**Abstract**

Residential relocation decision making is a complicated process, and modelling this complex course of actions requires careful scrutinisation of different aspects. The relocation decision comprises several different decisions, including the reason for the relocation, relocation timing, and attributes of the desired residence. Among these decisions needing to be taken, the reason for relocation and its timing are decided earlier than others. Depending on the variant reasons and motivations for relocating, its timing may be accelerated or decelerated. Relocation usually occurs because of a multiplicity of reasons, which necessitates using a multivariate model for relocation decision making that is jointly modelled with the timing decision. A competing accelerated failure model to jointly formulate these decisions. The housing search literature emphasizes on the importance of considering financial risk acceptance level of decision makers in residential relocation decision models. Therefore, a binary logit model is used to model whether the decision maker is financially risk averse or not. This paper used longitudinal data collected in Australia from the Household, Income, and Labour Dynamics in Australia Survey (HILDA). Further, the impact of group decision making on residential relocation is captured in this paper through the information provided in HILDA regarding the manner in which decisions are made within households.

**Introduction**

Studying residential relocation behaviour has drawn considerable attention, especially in disciplines such as economics, urban planning, decision making analysis, and transport engineering. Demand for the housing market is formed by the decisions of individuals as to when, why, and where to move. To model this demand at a disaggregate level of decision makers, a policy-sensitive and mathematically tractable structure to model the decision making process has been discussed in the housing market literature ([Tiebout, 1956](#_ENREF_55)). In such a structure, decision makers can be considered struggling to optimize their utility ([Rashidi et al., 2012](#_ENREF_47)) or minimize their loss or regret ([Chorus et al., 2008](#_ENREF_12)) to achieve an equilibrium at the market ([Epple and Sieg, 1998](#_ENREF_24)) or individual level ([Epple and Sieg, 1998](#_ENREF_24)). ([Chorus et al., 2008](#_ENREF_12))

Disaggregate (or bottom-up) housing search behaviour modelling eases the inclusion of several policy-sensitive variables such as built form, macroeconomic, socio-demographic. It also enables us to observe the impact of variables in an integrated structure in which several dependent variables are endogenously modelled. Using a disaggregate modelling approach, this paper models the timing of residential relocation jointly with the reason for relocation where the financial risk aversion of the decision maker is accounted for. Three major reasons for relocation are accounted for in this paper: i) change in demographic attributes, ii) seeking better amenities for the residence, and iii) change for professional reasons. These three rationales are combined with the decision maker’s propensity to accept financial risk, which is an emerging topic in residential relocation modelling (Morrison and Calrk, 2016).

The timing of relocation is used as the centric dependant variable to capture dynamics of residential relocation decision making. A competing hazard-based duration model with three reasons for relocation is developed where more than one reason can stimulate relocation. In other words, these outcomes are not independent and there is a possibility of more than one occurring at one time. The unique contribution of this paper is addressing the interdependencies among the relocation reasons by using a competing survival formulation. After a distribution fitting exercise covering a wide range of parametric probability density functions for proportional hazard and accelerated hazard functions, a weibull distribution ([Jenkins, 2005](#_ENREF_35)) is used. Furthermore, a Clayton-Oakes ([Clayton, 1978](#_ENREF_15), [Oakes, 1982](#_ENREF_41)) multivariate failure function is used to account for the correlation between marginal distributions because of its popularity in survival analysis studies ([Chen and Yu, 2012](#_ENREF_11)). The proposed competing hazard-based model provides a flexible closed-formed likelihood function allowing for inclusion of multiple outcomes in a jointly formulated structure which is a major contribution of this paper in the context of housing search behaviour modelling.

In this paper, several explanatory variables are utilized to represent the extent of group decision making happening among household members. Furthermore, the impact of social/economic environment factors on the relocation decision is explored. More specifically, the Socio-Economic Indexes for Areas (SEIFA) data is used to represent the social/economic environment of the area inhabited by the decision maker. The study is based on a longitudinal dataset collected in Australia known as the Household, Income, and Labour Dynamics in Australia Survey (HILDA). To the best of our knowledge, this paper presents the first application of a fully simultaneous survival analysis for residential relocation behaviour which can be later linked to a housing search model, while accounting for many factors that long have been discussed in the literature as essential to housing search behaviour. In addition to the methodological contribution of the paper, it is discussed how misleading policy analysis can be if an appropriate model specification is not used.

