Neighborhood Selection and Neighborhood Matching: Choices, Outcomes and Social Distance

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Abstract

In this paper, we ask how well are Australian households matched to their neighborhood social environments. We broadly replicate a previous study of matching and ask to what extent households live in communities that are similar in socio-economic status to their characteristics. And, when households move, do they relocate in such a way to increase similarity to their neighbors? The processes are at the heart of understanding the urban structure, how it changes over time, and the links to urban inequality. The paper uses data on household incomes from the Household, Income and Labor Dynamic (HILDA) Survey to measure the degree of similarity between households and their neighbors. We study the variation in matching for the population as a whole, and by quintiles of median neighborhood income. We also measure how individuals that change neighborhoods, increase their similarity to the destination neighborhood. We find with respect to matching that there is considerable diversity in the levels of matching, and with respect to residential change, households in general do not make major shifts to increase matching when we control for housing tenure and other household characteristics. There is a need for further replications to understand the nature of matching and the outcomes.

Introduction and framing

The distribution of households and individuals across neighborhoods in cities comes about through a complex process commonly described as residential sorting (Bayer et al., 2004; Clark and Morrison, 2012; Modai-Snir and Plaut, 2015). That research has shown that neighborhoods can be categorized by their ethnic composition and socio-economic status. At the same time, the research also shows that there is increasing diversity in ethnic status and considerable status variation across neighborhoods. The research on residential sorting asks the fundamental question, how do people select into neighborhoods in the urban fabric? In this paper, we focus on the choices by socio-economic status.

As others have observed, in democratic societies the freedom to decide where to live, and by extension who to live next to, is deeply ingrained as a right to choose where to live (Morrison, 2015). However, we also know that not all individuals and households have choices and many are constrained in their abilities to move, and even if they can move, they are limited in their choices. There is also research that points to the role of urban managers and how institutions play a role in creating urban opportunities, especially with respect to social housing (Whitehead, 2012). Still, for those who can make choices, we find that on the whole, they choose proximity to others like themselves, whether it is class or race and ethnicity (Clark and Ledwith, 2007; Catney, 2018; Coulter and Clark, 2019). The studies of ethnic and racial choices have documented the process across a wide range of urban contexts (Clark and Fossett, 2008; and others). The revealed preferences of high income households suggest that sorting into higher priced neighborhoods will be to their financial benefit and enhance their social status (Clark, et al., 2014; Morrison, 2015).

The literature on sorting has been more focused on the sorting process by race and ethnicity than by socio-economic status, but the growing focus on inequality across neighborhoods in cities has stimulated a concern with the process of sorting by income.

While we have a general sense that selection reflects income and status, the details are much less clear, and we do not know whether the matching is driven by a decision to "match" per se or is an outcome of the selection of tenure (owning or renting) and the reflection of other decisions in the housing market. In sum, is it an ancillary outcome or the primary motivator. Thus, we investigate the level of sorting by income with controls for family, characteristics, housing tenure, social status.[1] The paper first reviews the general literature on residential sorting, a previous research contribution on matching, and follows the review with a study of residential matching in Australian cities.

Previous research

The research on how residential sorting creates separation in the residential fabric was formalized with the work by Schelling (1971) who outlined a model of sorting for two ethnic groups in which slight differences in preferences for similar individuals led to strong residential separation in the residential fabric. As Vigdor (2003) showed, when the preferences of two groups are even slightly misaligned or incompatible with one another, the outcome patterns do not reflect the preferences of either group. Simulation studies show that the greater the correlation between status and wealth, the more that the agents in the simulation tend to choose different areas either due to choice (the wealthy) or from exclusion (the poorer) as Benard and Willer (2007) showed. The research which explored the Schelling conceptualization has been dominated by studies of ethnic and racial separation. That work has followed three paths. The first emphasizes racial differences in resources and human capital and that higher levels of education, income and wealth increase the ability to choose more advantageous neighborhoods (Crowder et al., 2006; South and Crowder, 1997; Clark and Ledwith, 2007). The second theme emphasizes the role of differences in preferences including choices about own group preference and out-group avoidance (Clark and Fossett, 2008). A third interpretation of separation appeals to place stratification, a structural explanation, which emphasizes white avoidance of minority neighbors, supported by discriminatory practices (Krysan and Crowder, 2017).

Social distance plays a role in creating residential patterns. Although race and ethnic preference have been, and continue to be important in the sorting process there is growing evidence that social distance also includes status measures. The discussion of sorting includes how level of education, cultural contexts, and government regulation can play a role in residential outcomes. Van Gent and colleagues (Van Gent et al 2019) show that socio-cultural factors play a role in sorting in concert with ethnicity. Similarly, Malmberg and Clark (2020) provide evidence that budget limits in association with ethnic preferences are important constraints in how sorting and clustering come about. From that perspective, it is about how growing concentrations of minority immigrant populations generate increased outflows by those with higher incomes, exactly the process of selective sorting by wealth that we would expect where those with choice can exercise their option to select out of poorer neighborhoods.

[1] As a reviewer pointed out, there is also a literature, some of it published in Urban Studies, which investigates matching by religion and sexual orientation. Space limits preclude discussing this literature here.

