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Towards a more realistic model of residential relocation: DDCM's dynamic, future-oriented approach

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Abstract

Understanding where and why people move homes is critical for land-use strategy and key to policymakers aiming to create sustainable, livable neighborhoods. Traditional models of residential relocation don't fully reflect the dynamic decision-making of households over time. To bridge this gap, this paper introduces a novel framework using dynamic discrete choice modeling (DDCM). This approach blends the predictive capabilities of DDCM with traditional models to consider factors from the past, present, and future all at once. It also incorporates the influence of potential job relocation on residential moves. The effectiveness of this framework is validated using data from Sydney's Household, Income, and Labor Dynamics in Australia (HILDA) survey. This study adds valuable insights into how residential relocations are decided and offers guidelines for both land-use and transportation planning.

Keywords: Dynamic discrete choice modeling (DDCM), home relocation, job relocation, land-use, residential mobility, transport economics and policy

1. Introduction

This research aims to explore a fundamental yet traditional question in residential relocation behavior: "When and why do households move?" The prevailing methodology in existing literature relies on hazard-based models, encompassing both parametric and semi-parametric techniques. However, these models are often criticized for their static character, which inadequately represents the fluid and evolving nature of household relocation decisions. To mitigate these shortcomings, scholars from various disciplines are increasingly utilizing dynamic models like the Dynamic Discrete Choice Model (DDCM). While some hazard-based models incorporate time-varying covariates to introduce a degree of dynamism (Guo et al., 2019) , they still fall short of authentically capturing the evolving intricacies of the decision-making process.

The process by which households decide to relocate is inherently intricate, governed by a myriad of variables. While there has been considerable research in the area of residential relocation modeling, a holistic grasp of the factors and mechanisms steering household decisions to move is still lacking. Prior research has approached the subject from various angles, such as exploring sociodemographic factors (Ghasri and Rashidi, 2016), life-course events (Mulder and Hooimeijer, 1999, Bostanara et al., 2021), integrated models of home and workplace relocation (Bostanara et al., 2023, van Ommeren et al., 1996), as well as frameworks linking home relocation and trip generation (Lim and Kim, 2019). In addition, models focusing on the dynamics within households have been considered (Ho and Mulley, 2015). Despite these efforts, existing studies have certain shortcomings that prevent a fully accurate portrayal of the decision-making process.

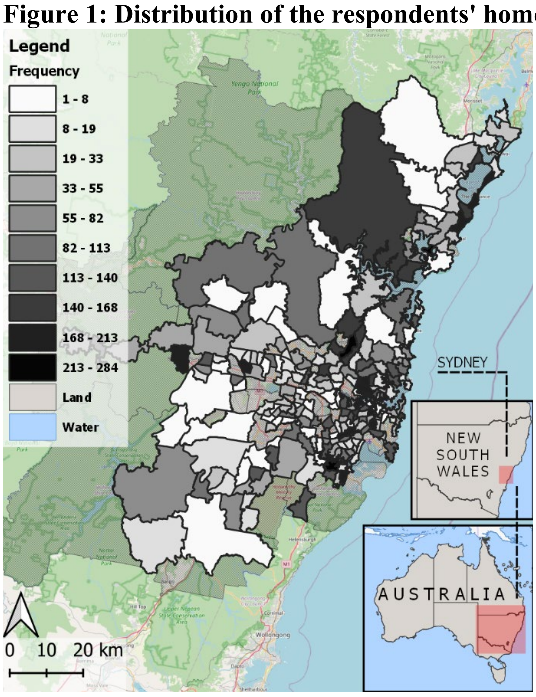
The act of decision-making is not static but rather a dynamic interaction shaped by a household's historical context, current situational awareness, and future projections. People are inherently oriented towards the future, factoring in both prospective outcomes and the ramifications of present actions. Consequently, the Dynamic Discrete Choice Model (DDCM) serves as an authentic framework for encapsulating the evolving complexities of residential relocation choices across the lifespan. This is because the DDCM not only contemplates the value of expected future decisions in the present moment but also iteratively updates the model yearly to account for changing conditions.

While numerous studies delve into residential relocation, none, to the authors' knowledge, have introduced a forward-looking structure like the DDCM. Moreover, only a handful have genuinely embraced the dynamic nature of decision-making in this domain. This research endeavors to bridge these gaps. Given the intertwined nature of home and workplace moves, it's essential to incorporate the workplace aspect into the equation. Thus, we've crafted a hazard-based model for workplace transitions, determining the annual likelihood of such relocations for households. This probability subsequently informs the residential model as a pivotal determinant.