The paper is structured as follows. Following a literature review of residential relocation decision making behaviour, the paper elaborates on the data and derives the applicable mathematical formulations. Thereafter, the modelling results are presented and discussed. The paper finally presents concluding remarks and a discussion on future research avenues.

**Literature Review**

The residential mobility is a vibrant research area in urban economics, with direct and indirect links to other domains, such as urban planning and geography, transportation, economic, and housing studies. This area is overwhelmingly dominated by studies on residential relocation ([Strassmann, 2001](#_ENREF_53)) and the duration of residence for different demographics ([Henley, 1998](#_ENREF_32)), especially minorities and their migration patterns ([Harding, 2003](#_ENREF_30), [Krivo, 1995](#_ENREF_36)), where an aggregate perspective is usually taken. Several disaggregate modelling studies have explored the complications associated with the decision-making process of individuals with regard to residential relocation ([Gronberg and Reed, 1992](#_ENREF_28)), however, this research stream is still quite vibrant due to its benefits to several disciplines.

Generally, there are several studies on understanding the production, consumption and distribution of housing. From a theoretical point of view, Clapham (2002) has categorised housing studies into four groups: (i) social policy studies which concentrate on describing and analysing government policy towards housing, (ii) neo-classical economics studies that put the emphasis on the relationships between different actors in the housing market, (iii) geographical approaches which study the spatial distribution of housing, and (iv) sociological approaches which focus on the application of general sociological theories to the field of housing (Clapham 2002). The last three of these approaches focus on the behaviour of households as the main actors in housing markets. Housing market often displays complicated behaviours like rapid swings in prices and the observed reluctance of prospective sellers to reduce asking prices in down markets ([Stein, 1993](#_ENREF_52)). This market attracted many researchers employing different techniques to model how the market is formed. Hedonic models are the most common economic modelling approaches which regress the price of a house on a vector of house’s physical and locational attributes ([Hill, 2013](#_ENREF_33)). Some of the domains, for which hedonic models have been developed, include i) models to explain variations in house prices as a function of certain characteristics such as pollution ([Zabel and Kiel, 2000](#_ENREF_61)), public school provision ([Gibbons and Machin, 2003](#_ENREF_26)) and distance to school ([Bayer et al., 2007](#_ENREF_5)), ii) to test for market segmentation ([Tu et al., 2007](#_ENREF_56)) iii) to evaluate the effectiveness of government policy initiatives ([Burge, 2011](#_ENREF_8)). These papers build on literatures in macroeconomics, microeconomics and applied microeconomics.

Other than price of house, dynamic aspects of consumer decisions in the housing market, more specifically dwelling durations, have attracted researchers, especially due to an increasing number of panel databases ([Henderson and Ioannides, 1989](#_ENREF_31)). Henderson and Ioannidis presented a model for the decision of tenure (owning or renting) and the length of stay while not concerning about the correlation between the error components of the two tenure decisions. Henderson and Ioannidis‘s work was later advanced by Henley ([Henley, 1998](#_ENREF_32)) to use a discrete competing hazard model to model the binary tenure decision and relocation timing. In a similar attempt a joint modelling formulation was proposed by Ioannides and Kan ([Ioannides and Kan, 1996](#_ENREF_34)) to model the same dependent variables of tenure type (rent and own) and dwelling duration. Clark and Withers (1999) and Clark and Huang (2003) also studied the impact of household life cycle and tenure choice by exploring the impact of household demographic changes over time on residential and job relocation decisions. The literature of dynamic housing market modelling is slim when it comes to modelling the reason for mobility which is crucial indicator revealing information to determine other characteristic of relocation. There are several studies examining the mobility for specific demographics ([Ludwig et al., 2001](#_ENREF_38)), migration patterns ([Clark, 1982](#_ENREF_13); Brown and Moore, 1970) and some relatively qualitative theories on the reasons supporting relocations such as contagion theories, competition theories and relative deprivation or social comparison models ([de Souza Briggs, 1997](#_ENREF_20)).