Empirically, there is a well-documented link between incomes and the ability to move out of less advantaged neighborhoods. Overall, the view of sorting and selection privileges the notion that the ability to *exercise tastes* depends on resources and that this exercise of choice leads to patterns of homogeneity *by class and race* – or to phrase it differently, money and status matter in terms of the outcomes of residential choices (South et al.. 2005; South et al., 2011; Bolt et al., 2008). The outcomes emphasize that people with higher income are more likely to move out of neighborhoods through a sorting process that reinforces the concentrations of the have and have-nots into selected neighborhoods. Just to what extent households are "trapped" or that only those who are successful can move out, as Cheshire (2012) argues, has been questioned, and the level of connection between low-income neighborhoods and the larger urban structure is still in question (Bailey, 2012).

The research by Bailey and Livingston in the UK context has shown that the higher the SES level of a household the greater likelihood of leaving disadvantaged areas. This is another way of stressing that where you begin does have an impact on your chances of moving up, or in the focus in this study on whether you can achieve a matching. Thus, as in the case of intergenerational movement, there are links between initial and later statuses. But, at the same time, when you look at the whole distribution of neighborhoods rather than just at poverty neighborhoods it seems that even the most deprived areas are not isolated within the city. About a half of all migrants in and out of deprived areas come from, or go to, non-deprived areas (Bailey and Livingston, 2007). This is an outcome that will certainly affect matching.

Nevertheless, it is not only about a movement out of poor areas. The Tiebout (1956) model also predicts residential sorting by economic status. Households that can pay for amenities such as school quality, green space, and protective services will likely sort together into communities with other residents who also value such amenities. Households willing to pay for such amenities are likely to have higher incomes, and the preference for these amenities further structures the sorting process. In effect, the Tiebout model predicts income segregation because households with similar preferences and ability-to-pay tend to form homogeneous communities.

Australian research also finds that individuals and households with higher social and economic status move out of lower decile areas (Ryan and Whelan, 2010). The most comprehensive recent study of spatial mobility in Australia, and an important context for the present study, examined mobility across areas of advantage and dis- advantage using the Australia socio- economic indices (SEIFA) created by the Australia Bureau of Statistics (Black et al., 2009). The study examined how SEIFA level affected locational choice, what caused upward and downward movement, and what were the natures of labor market outcomes from spatial mobility. Most moves are local and naturally there was substantial movement on the diagonal of the SEIFA matrix. However, unlike the US and European research, the study did not find clear patterns in the upward and downward movement of individual households nor did income explain social area choices. To some extent, it creates questions about the strictness of the sorting process and re-examining that question is central in the analysis section of this study.

Our study is not the first to look specifically at the level of matching across neighborhoods. Hedman and Galster (2013) pose the income sorting problem within the context of neighborhood effects on income outcomes. Although not a matching study per se it does raise the question of how selection plays a role in creating income homogeneity in neighborhoods. A more specific study of matching (Musterd et al., 2016) examined the social distance of an individual and their household from the median social position (defined as income) of their neighborhood. How many of the households were within a set percentage of all households in the neighborhood. Their paper aimed to measure the extent to which individuals who moved increased their "matching" in their social position to the social composition of the neighborhood. The study found that about 45% of the sample were in neighborhoods where they were within plus or minus 25 percent of the neighborhood median income. With respect to residential moves the study showed that there was a general tendency to improve their "fit" after a move and that the odds of moving was influenced by the level of fit before the move. Overall, although the study had relatively modest levels of explanation, R^2 values of less than 0.08, it suggested that there is evidence for social matching from residential moves from one neighborhood to another. We pursue some of the same issues with a sample of Australian households but with a number of important modifications to the structure of the analysis.

We expect the Australian findings, along with comparisons to the Dutch findings by Musterd et al. (2016), to contribute a greater understanding of how matching processes and associated outcomes vary under different institutional settings. Australia is one of the most residentially mobile countries across the OECD, with more than 40% of individuals moved over a five-year period leading up to 2012. The Dutch residential mobility rate over the same period was around half of Australia's at 21% (Cause and Pichelmann, 2020). These are likely attributable to sharp differences in the two countries' housing and welfare regimes. Australia's liberal welfare regime is characterised by a small role for governments and strong market orientation. Accordingly, the private rental sector in Australia is relatively large, lightly regulated and characterized by short-term rental contracts (Hulse et al. 2011). On the other hand, its social housing sector is small, making up less than 5% of total housing stock. In comparison, nearly 40% of the Netherlands' housing stock is social housing (Australian Institute of Health and Welfare, 2021). Overall, the Dutch housing system favours long-term renting much more than the Australian system (Hulse et al. 2011).

Data

The data for the analysis comes from The Household, Income and Labour Dynamics in Australia (HILDA) Survey. It is a household-based panel study that collects information about economic and personal well-being, labor market dynamics and family life in Australia. The survey is a longitudinal survey of approximately 7,600 households. It began in 2001 and follows over 17,000 Australians each year over their life course. The survey is modelled on and is similar to surveys in the US (the Panel Study of Income Dynamics) and the British Household Panel Survey, now the 'Understanding Society' study. In the present study, the

mobility measures and variables are drawn from the adult respondent file. The restricted version of the HILDA Survey provides more detailed information on specific items already in general version of the Survey. For the purposes of this paper, the detailed geography variables available in the restricted HILDA Survey are especially helpful as they drill down below broad state and capital city levels to present information at neighborhood levels, including postcodes, Local Government Areas and Statistical Local Areas[2].

