Wages, Wellbeing and Location: Slaving Away in Sydney or Cruising on the Gold Coast

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Motu Working Paper 17-07

Motu Economic and Public Policy Research

April 2017

Document information

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Acknowledgements

This research was funded through Marsden Fund grant MEP1201 from the Royal Society of New Zealand. We extend thanks to our Motu colleagues, particularly Dean Hyslop and David Maré, for their helpful advice on many aspects of this paper. We also thank seminar participants at the European Regional Science Association and the New Zealand Association of Economists conferences for their insightful comments.

Disclaimer

This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the authors and should not be attributed to either DSS or the Melbourne Institute.

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 ISSN 1176-2667 (Print), ISSN 1177-9047 (Online).

Abstract

We analyse the relationships between subjective wellbeing (SWB), wages and internal migration. Our study addresses whether people make (revealed preference) location and migration decisions based on SWB and/or wage prospects. We present both a theoretical intertemporal location choice model and empirical analyses using the Australian longitudinal HILDA dataset. Our theory predicts considerable heterogeneity in location choices for individuals at different life stages depending on their individual characteristics, including their rate of time preference. We find that people's location at a point in time is determined largely by their previous period's location reflecting high moving costs. In addition, labour market conditions affect location choice and influence individuals' decisions to migrate out of an area. Focusing on migrants, we find that place-based SWB is a highly significant ex ante predictor of a migrant's chosen location. Furthermore, we find a significant and sustained ex post uplift in individual SWB for migrants, which holds across a range of sub-samples. By contrast, wage income responses show much less significance, albeit with heterogeneity across groups. The estimated pronounced upturn in SWB for migrants substantiates the usefulness of SWB both as a concept for policy-makers to target and for researchers to incorporate in their studies.

JEL codes

D91, H75, I31, R23

Keywords

Regional migration, wages, subjective wellbeing, non-pecuniary amenities.

Summary haiku

Age, gender, patience.
Which people move and exchange
Wellbeing for wage?

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Tables and Figures

1 Introduction

We analyse the relationships between subjective wellbeing (SWB)[1], wages and internal migration. First, we develop an intertemporal theoretical model of these relationships and then test the resulting model predictions using longitudinal panel data from Australia. In examining these relationships, we test whether location and migration decisions – which are important revealed preference choices of individuals – are determined in part by SWB and/or wage considerations.

One motivation for the study is a prominent finding by Glaeser et al. (2016) that many people (in the USA) move to 'unhappy places', i.e. places where SWB is, on average, lower than elsewhere. Assuming that people are (at least boundedly) rational, this finding calls into question the contention that SWB is akin to utility, and poses the question of whether SWB is a useful concept for policy-makers to consider when making decisions. To shed more light on these issues, we test whether people make location and migration decisions based on the SWB and/or wage prospects of different places, and test also whether internal migrants actually achieve greater SWB and/or greater wages when they shift location within the country.

Throughout the study we concentrate on internal migration within Australia to avoid constraints associated with legislated barriers to movement across countries. Our key data source is the Household Income and Labour Dynamics in Australia survey (HILDA), a longitudinal panel dataset. Our sample includes over 16,000 Australians, including over 2,000 internal migrants across 13 Major Statistical Regions (MSRs) of Australia, for 14 annual waves from 2001 to 2014.

Our analysis comprises four main parts. In section 3, we develop an intertemporal theoretical model of location choice in which individuals can choose to live in places with different attributes at different stages of their life. We show that, depending on individual characteristics, a well-informed rational individual may choose to move to an 'unhappy place', either as rated by themselves or as viewed on average by others. Their choice will be influenced, *inter alia*, by their personal preferences over pecuniary versus non-pecuniary items, their age, the real interest rate, and their rate of time preference. Thus we expect considerable heterogeneity in location and migration choices across individuals.

Sections 4 and 5 outline our empirical model and data and in section 6 we present a range of descriptive statistics. One key descriptive feature that we observe is a large and sustained upward jump in SWB, on average, at the time of migration; by contrast, wage income, on average, does not lift after migration.

[1] SWB is derived from a survey question asking respondents to rate themselves on a 0 to 10 scale for the question: *All things considered, how satisfied are you with your life?*

In section 7.1 we estimate discrete choice models to predict which factors determine: (a) whether an individual is likely to leave a particular location, (b) in which location a migrant chooses to locate, and (c) the location choice of all survey participants whether or not they migrate. The first two models are migration *flow* models while the third can be conceptualised as a stock model explaining the location of the current population *stock*. For this full sample, the most important determinants of location choice reflect high moving costs and unobserved attributes of the places where they already live, with most people staying in the same location across years. Prospective labour market outcomes affect location decisions for this sample, while we find considerable heterogeneity in the effect of SWB on location choice. Wages have a stronger impact on location choice than SWB for the full sample.