Residential mobility, as initially discussed by Clark and Dieleman (1996), should be modelled in a unified system of models where spatial distribution of household in the housing market is determined not only at the market level, but also by how households’ decisions form demand for the housing stock. Clark and Dieleman (1996) discussed the significant role of household life cycle and its dynamic on housing decisions and the housing market, with a special focus on transition process from and to ownership and renting which has been also studied elsewhere in more recent works (Ghasri and Reshidi, 2015). The interaction between households and the macro-level economic is another important factor that has been discussed by Dieleman (2001) where he notes household relocation to be affected by housing market conditions. Huang and Clark (2001) also looked at the institutional relationships among major actors including households, employers, the state, the local government and developers to study tenure choice behaviour of people in the reforming market of China.

Household financial risk aversion is an important issue affecting housing search behaviour (Smith et al, 1979). It has been shown that loss aversion is an important phenomenon in metropolitan housing markets ([Engelhardt, 2003](#_ENREF_23)) especially under income shocks and credit constraints ([Ortalo-Magne and Rady, 2006](#_ENREF_42)). In this vein, an emerging area in psychology and demography domains is focusing on significance of risks/gains in relocation/migration using behavioural economic methods for nonstandard behaviour (Marsh and Gibb 2011; Morrison and Clark) with a special focus on loss aversion and investment behaviour of people. Therefore, being risk averse or risk prone is modelled in this paper to further emphasise on the importance of risks associated with residential relocation decision making ([Wieand, 1999](#_ENREF_59)).

Housing search is tightly related to transport infrastructure and urban form. Work and school trips, constituting the majority of daily trips and greatly contributing to the congestion of metropolitan areas, are highly affected by the location of home and job ([Bayer et al., 2005](#_ENREF_6)). Other activities that are commonly studied by travel demand modellers such as shopping and recreational activities are planned by travellers with a great consideration of home and work locations ([Waddell, 2002](#_ENREF_58)). As a result, there is a growing interest in developing integrated travel demand and land use models with a special focus on residential and job location ([Salvini and Miller, 2005](#_ENREF_51), [Pendyala et al., 2012](#_ENREF_43), [Rashidi et al., 2011](#_ENREF_49), [Rashidi and Mohammadian, 2011c](#_ENREF_50), [Farooq and Miller, 2012](#_ENREF_25)). The proposed residential mobility framework of this paper is part of a larger land use modelling structure that is integrated with the transport system models (Rashidi, 2014).

Using discrete choice modelling, such as logit formulation for the decision on tenure ([Clark and Huang, 2003](#_ENREF_14)), and basic survival analysis formulations for modelling the mobility decision ([Ioannides and Kan, 1996](#_ENREF_34)) is a common practice in the economics literature. The hazard-based duration method ([Cox, 1959](#_ENREF_18)) has long been used in many contexts to model the life of an event. However, several specifications of hazard-based duration models were overlooked when duration analysis was applied to relocation timing analysis ([Rashidi and Mohammadian, 2011a](#_ENREF_46)). The proportional hazard formulation using the Weibull baseline hazard is the most prominent type of hazard-based formulation used for housing search modelling ([Di Salvo and Ermisch, 1997](#_ENREF_21)). Alternative baseline hazard formulations, and accelerated competing hazard functions are just some of the specifications yet to be used in housing duration analysis ([Rashidi and Mohammadian, 2011b](#_ENREF_48)). Furthermore, competing hazard formulation provides a suitable platform for modelling the occurrence and duration of outcomes until at least one outcome ceases ([Jenkins, 2005](#_ENREF_35)). The competing hazard formulation is a suitable modelling approach for understanding why a failure with a specific cause is observed in a situation with multiple failure causes ([Jenkins, 2005](#_ENREF_35)). Building on the competing hazard method literature, this paper presents a flexible competing hazard formulation which is capable of incorporating multiple outcomes in a closed form formulation which significantly reduces the computational load.