We draw from the 2016 and 2017 HILDA Surveys for our analyses. Specifically, matching analyses are conducted for the year 2016. The analyses require comparisons of personal and average neighborhood incomes. Hence, we have chosen the 2016 wave to enable comparisons of personal income in the HILDA Survey with neighborhood median incomes from the latest 2016 Australian Census. We then uncover how matching patterns in 2016 are linked to moves between 2016 and 2017. In order to analyze levels of matching between individuals and their neighborhoods, we need to frame our sample and determine units of analysis from two levels – persons and neighborhoods.

In terms of individual units of analysis, we follow Musterd et al. (2016) and restrict our sample to fully interviewed respondents aged 25-48 years who live in urban areas. As explained by Musterd et al. (2016), the rationale for the age limits is to capture the segment of the population who are most economically active both in terms of employment participation and mobility. We do not however, exclude individuals who have marital status changes. We do this for two reasons. First, we believe that it is essential to keep those with marital status change in the sample as quite simply they are very larger proportion of all those who make residential changes and thus engage in the matching decision. Second, there would be a large reduction in our sample size and limit the significance of our estimates. Musterd et al. (2016) further restrict their sample to residents of four major urban regions in the Netherlands and we adopt a similar focus by restricting our sample to residents of Australia's major capital centres – Sydney, Melbourne, Brisbane, Adelaide, Perth and Australian Capital Territory. An obvious advantage of this sample alignment is the scope of testing whether the Dutch findings are universally applicable, or whether matching trends and processes vary across different countries.

In terms of neighborhood units of analyses, we draw on Statistical Areas Level 2 (SA2s) using the boundaries of the Australian Statistical Geography Standard (ASGS) in 2011. That is because the boundaries of SA2 in HILDA are defined using the ASGS 2011. There are 2,310 SA2s in total in Australia, with average populations of 10,000 residents per SA2. Within cities, SA2s represent gazetted suburbs. Each SA2 is defined by the Australian Bureau of Statistics (ABS) as a medium-sized general-purpose area that represent a community whose residents interact together economically and socially (ABS, 2016a).

We construct four analyses of the data from the HILDA Survey sample to address two research aims. Recall that our first research aim is to uncover to what extent individuals live in communities which are similar in socio-economic status to their own characteristics. A

[2] For more information regarding the restricted version of the HILDA Survey, please refer to https://dataverse.ada.edu.au/dataverse.xhtml?alias=hilda.

second aim is to shed light on whether households relocate in such a way to increase similarity to their neighbors when they do move. To address the first aim, we begin by analyzing the level of matching across the whole 2016 Australian population distribution and within quintiles of neighborhood median income. Second, we construct a model of the probability of being matched in 2016 using explanatory variables ranging across the domains of personal, housing and area characteristics. To address the second aim, we analyze mobility patterns between 2016 and 2017 across classes of matching. We then model the likelihood of moving in response to being un-matched, across a range of explanatory variables.

Are individuals matched to their neighborhoods?

Distributions across classes of matching

Following Musterd et al.'s (2016) previous study of matching and to provide a measure of comparability we utilize the same structure of whether or not an individual's income is matched to the neighborhood median income by splitting them into five classes: (i) individual income >75% higher than the neighborhood median income, (ii) individual income 25%–75% higher than the neighborhood median income, (iii) individual income within 25% higher and 25% lower than the neighborhood median income, (iv) individual income 25%–75% lower than the neighborhood median income, (v) individual income >75% lower than the neighborhood median income. The smallest social distances between individual income and neighborhood median income are captured by the third class and therefore this class comprises individuals who are 'matched' to their neighborhoods.

The individual income measure is equivalised total annual household income reported by respondents from the 2016 HILDA Survey. The HILDA Survey reports unequivalised income measures, so these are equivalised to account to differences in income attributable to household composition and size using the OECD modified equivalence scale which assigns a weight of 1 to the first adult, 0.5 to the second adult, and 0.3 per child aged under 15 years (ABS, 2016b). To ensure comparability, to measure neighborhood median income we draw on the SA2 equivalised total weekly household income from the ABS's 2016 Census, which is multiplied by 52 weeks to obtain annual equivalized total annual household income.

Because we believe, and the literature suggests, that mobility is income constrained we examine matching both overall and by quintiles representing different levels of socio-economic status (SES) across the Australian neighborhoods in our study. We draw on quintiles constructed from the Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD). The IRSAD is one of several Socio-Economic Indexes for Areas (SEIFAs) that has been developed and maintained by the ABS over time (ABS, 2018). We hypothesize that matching will be higher in more disadvantaged neighborhoods where there are greater constraints on moving. If the hypothesis is sustained, then the neighborhood deprivation gradient to matching outcomes will have implications for the design and implementation of area-based policies that seek to reduce barriers to economic opportunity for low-income households. It raises the issue of how mobility options for low-income

households can be enhanced and whether experiments like the income voucher options in the US could be considered in the Australian context.