2. Methodology

In this research, we employ a Dynamic Discrete Choice Model (DDCM) to explore both the timing and underlying reasons for household residential relocations. The DDCM framework is uniquely suited for capturing the complex, dynamic variables that influence households' decisions to move over time.

Figure 1: Distribution of the respondents' home locations in the greater Sydney area



The data for this study is sourced from the Household, Income, and Labour Dynamics in Australia (HILDA) survey (Summerfield et al., 2011), a nationally representative longitudinal survey. This rich dataset, frequently used in residential relocation studies, provides comprehensive insights into household and individual characteristics, as well as contextual factors. The survey annually queries participants on various topics, including their current residence, occupational status, household decision-making, socio-demographics, and significant life events. Figure 1 illustrates the geographical distribution of households within the Greater Sydney area.

The dataset spans 20 years from 2001-2020 and is organized into 20 waves. Within each wave, households face a binary choice: to stay put or relocate.

These decisions are influenced by a trinity of factors: historical data like past relocations, current status including home and job conditions and market trends, and future expectations such as planned moves or significant life events like a child's birth. The study employs Dynamic Discrete Choice Modeling (DDCM), a pioneering approach that merges Discrete Choice elements with dynamic programming features. This allows for a more nuanced representation of real-world decision-making by accounting for past, current, and future considerations in a single, forward-looking model.

DDCM looks at the decision-making behavior as an iterative utility maximization problem at each time interval (here, each wave or year). At each time interval t, a household i could earn a utility ($U_{i,t}$) by either (1) relocating to a more favorable location out of the k available suburb alternatives (earning a terminal period payoff of $E_{i,t} = \max(E_{i,k,t})$), or (2) by staying in the current home (earning the postponed utility $L_{i,t}$) and earning the maximized expected utility of the next year ($E(U_{i,t+1})$). That is, $U_{i,t} = \max\{E_{i,t}, L_{i,t} + E(U_{i,t+1})\}$, Where E_{it} and L_{it} are linear functions of $X_{i,k,t}$ variables and corresponding coefficients, in general, the expectation of future utility is complicated as the time horizon is technically set to infinity. However, it is assumed that although people are forward-looking, they can only consider future expectations of a short-term time horizon due to changes in circumstances over time. As a result, a fixed time horizon is considered for all, simplifying the estimation of future utility expectations (here, a time horizon of 3 years is considered).

The terminal period payoff is modeled using an MNL model with Gumbel-distributed error components, unlabeled alternatives (suburbs), and all-generic coefficients. This assumption assists in estimating the probability of not relocating and the probability of choosing alternative k, which, in the end, helps in estimating the model using the maximum likelihood estimation (MLE) method (Cirillo et al., 2016, Liu and Cirillo, 2018).
Weibull hazard-based modeling is applied to study workplace relocation duration, incorporating survival analysis principles and integrating covariates within the Accelerated Failure Time (AFT) model. This AFT framework models exact event times through a linear combination of covariates, enabling insights into how factors influence relocation timing, while baseline functions are established using the Weibull distribution.
The model estimation was performed following the below steps:

1. Estimating a primary residential relocation DDCM model to estimate the probability of home relocation at time t as a function of dynamic household and suburb variables.
2. Estimating a hazard-based job relocation model as a function of job-related and the probability of home relocation variables.
3. Estimating a final residential relocation DDCM model as a function of the dynamic household, suburb, and the probability of job relocation variables.

The results of the second and third step models are presented in the results section.

3. Results

3.1. Descriptive statistics

Descriptive statistics were analyzed for a sample of 1,065 Sydney households who participated in consecutive years of the HILDA survey. The majority, 65%, of these households had a male as the eldest member. The dataset comprised 14,646 household-wave entries, with each household participating in up to 20 waves and at least a minimum equivalent to the time horizon plus one wave (where the time horizon is three years). The data captured 2,322 home relocation decisions, revealing that 31% of households did not move at all during their participation, while 22% and 14% moved once and twice, respectively. Table 1 presents a thorough descriptive statistics report of household characteristics over the years.
A descriptive analysis of Greater Sydney's suburbs, defined at the SA2 level, was also conducted, with 2020 data highlighted in Table 2. The average travel time to the Central Business District (CBD) was 2.16 hours by private car and 3.42 hours via public transport. Suburbs had an average population of 14,600 residents and offered 10,900 job positions. The average median rent stood at AU$ 480, while the average home price was AU$ 1.59 million.