**Study Contributions**

Understanding household decision making process for residential relocation is a challenging problem both empirically and theoretically. Addressing challenges associated with this problem requires identifying factors affecting the decision making process, developing mathematical models incorporating these factors and having access to rich databases that support the model development exercise. Research about residential relocation assumes that movers’ behaviour can be explained by changes in socio-economic and demographic attributes of households (Morrison, 1973), housing market (Myers, 1997; Nordik, 2001), and job market (Harrison, 1990). One of the major contributions of the current work pertains to the formulation presented for capturing motivations behind residential relocation decisions which is of great significance in understating the mobility pattern of households ([Rashidi et al., 2012](#_ENREF_47)).

 Dynamics of mobility have been another important factor studied in the literature from two angles. Some studied the duration of a unit being empty (Zuehlke 1987, Emmi and Magnusson 1994, Sternberg 1994, Gabriel and Nothaft 2001), or the turnover of ownership or liquidity (Kluger and Miller 1990, Archer, Ling et al. 2010). Some other studies investigated the impact of exogenous variables on residential mobility in order to provide better insights into people’s behaviour (Gronberg and Reed 1992; Clark et al. 1997; Deurloo et al. 1997; Deng et al. 2003). Following the second paradigm, the current work also emphasizes on the importance of understanding the residential relocation timing which can be modelled jointly with the reason for relocation in a closed-form and flexible formulation introduced in this study. Including the financial risk acceptance of decision makers, group decision making attitude of the household or the decision making unit, and social/economic environment form variables is another unique feature of the presented formulation of this paper.

**Data**

***HILDA Data***

The main database used in this study is the longitudinal HILDA database which is a nationally representative panel study of Australian households. HILDA includes data on economic and subjective well-being, the labour market, family dynamics, housing information, household expenditures, rent or mortgage rates, and general socio-demographic information. It contains data collected from 7,682 households and 19,914 individuals, and in the 11th wave of this survey conducted in 2011, an additional 2,153 households and 5,477 individuals were included. This longitudinal dataset is a unique and ideal resource for modelling the behaviours influencing housing searches. This study utilized the three latest released waves (collected in 2010, 2011 and 2012) of HILDA survey for its modelling purposes. These waves contain more information regarding people risk attitudes.

After combining the collected data for wave 10, wave 11, and wave 12 and cleaning the data, 7424 observations are included in the dataset of this study. Further information about the sample, weight factors and other characteristics of the database can be found in the HILDA User Manual ([Summerfield et al., 2014](#_ENREF_54)). Figure 1 shows the spatial distribution of individuals from Brisbane, Melbourne and Sydney included in HILDA.

[Figure 1]

HILDA data has been used in a few projects to study mobility pattern of people. For example, Sander and Bell (2014) studied retirement and migration patterns as two main life cycle attributes. Clark and Mass (2016) also examined the spatial mobility of Australian people with regard to residential location selection. Further, Clark (2013) studied how a group of life course events intersect with the distance of move, using HILDA data. This paper used waves 10, 11 and 12 of the data which were the three latest released waves of HILDA survey at the time of this study, due to the availability of risk aversion variables in these waves. Using only three years of data limits this study from examining the long term impact of economic factors on the housing search behaviour over a period of time. The questionnaire asked about the amount of financial risk that the respondent was willing to take with their available money for saving or investment. Four categories were provided to respond to this question: 1) taking substantial financial risk; 2) taking above-average financial risk; 3) taking average financial risk; 4) not willing to take any financial risk. Based on this question, respondents were categorized as either risk-prone or risk-averse ([Summerfield et al., 2014](#_ENREF_54)).

In addition to the residence duration data, the questionnaire enquired about the reason for relocation. Among the 32 reasons for moving as provided in the questionnaire, the principal ones were as follows: proximity to work, looking for a job, better neighbourhood, family reasons, and better quality of residence. These responses may be grouped into three major categories: family or demographic, housing or neighbourhood, and professional reasons (or alternatively, change in demographic attributes, seeking better amenities for the residence, and change for professional reasons). The respondents were also able to select more than one possible reason.