The initial question is how well matched are individuals aged 25-48 to neighborhoods across Australian urban regions. We present the results in a table of matching using the measures above. To ensure that our estimates are representative of the cross-section of Australian population in 2016, we apply the HILDA Survey's cross-sectional population weights to adjust the sample for biases and produce population-level estimates.

With respect to the overall matching in the sample, we find that the levels of matching are lower than those in the Dutch context. Specifically, approximately one-third of the Australian individuals report having incomes that are within 25% higher or lower than their neighborhood median income (that is around the median). Over 50% report being in neighborhoods where they have higher incomes than the category of plus or minus 25% of the neighborhood median. Less than 15% report being in neighborhoods where their income is lower than that of the neighborhood median. In contrast, there is overall a greater level of matching in the Dutch context, where 45% of the sample in Musterd et al. (2016) have incomes matched within 25% higher or lower than their neighborhood median. One explanation for the greater level of matching in the Netherlands may revolve around the long-term Dutch urban policy of social status integration across neighborhoods in Dutch cities (Bolt et al., 2010).

The finding that 50% report being in neighborhoods where their income is higher than those of the neighborhood raises intriguing questions about the neighborhood and its characteristics. Although we do not have the data to further investigate neighborhood characteristics it has been suggested that this may represent movement into affordable neighborhoods which might then be gentrified by the new residents. This observation also reminds us that neighborhoods are not static though the relatively limited sample period time (2016-2017) means that we are unlikely to have associated gentrification.

When we unpack the distribution of matching by the IRSAD quintiles, we find, as hypothesized, that there is a somewhat greater level of matching in lower quintiles than there is in the top two quintiles. The Australian results show much greater similarity to the Dutch results for the lower IRSAD quintiles. In fact, the class reflecting individuals highly matched to their neighborhoods – incomes within 25% higher or lower than the neighborhood median income – is between 37 and 46% in the lowest three IRSAD quintiles, which approaches the 45% found in the study of matching in Dutch cities. In contrast, the share of Australian individuals who are matched to within 25% higher or lower than their neighborhood median income is just above 20% for the top IRSAD quintile. These individuals in general are not matched to the neighborhoods they live in and in fact 40% are in neighborhoods where their income is more than 75% different from that of the neighborhood median. Overall, what we are establishing here is that individuals in lower SES neighborhoods in Australia are more likely to be matched or closer to being matched than those with higher incomes and living in higher SES neighborhoods.

[Insert Table 1 here]

Predictors of matching

The obvious question is to ask who is matched and who is not matched. Can we in fact explain the level of matching beyond the observations of table 1 which document that those living in the top IRSAD quintile are more likely to be unmatched? A logit model of matching is implemented where the dependent variable takes on a value of 1 if an individual is matched to within 25% higher or lower than neighborhood median income, and 0 otherwise. The reference predictor categories are age <30 years (young adults), male, couple families without children, highest qualification from high school, outright owners, Sydney, and highest IRSAD decile.

Midlife individuals have odds ratios which are significantly smaller than 1, all else being equal. The model suggests that with respect to younger individuals they are much less likely to be matched to their neighborhood residence. They are also in the settling down process with much lower likelihoods of moving. It is stability over mobility. Couples with children and lone parents with children have odds of being matched that are over three times as high as the odds of being matched for couples without children. Extrapolating from these findings would suggest that we are observing life course affects in the outcomes of matching, and that age in combination with household type is at least a partial explanation for the extent to which there is matching or not. The odds of being matched are much lower among those possessing university degrees relative to those who have only completed secondary school, potentially due to fewer constraints on mobility among the former group.

With respect to housing and neighborhood effects, private renters are nearly 1.5 times as likely to be matched to their neighborhoods as outright owners (the omitted category). On the other hand, those living in public housing, rent-free and other tenures are less likely to be matched to their neighborhoods than outright owners. Among mortgagors, it is those with high loan-to-value ratios (LVRs) who appear to be unable to achieve a match with their neighborhoods. Mortgagors with relatively low LVRs of under 60% are as likely to be matched as outright owners. Turning next to neighborhood SES, the odds ratios attached to the 1st to 9th IRSAD deciles are all greater than 1. In fact, those in the six lowest deciles are more than twice as likely to be matched to their neighborhoods as those in the highest decile. In the 7th to 9th deciles, the odds ratios are somewhat lower but still greater than 1. These findings confirm our earlier hypothesis that all else being equal, those in low-SES neighborhoods are more likely to be matched to their neighborhoods than those in high-SES neighborhoods.

The model diagnostics show a likelihood ratio Chi-square statistic of 444.6 which is statistically significant at the 1% level. However, the model pseudo R^2 is relatively modest at 0.078.

[Insert Table 2 here]

Do individuals move to match?