3.2. Job relocation results

The results from the Weibull hazard-based job relocation model indicate that age and job characteristics significantly affect job relocation probability. Younger individuals are more likely to change jobs more quickly compared to older age groups. In alignment with existing literature (Agarwal et al., 2001), job types are closely related to the duration of job retention. Furthermore, the model reveals that full-time workers are more likely to maintain their employment for longer periods compared to part-time workers, a factor identified as the most influential in job relocation decisions.

Table 1: Descriptive statistics of residential relocation data

Variable	Mean	SD
Residing duration	4.14	7.27
Is apartment?	0.18	0.39
Is owner?	0.68	0.47
Is less than two bedrooms?	0.28	0.45
Is single household?	0.28	0.45
Household income (in 100,000 AU$)	0.95	0.96
Number of females	1.07	0.66
Number of eighteen and below members	0.14	0.42
Household weekly rent payment (in 10,000 AU$)	0.03	0.07
Household mortgage payment (in 10,000 AU$)	0.06	0.12
Making day-to-day decisions shared?	0.34	0.47
Making large decisions shared?	0.51	0.5
Making work-related decisions shared?	0.17	0.37
Making savings decisions shared?	0.44	0.5

Table 2: Descriptive statistics of suburbs' characteristics in the year 2020

Variable	Mean	SD
Travel time to CBD by car (in hours)	2.16	2.27
Travel time to CBD by public transport (in hours)	3.42	2.2
Population in the suburb (in 10,000)	1.46	0.8
Number of jobs in the suburb (in 10,000)	1.09	0.72
Suburb’s median weekly rent (in 1,000 AU$)	0.48	0.19
Suburb’s median home price (in 1,000,000 AU$)	1.59	1.07

3.3. Home relocation results

The DDCM residential relocation model's findings, presented in Table 4, outline the life-course impact of various factors on household relocation decisions. Coefficients signify the influence of each factor on the utility for staying in or relocating from a current residence, as well as future suburb choice. A positive coefficient for staying suggests a higher likelihood of a longer stay, while a negative one indicates a greater chance of quicker relocation. In terms of suburb selection, a positive coefficient implies higher utility, thereby indicating a higher likelihood of moving to such areas.

Table 3: Results of the workplace relocation hazard-based model

Variable	Coefficient	t-statistic	P-value	Significance
Age	0.02	13.68	0	***
Gender (male = 1)	0.01	0.22	0.41	
Managerial job	0.21	3.36	0	***
Professional job	0.13	2.84	0	***
Full-time job	0.28	7.17	0	***
Home relocation probability	0	0.05	0.48	

Intercept: 0.73, Shape: 0.95, Likelihood: -6629.74, BIC: 13338.37

3.3.1. Utility of stay

A critical factor in home relocation decisions is the commute time to work and other key destinations, with proximity to the CBD serving as a metric in this study. The findings indicate that a longer car commute to the CBD is positively correlated (0.28) with a higher likelihood of remaining in one's current residence. In essence, residing in a rural area and owning a car tend to make staying in a current home more attractive. On the flip side, longer commutes via public transport have a small negative association (-0.04) with satisfaction, increasing the odds of relocating. Living in a pricier suburb is seen as a positive (0.11), but higher rent (-1.21) and mortgage payments (-0.67) adversely affect the decision to stay.

The data reveals that the longer individuals reside in a location, the more inclined they are to stay, as indicated by a positive correlation (0.64). Conversely, factors like homeownership (-0.29), living alone (-0.14), and having fewer than two bedrooms (-0.14) tend to lower the appeal of remaining in the current home. The decision to relocate is typically a collective household choice. The study shows that households who make daily decisions together are more likely to prefer staying, while those who collaborate on major decisions tend to be more open to relocating.

3.3.2. Utility of suburb choice in relocation

When evaluating potential suburbs for relocation, homes nearer to the CBD by car are more appealing to households. However, proximity to the CBD via public transport isn't as favorable. This suggests that households prefer suburbs that allow easy car access to the CBD, rather than those located directly within or close to the crowded urban center. Essentially, households value closeness to the CBD but desire to avoid the hustle and bustle of its immediate vicinity.