The HILDA data includes information on how decisions are made within the household. The questionnaire enquired about decision making relating to large household purchases, number of hours spent in paid work, social life and leisure activities, child rearing, and savings, investment, and borrowing. For each of these household decisions, the questionnaire asked how they were made, that is, whether the decision is made by one person or through a group decision-making process. Dummy variables were used for these decisions in the analysis to represent whether or not they are individually made. The impact of major changes occurring over the last year, such as marrying, having a new child, divorcing or changing employment status are included in the study. Several socio-economic and demographic attributes of the decision maker are included among the explanatory variables. Thus, annual income, age of the eldest and youngest members of the household, education level, years of unemployment, and home value were examined in this study. By including these demographic and economic variables, a wide range of policy sensitive aspects are included in the models of this study. Table 1 presents a summary of the variables found to be statistically significant in the final model of this paper.

Table 1 Mean and standard deviation values of the variables used in the modelling



SEIFA data were used to represent the social/economic environment of the area inhabited by the decision maker. SEIFA was developed by the Australia Bureau of Statistics to rank the areas in Australia according to their relative socio-economic advantage and disadvantage. The indexes are based on information from the five-yearly census. The following four SEIFA indices were thus considered in this analysis:

1. Index of Relative Socio-Economic Disadvantage (IRSD)
2. Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD)
3. Index of Education and Occupation (IEO)
4. Index of Economic Resources (IER)

Common ways of interpreting SEIFA include determining the level of funding, services, and business opportunities in a geographical zone and identifying equity by understanding the relationship between socio-economic disadvantage and various health and educational outcomes. In order to avoid endogeneity, SEIFA values of households’ previous residence locations were used to develop the models. For ease of interpretation, the index rankings of SEIFA are used in this analysis by defining a dummy variable which is equal to 1 if the SEIFA index score is larger/smaller than a specific range (SEIFA indices rankings vary between 1 to 10) and zero otherwise.

***Australian Housing Market***

The price index for established houses for the weighted average of the eight capital cities experienced a declining pattern during 2010 and 2011 after a climbing trend in 2009 ([ABS, 2010](#_ENREF_1)). Before 2010, house prices in the main eight cities of Australia increased (for example in 2009 increased 13.6 percent) despite the fact that many advanced economies continued to experience price falls ([Randolph et al., 2013](#_ENREF_45)). During 2010 and 2011 the residential property price increase started to slow down so that in the first quarter of 2011 the index decreased 1.7 percent ([ABS, 2011](#_ENREF_2)). Regarding the housing market in Australia during 2010 and 2011, it is important to note that in December 2010 flooding happened in Queensland which can be one of the factors affecting the economy in general and the housing market, although the “rental, hiring & real estate” industries have been relatively stable compared to other industries such as “Financial & insurance”, “Professional, scientific & technical” and “Media & telecommunications” during the last decade ([Manalo and Orsmond, 2013](#_ENREF_39)).

 The study period of this paper (2010-2011) follows the year 2009, when the First Home Owner Grant was introduced by the Australian Federal Government to respond to the global financial crisis ([Government, 2009](#_ENREF_27)). The grant seems to be successful in term of keeping the “rental, hiring & real estate” industry resilient, although Australia‘s housing market is one of the most expensive in the world ([Gurran and Phibbs, 2013](#_ENREF_29)). Other than conservative policies adopted by the Australian government ([Batten, 1999](#_ENREF_4)) to maintain the stability of the housing market, the structure of the housing market of Australia (which includes 70% of households to live in owner-occupied housing, around 25% to live in dwellings rented from private landlords and the remaining 5% live in social or affordable housing) makes it a special case ([Yates, 2013](#_ENREF_60)). All of these special characteristics of the housing market of Australia make it an interesting instance to be thoroughly modelled for planning purposes as it is expected that major Australian cities would follow patterns like those of other metropolitan cities around the world as a large flow of low to medium income people and immigrants start moving to the outskirts of major cities ([Vidyattama et al., 2013](#_ENREF_57)).

**Methodology**

As discussed in the “Study Contribution” section, the literature recognizes relocation timing to be an important decision along with the reason for relocation. Hazard-based formulations have been discussed in the literature as a suitable tool for modelling relocation timing. This section, discusses a flexible (in terms of the base line hazard function) competing formulation for modelling both relocation timing and reason in a unified structure.