When we concentrate just on migrants we find that factors determining emigration from a location are again mostly labour market related. Conversely, SWB differences are estimated to be the main determinant of new location choice, accompanied by considerable heterogeneity.

Section 7.2 presents estimates of actual (*ex post*) outcomes for SWB and weekly wage income (from here on in we refer to weekly wage income as 'wages' in the context of our *ex post* analysis). We do so both for migrants as a whole and for a range of migrant sub-samples, controlling for a range of personal characteristics and for national factors as well as individual fixed effects. For wellbeing we estimate a downward trend in SWB prior to migration and then estimate a large jump in SWB in the year of migration; this jump is sustained over the following four years. The jump in SWB is statistically significant in each year from the time of migration onwards and is material relative to other sources of SWB changes such as marriage. Similar SWB findings occur across virtually all our sub-samples – by age, gender, time preference, and various reasons for moving.

For wages, our estimates show that none of the wage differentials across years is statistically significant from zero when we consider the full migrant sample. Wage outcomes do, however, display considerable heterogeneity across sub-samples.

We test predictions from our theoretical model for the influence of SWB and wage changes on migration across age groups with differing time preference profiles. Our results are mostly consistent with the theoretical predictions, though the differences in behaviour are not statistically significant. Young people with high time preference (i.e. those who 'live for the present') experience a greater boost to SWB after migration than do more patient young people. The opposite outcome occurs for older people, where more patient people have the higher SWB payoff. We find older people with low time preference experience a greater fall in wages immediately following migration than do those with high time preference and this difference is sustained thereafter. However, in contrast with the theoretical predictions, we find that for younger people, wages rise similarly immediately upon migration for high and low time preference individuals, and wages then rise less rapidly for those with low time preference.

Our sub-sample results show that life-satisfaction improvements tend to be larger in cases where wage gains are relatively smaller, and these differences relate closely to migrants' stated reasons for moving. This result is consistent with the theoretical prediction that migration facilitates trade-offs between wages and SWB.

Overall, both the theoretical and empirical aspects of our paper show that location decisions reflect individual preferences and characteristics. High moving costs constrain many people to remain in their existing location even though that location may be characterised as an unhappy place. However for migrants, both the *ex ante* and *ex post* evidence validates the importance of SWB in human decision making. While we observe heterogeneity in location choices with respect to place-based SWB (i.e. the average wellbeing of a place), we nonetheless find a consistent pronounced upturn in individual SWB for migrants that is sustained for at least four years after migration. This implies that though people may move to an *unhappy place*, this choice does not, in general, reduce their own *individual* life-satisfaction.

Our findings therefore substantiate the usefulness of SWB as a concept for policy-makers to target, and confirm the importance of researchers taking SWB seriously as a determining factor in people's decisions. In section 2 we briefly review related studies, prior to outlining our theoretical model and empirical results in subsequent sections.

2 Related Literature

Spatial equilibrium theory predicts that, in equilibrium, no person should be able to improve their wellbeing by moving. However, Glaeser, Gottlieb, and Ziv (2016) present a range of evidence showing that there is significant variation in individual SWB across metropolitan areas of the United States, even after controlling for individual characteristics and fixed effects. To explain this empirical finding, they present a model in which wellbeing is a component of the utility function, rather than equal to utility itself. "Achievements", such as raising a family, can enter the utility function alongside wellbeing. Individuals may be willing to give up some subjective wellbeing in return for achieving some other objectives. Hence, in equilibrium we could expect people living in low-SWB areas to be compensated by higher levels of other factors that could facilitate achievements, such as real income or by lower housing costs.[2]

The Glaeser et al model does not explicitly include intertemporal decision-making in their analysis of location choice and, in this respect, it is incomplete given that location choice is an inherently intertemporal optimisation problem for the household. In Section 3 we show that a

[2] For the USA, the means of such compensation has changed over time: in the 1940s, declining cities were compensated by higher real incomes; in 2000 declining cities were compensated by lower housing costs.

dynamic model of location choice shares some similar implications to their model. However, by including intertemporal considerations, we show that it may not be necessary to distinguish between subjective wellbeing and utility to explain what may at first sight appear to be sub-optimal location choices. To test the plausibility of our theory, we employ two distinct empirical approaches: *ex ante*, how people decide where to live; and *ex post*, the wellbeing outcomes of individuals who do move. Relevant literature covering these different perspectives of location choice are discussed in the following two sub-sections. We pay most attention to studies that have incorporated variables reflecting wellbeing or amenities, as well as income, in their analysis.