Table 4: Results of the residential relocation DDCM model

Variable	Coefficient	t-statistic	P-value	Significance
Utility of stay				
Travel time to CBD by car (in hours)	0.28	1.65	0.1	**
Travel time to CBD by public transport (in hours)	-0.04	-2.64	0.01	***
Population in the suburb (in 10,000)	0.12	3.72	0	***
Number of jobs in the suburb (in 10,000)	-0.02	-0.66	0.51	
Travel time to CBD by car X petrol price	0	0	1	
Suburb’s median rent (in 1,000 AU$)	0	0.01	0.99	
Suburb’s median home price (in 1,000,000 AU$)	0.11	2.24	0.02	***
Residing duration	0.64	31.96	0	***
Is owner?	-0.29	-4.7	0	***
Is apartment?	-0.06	-1.14	0.25	
Is less than two bedrooms?	-0.14	-3.65	0	***
Is single household?	-0.14	-2.78	0.01	***
Eldest household age	-0.01	-10.98	0	***
Household income (in 100,000 AU$)	-0.02	-0.95	0.34	
Number of females	0.03	1.14	0.25	
Number of eighteen and below members	-0.03	-0.62	0.53	
Total full-time workers	0.02	0.86	0.39	
Household rent payment (in 10,000 AU$)	-1.21	-3.97	0	***
Household mortgage payment (in 10,000 AU$)	-0.67	-3.91	0	***
Making day-to-day decisions shared?	0.09	1.93	0.05	**
Making large decisions shared?	-0.14	-2.44	0.01	***
Making savings decisions shared	0.01	0.15	0.88	
Probability of job relocation	-0.46	-1.43	0.15	.
Utility of suburb choice in relocation				
Travel time to CBD by car (in hours)	-2.33	-6.94	0	***

Suburb's average rent (in 1,000 AU$)	0.41	1.32	0.19	.
Number of jobs in the suburb (in 10,000)	-0.03	-0.48	0.63	
Travel time to CBD by public transport (in hours)	0.32	15.09	0	***
Suburb's average home price (in 1,000,000 AU$)	0.04	0.56	0.58	
Travel time to CBD by car X petrol price	0	0	1	
Population in the suburb (in 10,000)	0.55	9.99	0	***

Likelihood: -2433 | AIC: 4926 | Significance levels: '***': <0.05, '**': <0.10, '*': <0.15, '.': <0.20

4. Conclusions

In conclusion, this study proposes a brand new and more realistic framework for understanding the complexities of household decisions about residential relocation through the use of a Dynamic Discrete Choice Model (DDCM). This model successfully simulates how households weigh past experiences, current circumstances, and future expectations, including life events and collective decision-making factors. The findings offer crucial insights for policymakers, urban planners, and academics who can use this information to formulate more sustainable and equitable housing strategies.

The study also underscores a commonly overlooked aspect in existing literature: people's forward-looking approach in decision-making, particularly for long-term commitments like moving homes. To capture such intricate behavior, we need a modeling approach that takes into account the dynamism of household conditions and expectations for future events and consequences.

The DDCM results reveal the varying influence of home features, local amenities, and individual household attributes on the likelihood of staying put, relocating, or choosing a particular suburb. For instance, the study found that higher rent and mortgage payments decrease the appeal of staying, while joint decision-making on big expenditures makes relocation more appealing. Interestingly, households with cars that are situated farther from the Central Business District (CBD) tend to prefer their current locations. However, when they opt to move, they gravitate towards suburbs that offer proximity to the CBD without being too close.

While the study is enlightening, it's essential to recognize its limitations for further research. There's room for model validation, sensitivity testing, and the inclusion of omitted variables like travel costs and neighborhood desirability. Moreover, the study could be improved by incorporating a daily bid-auction housing model to better gauge housing price fluctuations. Future research might also compare DDCM with hazard-based models, explore the impact of life events such as buying a car, and delve into other characteristics of suburbs.
Overall, the study enhances our understanding of the multiple factors influencing residential relocation decisions and illustrates the DDCM's utility in capturing this complexity. This research holds significant promise for influencing not just academic discourse but also practical policy decisions and urban planning strategies.

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