 The timing failure *ts* for the relocation reason *s* is latent and only observed for one relocation reason (or several if multiple situations are considered). The hazard of failure for an individual *i* can thus be written as:

 (1)

where *fi* is the probability density function, *Si* the probability of surviving until time *ts*, and *Fi* the cumulative density function. When an accelerated hazard function is considered the survival and probability density functions in consideration of the covariant variables for individual *i* can be written as:

 (2)

 (3)

where and  are univariate baseline functions—in this paper, a Weibull distribution is used—and . Basically, is the vector of coefficients to be estimated in the model in addition to parameters of the risk-aversion model to be explained later in equation 9. Equations 2 and 3 are slightly changed if a proportional hazard-based formulation is used (please refer to Jenkins, 2005 page 38 for proportional formulations). To make the formulation more flexible a Weibull distribution is used for the baseline hazard function which is compatible with both accelerated and proportional hazard formulations.

Three failure situations (professional, housing-related, and demographic reasons) were considered when constructing the competing hazard formulation. As stated in the previous section, any of the failure situations could happen at a given time, meaning that they were not independent. As a result, the hazard function could not be simplified to the sum of the hazard for the three failure situations.  was thus the joint survival function of the three situations (*h* for home related reasons, *w* for work related reasons, and *d* for demographic related reasons). The *crude* hazard function for a housing-relating relocation was thus formulated as follows (for more details, see Escarela and Carriere, 2003 and Elandt-Johnson, 1976):

 (4)

Similarly, when two situations were simultaneously observed, the *crude* probability density function was obtained using the following equation:

 (5)

Using the standard form of the joint survival function as presented by Cook and Johnson([Cook and Johnson, 1981](#_ENREF_16)), also discussed by Chen and Yu([Chen and Yu, 2012](#_ENREF_11)), the survival function was approximated based on the marginal functions as follows:

 (6)

where . Therefore, to estimate the marginal probability density function, the first derivative of the survival function should be estimated:

 (7)

Similarly, the joint probability density function for more than one situation was estimated by taking the higher order of derivatives of the survival function.

The probability of all of the situations occurring simultaneously at time *t* could thus be written for individual *i* as follows:

 (8)

whereshows whether a situation is observed or not and is equivalent to one if all situations survived.

As the financial risk acceptance or aversion of the decision maker can highly affect the residential relocation decision, the riskiness of individual *i* was modelled using the following binary logit model:

 (9)

where is the vector of explanatory variables and *B* the vector ofparameters to be estimated jointly with  for different outcomes. Thus, the likelihood in which risk aversion is incorporated into residential relocation will have a close form as follows:

 (10)

where equals 1 for an individual with risk-seeking behaviour and 0 with risk aversion. The log-likelihood function in equation 10 results in a set of parameters being estimated for the risk-aversion binary logit model and two sets of parameters for the risk-seeking and risk-averse hazard function in each three groups of parameters. Thus, in addition to the set of parameters for the risk-aversion model, a total six  parameter groups were estimated in the accelerated failure time models.

**Results**

The first necessity for developing a parametric hazard-based duration model is to consider a baseline hazard function. In this paper the most commonly used Weibull distribution is used as it provides a flexible formulation working with both accelerated and proportional structures. Weibull distribution can obtain decreasing or increasing pattern depending on the distribution shape parameter.

Using the likelihood function presented in equation 10 (coded in SAS version 9), seven sets of parameters were estimated in the joint model which are presented in Table 2. Table 2 only reports variables found to be statistically significant. As it can be seen in Table 2, by using LR statistics, which has a chi-squared distribution and is the difference between the likelihood function values of the final model reported in Table 2 and the model with only constant, it can be concluded that inclusion of covariates in the final model is statistically acceptable.

All distribution parameters were found to be statistically significant. The copula parameters also exceeded zero and were statistically significant.