We evaluated the level of actual matching in an attempt to provide a more complete picture of the sorting and matching process. However, the principal issue in the analysis is the extent to which the behavioral outcome of a move leads to increased matching and can we add to the picture which has been developed by the study of matching in the Netherlands. In this next section, we take up the question of who moves out of their SA2 between 2016 and 2017 and whether those SA2 moves replicate the findings of the Dutch analysis. To ensure that our estimates are representative of the Australian population in these years, we apply the HILDA Survey's paired 2016-17 population weights to produce population-level estimates.

The first question in this replication is whether a greater social distance between the individual and the neighborhood leads to a higher probability of moving. We first provide results without controls and explore results with controls later in the paper. In the analysis of change in urban areas in the Netherlands, the research showed that the larger the social difference, either at negative or positive levels, the greater the probability of a move (see figure 1 in Musterd et al., 2016). Those results were true whether the move was within the urban region or between urban regions.

The data for Australia tells a generally different story, although the results are consistent with the Netherlands in high levels of mobility for those who are in neighborhoods below 75% of the neighborhood median income when a move is within the urban region (see figure 1). Beyond that finding, the results do not parallel those in the Netherlands. There is clearly greater mobility across Australia than the Netherlands. For moves within the urban Australian regions, the most matched neighborhoods have the second lowest mobility rates (13%). For moves between urban regions, the most matched neighborhoods have the second highest mobility rates (3%). The distinct U-shaped curve for the Dutch data is not replicated in the Australian data. There is little difference across the other levels of matching and in fact matched individuals were just as likely to move as those who were "overmatched".

Insert Figure 1 here

The second question with respect to matching is whether individuals reduce the social distance when they move. In the Dutch context, Musterd et al. (2016) suggested that in addition to moving from neighborhoods where they do not fit well socially, that households seem to reduce social distance. That is, they become more matched after the move. We examine this question with Australian data on the shares and numbers of movers who change between matched and unmatched contexts. As shown in Table 3 below, among Australian neighborhood movers, the majority moved from unmatched to unmatched (58%), followed by matched to matched (28%). Thus, the group that move from unmatched to matched is very small (10%). We will explore this in our models of matching later in the presentation.

[Insert Table 3 here]

We further elaborate these findings by replicating the table of neighborhood moves between categorization in 2016 and 2017. The overall finding in Table 4 shows that moves on the diagonal predominate, a finding in many studies of sorting and selection. Overall, people generally move into another neighborhood in the same matched or unmatched category in 2017. For instance, between 2016 and 2017, 89% of SA2 movers in the matched category in 2016 moved and stayed matched. How many moved to matching? About 9% of those in the '25-75% lower' class moved up into the matched class, and another 13% of those in the '25-75% higher' class also shifted into a matched class by moving into another SA2. Nearly all those in the '>75%' categories in 2016 remained in the same categories in 2017 while moving to a different neighborhood. Of course, this reflects short-distance moves, but it also reflects the reality of the hold of the initial locational choice.

[Insert Table 4 here]

The third issue we address is whether individuals replicate the Dutch finding that more households move to neighborhoods where the median is somewhat higher than their own income than to neighborhoods where the median is lower. The results again do not support this finding. Only 14% move to neighborhoods where their personal income is lower than the neighborhood median. This is not a finding which supports the idea of upward aspirations. However, 34% do move to neighborhoods where their personal income is similar to the destination neighborhood median. We argue that this is, in fact, what we would expect, and is a reiteration of the actual sorting that takes place. Individuals move to and move within neighborhoods that are like themselves even if they are not actively seeking to match their social distance to the neighborhood itself. When we examine the explanatory model of choice below, we elaborate on this process and how the role of housing tenure plays a major role in the sorting outcome.

Finally, we compute explanatory logit models of the probability of moving to another SA2 (neighborhood) with reference to being in the matched category (see table 5). The models proceed from a model with relatively few controls (model 1) to increasing controls for other socio-demographic, human capital and housing predictors (model 2). Model 2 broadly follows the model outlined by Musterd et al. (2016). However, we make several important adjustments related to sample issues and to our conception of the matching process. As our sample size is considerably smaller than that of the Dutch study, we do not distinguish between moves into another neighborhood within the urban region and moves out of the urban region. As the main issue is about matching, we do not believe this change affects the ability to capture how much matching is occurring. The models in their most complete form have relatively good levels of fit for social science explanations.[3]

With respect to the range of variables used in the Dutch formulation, we include almost all the variables used in the Dutch analysis. However, we do not include a variable representing a mismatch of household income and housing value, which is captured in the

[3] The analysis is computed for all neighborhood changes in Australian major cities. We also estimated the model for moves across all of Australia and for the total population, not restricted by age. The results are comparable and are available from the Authors on request.

Dutch model. We exclude this variable due to concerns over collinearity with the matching classes, i.e. high housing values are strongly correlated with high median neighborhood incomes. Although not a perfect replication, we believe the modelling strategy is a reasonable approximation of the Dutch formulation.

The question at the heart of the Dutch study and in this study is to what extent are people matched, and do people move to match. The models which we report in this section follow the same process as the Dutch study and examine the extent to which we can predict the likelihood of matching. The initial model – model 1 – focuses on the likelihood of choice as a function of matching with one's neighborhood, with controls only for age and gender. In other words, if someone moves, to what extent do they match. In this model, the odds of moving from neighborhoods where one's income is >75% higher and 25%-75% higher than the neighborhood median income is just 70% of the odds of moving from a neighborhood where individual income is matched to the neighborhood median income. In other words, there is little evidence of matching. As we expect, the age variables are significant, with the odds of moving falling the older the age group. As would be expected from a model with few controls, the goodness-of-fit measure is quite low at 0.04.

