change and a residential relocation toward an urban area is almost statistically significant at the 10% level. Family income could be interpreted as the opportunity cost of a job change such that any job-related changes \((MJ_t = 1, 3, 4)\) are discouraged by a higher family income. The ambiguous effect of family income on residential mobility is that, while a high \(FINC_{t-1}\) implies high transaction costs (in terms of foregone earnings during the moving process) such that a residential move is impeded, it also hints that the household could afford monetary transaction costs so that residential mobility is spurred by this income effect. Thus, an ambiguous effect of \(FINC_{t-1}\) is not very surprising. It is noted that the magnitudes of \(FINC_{t-1}\)’s marginal effects are small.

The household head’s job tenure \((JOBTEN_t)\) has a negative and statistically significant effect on job-related mobility \((MJ_t = 1, 3, 4)\), while it has a statistically imprecise effect on a pure change in residence \((MJ_t = 2)\).\(^{17}\) This suggests that job tenure does not have a direct effect on residential mobility. It affects residential mobility only indirectly, through its effect on job changes. In terms of the marginal effects, \(JOBTEN_t\) is one of the most important variables explaining an isolated job change.

It is noted that \(JOBTEN_t\) and \(JOBTEN_t^2\) are likely to be endogenous, because a shock to job stability will have a positive impact on a job change and a negative one on the current job tenure, implying a negative correlation between job change and job tenure. However, since the coefficients of \(JOBTEN_t\) are not among the primary parameters of interest in the current study, in the estimation we choose not to account for this potential endogeneity in order to avoid further complicating the econometric model. Given that we are not dealing with the endogeneity problem, caution should be applied in evaluating the coefficients of \(JOBTEN_t\) and \(JOBTEN_t^2\). Since the error terms associated with a job change, i.e., \(\{v_{1t}, v_{3t}, v_{4t}\}\) and \(\{\epsilon_{1t}, \epsilon_{3t}, \epsilon_{4t}\}\), are likely to be negatively correlated with \(JOBTEN_t\) and \(JOBTEN_t^2\), their coefficients are likely to be downward biased. That is, for \(MJ_t = 1, 3, 4\), \(JOBTEN_t\)’s coefficients (which are negative) should be smaller in absolute terms, and \(JOBTEN_t^2\)’s coefficients (which are positive) should be smaller than they appear to be.

Variables pertaining to changes in the number of children (denoted as \(INCKID_t\) and \(DECKID_t\), for an increase and decrease, respectively) have a positive and statistically significant effect on almost all types of mobility. The exceptions are that the coefficient estimate of \(INCKID_t\) is insignificant for \(MJ_t = 1\) and almost significant at the 10% level for \(MJ_t = 4\). Our results are very similar to those obtained by Linneman and Graves \([15]\), who categorize these variables as proxies for disequilibria. On the other hand, a change in marital status for the household head (denoted \(DMS_t\)) prompts a household to

\(^{17}\) The variable \(JOBTEN_t^2\) has a positive and statistically significant effect on an isolated job change \((MJ_t = 1)\), a joint change in job and residence to a CBD residence \((MJ_t = 3)\), and a joint change in job and residence to a non-CBD residence \((MJ_t = 4)\), suggesting that job tenure has a quadratic effect on these changes. This indicates that when job tenure increases, it initially has a negative effect on job changes. As job tenure reaches a certain level, it starts to have a positive effect on job changes.
make a residential move, either as an isolated move or a joint change (i.e., \( MJ_i = 2, 3, 4 \)). This seems to indicate that a marital change has a direct effect only on one’s residential relocation decision, and it affects one’s job change decision only indirectly, through the residential relocation decision. The effects of an increase and a decrease in income (denoted \( INCFINC_t \) and \( DECFINC_{t-1} \), respectively) are negligible on almost all changes.

The coefficient estimates for the elements of the covariance matrices of \( v_i \) are reported in the lower panel of Table 5. All elements of the covariance matrix are statistically significant. The magnitudes of most coefficient estimates of the covariances of \( v_i \) are far from trivial, too. The magnitude of the estimate of \( \text{cov}(v_1, v_2) \) is the smallest among all covariances estimates, while the estimates of all other covariances are quite similar in magnitude. The relatively small \( \text{cov}(v_1, v_2) \), which pertains to isolated changes in job and residential location, could be explained by the fact that even though both a job change and a residential move involve a “change,” the two decisions are not so similar. See Kan [13] for a similar finding.

From the pattern of the covariances, some implications can be drawn. Firstly, the statistical significance of the covariances hints that the “independence of irrelevant alternatives” restriction does not hold. Therefore, if cross-equation correlations are ignored (e.g., if a multinomial logit model is estimated), then the estimation results may not be reliable.

Secondly, the statistical significance of the covariances of \( v_i \) suggests that household heterogeneity is very important in explaining the correlation among the various events of residential and job mobility. This is especially so since the null hypothesis of \( \epsilon_i \) being independent across choices is accepted, which means that the correlation between the joint events of a job change and residential move can be attributed almost entirely to household heterogeneity (i.e., \( v \)).

In summary, we find that households with different degrees of risk aversion have differential tendencies to undergo joint residential moves and job changes. This result expounds the fact that uncertainty is an important factor that households take into consideration for their mobility decisions. Moreover, household characteristics do not have a uniform effect on different types of residential mobility (e.g., isolated or a joint move in job and residence). This suggests that in order to gain a full understanding of the household residential mobility process, we must take into account job changes, which may be a direct cause or a facilitator of residential mobility.

6. Conclusion

This paper empirically investigates households’ joint decision to change residence and jobs under uncertainty. Existing studies in the empirical housing literature rarely allow uncertainty to play a role. Our study departs from the literature by allowing a household’s degree of risk aversion to be a confounding factor in its residential and job mobility joint decisions. By doing so, we recognize the importance of uncertainty in a household’s decision-making process. If uncertainty is an important factor in households’ mobility decisions, then households with different degrees of risk aversion will have different tendencies to change jobs and residence.
Based on data from the Panel Study of Income Dynamics, we estimate a random effects multinomial probit model. The dependent variables pertain to whether a household (0) makes no changes, (1) changes jobs only, (2) changes residence only, (3) changes jobs and moves to an urban district, or (4) changes jobs and moves to a non-urban district.

Our main findings are that risk aversion discourages a household from making any changes. When compared to single changes in either job or residential location, risk aversion is more discouraging for joint changes to more centrally-located residential areas and less discouraging for joint changes to more distant residential locations. These findings corroborate our conjecture that households take into account uncertainty in their decision making. Our empirical results are also consistent with the predictions of Andrulis [1]. Nevertheless, our empirical results suggest that even though an individual’s degree of risk aversion does play a role, the magnitude of its impacts is not substantial.

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