*Risk acceptance model*

The binary logit model is presented at the bottom of Table 2 with 13 explanatory variables. In the risk aversion/acceptance model, it was attempted to minimize the overlap between the variables included in the risk aversion/acceptance model and the hazard-based model. Age was found to play a significant role in determining whether a person is risk-averse or not; where experienced people were thus more risk-seeking with regard to financial decisions (average age in the data is 41 with the standard deviation of 12 years) showing that as people get more involved in financial businesses, they more consider investments. Nonetheless, the age of the oldest member of the household reduces the chances of accepting high financial risks, possibly due to the stability that more senior people seek. Females show less propensity to accept higher financial risks. Household financial stability is reflected through the home value for owners and the rent amount for renters, where more stable households are more likely to accept financial risks. It was also found that having a bachelor degree increases the chance of accepting financial risk. Several job categories are also tested in the model, where it was found that machinery operators are more risk averse and technicians are less risk averse.

Table 2 Results of the joint duration and risk aversion models, the value in parentheses are t-values****

Some of the social/economic environment variables included are found to be statistically significant in the risk aversion model. The IRSD index has a positive sign in the model for values more than 8, resulting in an increase in the utility function with an increase in the value of the score. A high score indicates a relative lack of disadvantage in general, meaning that if the individual live in an area which is not economically disadvantaged, (IRSD >8) then this increases the chance of being risk averse. The IER index also appears in the model with a negative sign for lower scores indicating a relative lack of access to economic resources in general. This results in reducing the chance of being risk prone.

*Economic and demographic attributes*

Being married appears with a positive parameter in all relocation decision models for risk averse people and in the job-related decision for risk prone people. The positive coefficient implies longer duration of relocation which can be explained by the impact of household members on relocation decision especially for risk averse people.

Households’ lifestyle affects the decision on relocation, specifically because of household and demographic reasons. Couples without a child, like being married, are less likely to relocate due to housing or demographic-related reasons for risk averse people. Having a child also results in delaying relocation as a result of housing or demographic-related reasons. Education-related variables only appeared in the risk-prone model with a positive sign, indicating that highly and moderately educated individuals who are risk-prone tend to relocate later, especially for professional reasons. The appearance of these demographic related variables in the models, especially in the demographic reason model, emphasizes on the fact that housing search behaviour and the housing market are affected by changes in socio-demographic attributes of people ([Myers, 1990](#_ENREF_40)).

*Life-course change attributes*

Among the five life-cycle change indicators discussed earlier in the data section, four appear (pregnancy is excluded) in the final model all with positive signs reflecting their significant impact on slowing down changes in the household housing attributes. In other words, if households have experienced changes in the last year, especially for risk-averse households, they become quite sensitive about another major decision with regard to housing. This finding confirms what others found about the relationship between residential and job relocation and commuting cost in Australia ([Vidyattama et al., 2013](#_ENREF_57)) or UK (Clark and Huang, 2003).

*Intra-household decision making*

The next set of explanatory variables relates to how group decisions are made within the household. Regarding the purchase of large and durable products, the variable appears in all models of risk-averse people and the job-related decision of risk prone people with a positive sign, implying that household-level decisions over such matters enlarge the relocation timing. Similarly, collective decisions on day-to-day issues such as paying bills and also on saving and investment related issues extend the stay of the household in the existing residence. If decisions regarding the workload of household members are jointly made, risk-averse people see it as a reason to decelerate the relocation due to demographic-related reasons. The appearance of group decision making variables with statistically significant and positive parameters in the housing search models of this study confirms the findings of other studies ([Levy and Lee, 2004](#_ENREF_37)), meaning that households collectively making decisions typically relocate less often.

*Social/economic environment-equity variables*

For the social/economic environment variables, the IRSAD, IEO and IER are statistically significant in the models. The IRSAD variables (for high scores) appeared in the risk prone models with negative sign and in the risk averse models with positive signs (for low scores) meaning that people living in areas with higher average incomes, or many people who are skilled occupations are more likely to consider relocation more often if they accept financial risks. Similarly, risk averse people who live in areas with low income people and low skilled occupations consider relocation less often. The IER index has a similar impact as the IRSAD does by having a negative sign (for high scores) in the rise prone models and a positive sign in the risk averse models (for low scores) meaning that risk seeking people living in areas with more economic resources consider relocation more often, while the impact is opposite for risk averse people living in neighbourhoods with lower levels of economic resources. Unlike the IER index, the IEO index appears in the housing and demographic-related models for only the risk averse people saying that living in areas with higher level of education accelerates the relocation timing. The combination of SEIFA variables with risk acceptance level and the reason for relocation of people creates several combinations of possible situations which can reflect the diversity of preferences of people in different situations.