Model 2 is a relatively close replication of the variables used in the Dutch analysis. However, recall that we include those who have a marital status change in the sample. When we add in the full range of socio-demographic, human capital and housing tenure variables, all the classes of matching become insignificant. Tenure in effect absorbs the effect of matching. Clearly the tenure characteristics play an important role in the choices that are being made within neighborhoods in Australian towns and cities. In fact, private renting has the greatest impact on the choices that are made. The odds of choosing another neighborhood among private renters is nearly five times the odds of making a new choice of a neighborhood by outright owners, holding other factors constant.

As in the Dutch study, changes in family composition, namely the addition of children is significant. The odds of moving associated with a reduction in the number of children is three times the odds of moving associated with having no children or no change in the number of children. An increase in the number of children also prompts moves, though the odds are more muted at 1.6 times the reference category. As much of the Australian housing market comprises three- and four-bedroom homes that are suitable for family occupation, it is unlikely that supply is a constraint in moves. Changes in employment are also important predictors linked to higher odds of moving. Specifically, becoming employed between 2016 and 2017 increases the odds of moving relative to remaining employed across the two years. Those who remain out of work between 2016 and 2017 also have heightened odds of moving, holding other factors constant, perhaps due to the need to relocate into areas with greater job opportunities or lower housing costs.

Although the major issue is the level of explanation about matching, we also report the level of fit of the model, which, in fact, is a relatively close replication of the Dutch model. Unlike the results from the Dutch analysis, we do not find that the social distance between the individual and the neighborhood is significantly related to the odds of moving once we control for tenure, life-course variables, and changes in employment and family composition.

If we think of this in the context of the housing ladder, it is a reflection not that matching is irrelevant but that individuals are selecting into neighborhoods they can afford as they make housing tenure and employment decisions and as their family composition changes. The greater social distance alone, does not seem to be a reason to leave the neighborhood. From our perspective, the results reiterate that it is the life course that is the powerful force in both moving and leaving the neighborhood.

A question was raised about controlling for the fact that we include households with status change in the sample. We added an additional variable that captures the impact of marital change., including dissolution on choice outcomes. To control for this status change, we now report those results in Table 5 (model 3). Although the variable does not change the fit of the model it is clear that the measure of status change is a factor in changing neighborhoods. But to reiterate, while the model is showing the powerful force of life course decisions of which matching is a part it does not alter the conclusions of the lower tendency to match in the Australian data.

[Insert Table 5 here]

Discussion and conclusion

The focus in this paper was on replicating an earlier study of the extent of social matching in Dutch cities. That study and the analysis in this paper were designed to increase our knowledge about the "social fit" between individuals and their neighborhoods as they leave and enter, a topic which is of considerable interest in understanding how residential sorting comes about. Using the same categorical framework as the Dutch study we investigated the extent to which individuals engaged in matching their economic status to the status of the neighborhood. Specifically, we explored the extent to which individuals were matched to their neighborhoods, whether they moved in response to being unmatched, and whether they increased the outcome of being matched after they moved. In the Dutch study, there was modest confirmation (relatively low R^2 values) of moving in response to being more socially distant in their neighborhood. Those who were unmatched either negatively or positively were more likely to move.

We know that sorting and selection across neighborhoods creates the patterns of residential differentiation we see in our cities, and there is a sense that when people move they select neighborhoods which reflect their preferences for the social mix in the neighborhood, and a selection which reflects budget constraints. We also know there is considerable "stickiness" in the mobility process – people move nearby and to locations that are similar to the one they are already in. In this context the study is about how much matching drives residential choices?

From our analysis we can make four important findings about the process of matching as individuals select from amongst the neighborhoods in major urban regions in Australia.

First, as we would expect, there is matching across neighborhoods in Australian cities although it appears there is greater heterogeneity overall in Australian neighborhoods than in Dutch urban areas. Matching in the Australian context reveals about a third are matched overall. When we unpack the nature of matching, we find that the level of matching is higher in lower-cost neighborhoods where nearly 50 percent of all individuals have a similar status to the median for the neighborhood. This is also true, though at a lower matching rate for the next lowest quintiles. For the highest quintile, the matching falls to less than a quarter of all respondents. Families with children are more likely to be matched and those with tertiary education are less likely to be matched. Private renters, who have the greatest mobility, are most likely to be matched among all the housing tenures. However, social housing tenants and highly leveraged mortgagors less likely to be matched than outright owners and low-LVR owners. Clearly, tenure is a critical dimension of the matching process. These findings also potentially reflect the special characteristics of Australia's housing system. As noted earlier in the paper, Australia is one of the most residentially mobile countries in the OECD. This has clearly been supported by a relatively large private rental sector, which supports geographic mobility by private renters seeking to locate themselves in well-matched neighbourhoods.