**Comparative Analysis**

An independent estimation of all models leads us to different sets of parameters. To show the significance of jointly modelling the decisions, a comparison was conducted to compare the productivity potential of the presented model. The null hypothesis in this analysis is if there is no difference between the intendent (a model where no competition is considered among the relocation research decisions) and the joint model. Figure 2 shows the probability of relocating for people who actually relocated in the data (it is expected that the model returns high probabilities for movers). As it can be seen from this figure, the joint model predicts non-zero probabilities for a larger portion of movers while the independent model is rather unsuccessful in providing non-zero failure probability for movers.

[Figure 2]

It is noteworthy that the superiority of the competing hazard model over the independent model could also be understood by looking at significant and large theta values in Table 2 as well as using Bayesian information criterion (BIC) statistics. BIC is thus estimated using the following equation:

 (11)

The BIC statistics for the independent model would be 7,791, which is outperformed by the considerably smaller BIC for the competing hazard model, which would be 7,831 for 7400 observations and 75 and 73 parameters for the joint and independent models, respectively.

**Conclusion**

This paper discussed a competing hazard-based model for residential relocation reason and timing decisions. This paper emphasized on the importance of modelling housing relocation timing jointly with the reason of relocation. This hypothesis about the relocation behaviour is in line with what the literature explains about dynamic behaviour of households with regard to home relocation (Rashidi et al, 2011). It is discussed in the literature that households do not relocate unless a change happens in their socio-demographic and economic attributes triggering or/and motivating them to move to improve their utility or decrease their loss/regret (Rashidi et al, 2011). This interpretation about the behaviour of households requires attention to three important factors: i) the model specification should capture the dynamic decision making behaviour, ii) the reason for relocation is an important factor to be endogenously modelled within the modelling structure, iii) and household group decision making factors should be accounted for to capture the behaviour of decision makers. This paper introduced a modelling structure which includes all three noted requirements of a dynamic housing relocation timing decision. Furthermore, the proposed model can be integrated with a housing search model by generating a feasible choice set which is constructed based on the reason of relocation.

 Housing related decisions affect the financial situation of households as home includes a large portion of household expenditure. As a result it is critical to take into account the financial profile of the household and how household members make financial decisions. This paper integrated a financial risk acceptance model with the housing relocation timing model to further emphasize on the impact of financial decisions on housing relocation decisions. This paper showed the significance of household expenditure on housing, social/economic environment variables and socio-economic variables in determining the level of financial risk acceptancy. Furthermore, collaborative decision making among household members on saving and investment related matters found to be an important indicator of the level of risk aversion of household members (Bengtsson, 1998).

The competing hazard-based model proposed in this paper captured the correlation between different reasons triggering the housing relocation. The competition between different reasons was reflected in the formulation by significant correlation parameters showing the importance of using a competing hazard formulation to precisely explain the relocation behaviour. The group decision making variables found to be significant in the model showing another special feature of the the proposed formulation. It was found that if household members make decisions collectively on major expenditures, day-to-day billing management, workload and investments, then the relocation is less likely to occur. The collective decision making requires consensus among members which can be the reason the variables are shown with a positive sign in the models. Several social/economic environment variables found to be statistically significant in the model, especially variables reflecting the economic situation of the neighborhood in which the household resides. According to the findings, living in areas with higher levels of income and education increases the chance of relocation. This finding can imply the impact of financial stability as an indicator in being more active in the real estate market.

The next immediate stage after the development of the models discussed in this paper is to use the reason for relocation model to construct a choice set of decision makers to model housing search behaviour. Household composition formation behaviour and individual job change behaviour are two other major long-term decisions taken by household members, which are modelled in parallel to the residential relocation model. It is envisioned to integrate these three aspects into a unified structure to account for their interdependencies. Once the behavioural housing search model is operational, it is envisioned to be integrated with a housing supply model to include the interaction between supply and demand reflected in setting price and rent.

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