Second, on the whole, we do not find strong evidence of moving in response to being un-matched per se. It is correct that individuals with incomes below their neighborhood median do have higher probabilities of moving in response to their mismatch (although not significantly in the decision to move model). Overall, as in other studies of mobility, the "stickiness" of mobility plays a major role in the overall choices. We do not find the U-shaped curve of lower mobility in the match category and higher mobility in the negatively and positively matched categories as in the Musterd et al. (2016) study.

Third, our models of choosing to change neighborhood reiterate the powerful role of age, family status and the changes in household composition (increases or decreases in the number of children, and changes in employment (as is true in the Dutch study). Of course, tenure choice plays a major role, and private renters are much more likely to make changes in the urban mosaic than are owners.[4] As we noted above, people generally move into another neighborhood in the same unmatched category in 2017. For instance, between 2016 and 2017, 89% of movers in the matched category in 2016 moved neighborhoods but stayed matched. We argue that this is, in fact, what we would expect from the life cycle process and is a reiteration of the actual sorting that takes place. Individuals and households move to and move within, neighborhoods that are like themselves but they also move between neighborhoods where they are unlike, in social distance, their neighbors. We find that the explanatory power at matching motivation in the decision to move is subsumed in tenure decisions and the stage in the life course. Employment, and tenure play major roles in the sorting outcome too.

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That the Dutch study found somewhat higher overall levels of matching (though not as high as the lowest quintile in this study) may reflect both the national housing context (a housing market with about 40 percent social subsidized housing). Now the issue is to replicate this study in additional national contexts to further examine the sorting and matching process. There are two other reasons for differences which we also acknowledge. First, the sample size is smaller, and except for the unusual case of full register data, it is difficult to find test cases of matching which will have larger samples, and we concede this may influence the results. Second, the size of the units in the Dutch case and the Australia case are different. On average, SA2s have populations in the range of 10,000 persons (ABS, 2016a). The Dutch neighborhoods are smaller. However, the effects of scale are unclear. It is entirely possible that the larger units might generate greater matching, but in any event, this is an empirical question which requires further research.

Fourth, although there is only modest evidence of aspiration mobility in the analysis of Australian residential moves we can say that it is likely to be an underpinning if unstated logic in the move for some movers. The empirical evidence is that about 14% move to neighborhoods where their personal income is lower than the neighborhood median.

Finally, we recognize that matching occurs not in a static context but in a changing world in which the choices change and are changed by the selection process. It is a dynamic process, and there is much to be unpacked in that process. Specifically, future research will need to confront the way in which gentrification is a process which affects the matching outcomes.

At this point the analysis demonstrates a combination of two powerful choice processes in the urban housing market. The first is buying into ownership in neighborhoods which are similar to the ones they currently reside in, and the second is the power of the life course in the process of moving up the housing ladder and that matching is an ancillary but not a driving force once we control for tenure choice and family composition.

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LIST OF TABLES

Table 1. Distribution of individuals across classes of matching, by SEIFA quintile, 2016

Classes of matching (individual to neighborhood median income)	Population count ('000)	Share (% by column)					
		All	Lowest quintile	2nd quintile	3rd quintile	4th quintile	Highest quintile
>75% higher	1,465.9	26.1	12.4	19.0	19.2	27.4	39.6
25%-75% higher	1,538.3	27.4	21.5	25.1	29.6	33.3	25.9
25% +/- (matched)	1,861.2	33.2	46.3	37.3	40.7	28.2	23.7
25%-75% lower	699.0	12.5	19.0	16.5	10.0	10.0	10.3
>75% lower	50.4	0.9	0.7	2.2	0.5	1.0	0.5
Total	5,614.8	100.0	100.0	100.0	100.0	100.0	100.0

Source: Authors' calculations using the 2016 HILDA Survey.
Notes: Estimates are population weighted.

Table 2. Logistic regression of the probability of matching, odds ratios, 2016

Predictors	Odds Ratios	
Age (Reference: <30 years - young adults)		
30-40 years - family formation and development	0.865	(0.0790)
40-48 years - midlife	0.725***	(0.0724)
Female	1.098	(0.0756)
Household type (Reference: Couples with no children)		
Couple family with children	3.243***	(0.332)
Lone parent with children	3.373***	(0.501)
Lone person	1.617***	(0.210)
Group household	1.527	(0.533)
Other (multi-family etc.)	2.688***	(0.528)
Education (Reference: Completed secondary school)		
University degree	0.522***	(0.0541)
Other post-secondary school qualification	0.874	(0.0888)
Did not complete secondary school	0.802*	(0.107)
Housing tenure (Reference: Outright owner)		
Mortgagors with LVRs>0% and ≤60%	0.970	(0.157)
Mortgagors with LVR >60%	0.784**	(0.0831)
Private renters	1.476**	(0.237)
Public Renters	0.389***	(0.118)
Rent-free	0.625**	(0.125)
Other tenures	0.562**	(0.149)
Region reference: Sydney		
Melbourne	1.124	(0.103)
Brisbane	1.269**	(0.133)
Adelaide	1.179	(0.147)
Perth	1.144	(0.139)
Australian Capital Territory	1.641**	(0.316)
Neighborhood SES (Reference: Highest IRSAD decile)		
Lowest IRSAD decile	2.458***	(0.440)
2nd IRSAD decile	3.092***	(0.485)
3rd IRSAD decile	2.176***	(0.353)
4th IRSAD decile	2.807***	(0.435)
5th IRSAD decile	2.464***	(0.378)
6th IRSAD decile	2.570***	(0.375)
7th IRSAD decile	1.701***	(0.253)
8th IRSAD decile	2.155***	(0.302)
9th IRSAD decile	1.760***	(0.245)
Constant	0.131***	(0.0300)
Observations	4,535	
Log-likelihood	-2,617	
Pseudo-R^2	0.0783	
Likelihood ratio Chi^2	444.6***	

Source: Authors' own calculations from the 2016 HILDA Survey.
Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Shares and numbers of movers moving between matched and unmatched

Moved SA2 between 2016 and 2017	N ('000s)	%
Matched to matched	284.4	28.3
Matched to unmatched	41.0	4.1
Unmatched to matched	95.0	9.5
Unmatched to unmatched	583.8	58.1
Total	1,004.1	100.0

Source: Authors' own calculations from the 2016-17 HILDA Survey.
Note: The estimates are weighted using paired 2016-17 population weights.

Table 4: Spatial mobility matrix of SA2 movers by SA2 of origin and destination, percent by row, population numbers in '000s in parentheses

		2017: Destination					
		>75% higher	(25%,75%] higher	25% +/-	(25%,75%] lower	>75% lower	Total
2016: Origin	>75% higher	92.6	7.4	-	-	-	100.0
		(1,349.3)	(108.2)	-	-	-	(1,457.5)
	(25%,75%] higher	4.9	82.6	12.5	-	-	100.0
		(75.1)	(1,269.9)	(192.1)	-	-	(1,537.1)
	25% +/-	0.1	5.0	88.9	6.0	-	100.0
		(1.8)	(89.7)	(1,611.2)	(109.5)	-	(1,812.2)
	(25%,75%] lower	-	-	9.0	90.4	0.6	100.0
		-	-	(62.4)	(627.8)	(4.1)	(694.4)
	>75% lower	-	-	-	18.1	81.9	100.0
		-	-	-	(9.2)	(41.6)	(50.8)
	Total	25.7	26.4	33.6	13.5	0.8	100.0
		(1,426.3)	(1,467.8)	(1,865.8)	(746.5)	(45.7)	(5,552.1)

Source: Authors' own calculations using the 2016-17 HILDA Survey.
Note: The estimates are weighted using paired 2016-17 population weights.

Table 5: Logistic regression of the probability of moving into another SA2, 2016-17

Predictors	Model 1 odds ratios	Model 2 odds ratios
Classes of matching (Reference: 25% +/-)		
>75% higher	0.742**	0.726
	(0.0869)	(0.146)
25%-75% higher	0.702***	0.822
	(0.0827)	(0.112)
25%-75% lower	1.169	0.853
	(0.168)	(0.142)
>75% lower	1.804	1.267
	(0.717)	(0.544)
Age group (Reference: <30 - young adults)		
30-40 years - family formation and development	0.558***	0.699***
	(0.0571)	(0.0799)
40-55 years - midlife	0.276***	0.417***
	(0.0337)	(0.0592)
Female	0.897	0.847*
	(0.0806)	(0.0844)
Ethnicity (Reference: Australian-born)		
Main English-speaking countries		0.655**
		(0.131)
Other		1.009
		(0.132)
Household type (Reference: Couple family without children)		
Couple family with children		0.868
		(0.174)
Lone parent with children		1.288
		(0.300)
Lone person		1.508***
		(0.233)
Group household		0.210**
		(0.157)
Other (multi-family etc.)		1.141
		(0.310)
Number of children (Reference: No children)		
No additional children in 2017		1.018
		(0.201)
Less children in the household in 2017		3.398***
		(1.018)
More children in the household in 2017		1.563**
		(0.296)
Education (Reference: Completed secondary school)		
University degree		1.139
		(0.171)
Other post-secondary school qualification		1.021
		(0.151)
Did not complete secondary school		0.674*
		(0.138)
Change in employment status (Reference: Employed in 2016 and employed in 2017)		
Employed in 2016 and not employed in 2017		0.953
		(0.229)

Predictors	Model 1 odds ratios	Model 2 odds ratios
Not employed in 2016 and employed in 2017		1.685***
		(0.308)
Not employed in both 2016 and 2017		1.453**
		(0.230)
Total household equivalised gross income in 2016 ($'000s)		1.004**
		(0.00171)
Tenure type (Reference: Outright owners)		
Mortgagor owners		0.955
		(0.285)
Private renters		4.934***
		(1.448)
Public Renters		1.898
		(0.883)
Rent-free		2.974***
		(1.014)
Other tenure		2.159*
		(0.935)
Constant	0.430***	0.0936***
	(0.0465)	(0.0337)
Observations	3,840	3,840
Log-likelihood	-1617	-1455
Pseudo-R^2	0.0430	0.139
Likelihood ratio Chi^2	145.3***	468.2***

Source: Authors' own calculations from the 2016-17 HILDA Survey.
Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.