2.1 Ex Ante: Location Choice

Previous research on within-country location choice and population movement has primarily focused on economic and geographic motives and constraints. Labour market characteristics and moving costs have been well established as determinants of location choice in empirical studies e.g. Davies, Greenwood, and Li (2001). Several empirical studies have also tested the influence of non-pecuniary amenities on location choice, including measures of specific factors, such as climate, and aggregated indices of more general concepts, such as quality of life.

One approach to examining the importance of amenities is to include measures of them as covariates in probability models for the propensity to move. Findings from studies using this method generally support the hypothesis that people are more likely to leave from areas with lower amenities (e.g. see Berger and Blomquist 1992; Whisler et al. 2008; Herzog and Schlottmann 1986).

Some similar work has included subjective measures of location quality as an explanatory variable for the decision to move. Rabe and Taylor (2010) estimate the influence of a binary indicator for whether or not the individual 'likes' their neighbourhood on their likelihood of moving, finding that people who are satisfied with their area are less likely to leave. On the other hand, Landale and Guest (1985) find that satisfaction with where one lives plays little role in revealed preferences for mobility, even though it is important for stated preferences.

A broader assessment of location choice considers both inward and outward migration. There is considerable evidence that at least some amenities (disamenities) attract (deter) people within a country. Numerous studies, for example, show that climate factors significantly affect migration flows (e.g. Rupasingha and Goetz 2004; D. E. Clark and Cosgrove 1991; Schachter and Althaus 1989; Mueser and Graves 1995; D. E. Clark and Hunter 1992).

Some studies that rely on individual-level data have applied a multinomial choice framework under the assumption that the utility someone derives from choosing a particular location depends on its characteristics.[3] Liu and Shen (2014) find several specific amenity features, including climatic, social and cultural attributes, significantly predict location choice of skilled migrants in China. However, the findings show job-related location attributes do more to explain behaviour. On the other hand, Duncombe, Robbins, and Wolf (2001) emphasise the role of a broad range of amenities as well as low tax rates in attracting retirement-age individuals.

Several papers have included amenities as explanatory variables in a mixed logit model of location choice.[4] Gottlieb and Joseph (2006) find weak evidence for the importance of amenity factors in the location choice of recent college graduates: recreational facilities have no significant effect; the influence of climate is small and only weakly significant on average, though it is valued more by some than others; and low crime rates have varying effects for graduates at different levels. In examining the simultaneous choice of residential and work location choice, Ebertz (2009) shows consumers are significantly deterred by the disamenity of longer commuting times, but there is significant variance in tastes among the sample. Steele et al. (2016) find that deprivation of an area significantly encourages outmigration and discourages inwards migration of households. The level of aversion to deprived areas is found to vary significantly among households.

A handful of studies have examined differences in preferences for amenities over the life-course. Liu and Shen (2014) find little evidence that preferences for amenities differ throughout the life-course. The opposite result is found for the effect of amenities on the propensity to move by Whisler et al. (2008). Clark and Hunter (1992) and Chen and Rosenthal (2008) show younger individuals more heavily favour areas with better economic conditions and business environments, while older individuals shift towards areas richer in amenities and quality of life.[5]

Grimes, Oxley, and Tarrant (2014) investigate the importance of *subjective* wellbeing measures in predicting location choice, which they use alongside *objective* measures to predict international migration. The authors consider net immigration rates across 20 countries, with macro-data spanning up to 50 years. Results provide evidence that SWB has predictive power even when controlling for country gross national income (GNI) per capita. However neither this

[3] Examples of the use of a conditional logit model in the context of location choice in the US include Bartel (1979); Bauer, Epstein, and Gang (2002); Jaeger (2000) and Jaeger (2006). However, these studies have focused primarily on the influence of labour market conditions in the location decision.

[4] The mixed logit model is a subset of the multinomial choice model, in which variation in preferences is allowed across individuals.

[5] The methods used in these latter studies deviate from multinomial models of location choice. Chen and Rosenthal (2008) develop indices for quality of life and quality of the business environment in locations throughout the US. The difference in each of these indices is calculated for an individual's location in 1995 to that of where they resided in 2000. The difference is then regressed on individual characteristics. Clark and Hunter (1992) consider a large number of specific amenity attributes and compares them to indicators of economic opportunity and fiscal factors as arguments of U.S. county net migration rates of white males. Results are compared by age groups.

study, nor others surveyed, tests the relationship between SWB and location choice using individual-level data, which is our focus.

2.2 Ex Post: Payoffs to Migration

In addition to studying the influence of SWB and economic factors on *ex ante* location choice, we consider the *ex post* SWB and income payoffs to migration. Few studies have analysed both of these aspects, especially for intra-country migration.

Stillman et al. (2015) exploit a migration lottery of individuals from Tonga to New Zealand to estimate causal effects of international migration on income and wellbeing measures. Because those who migrate were selected randomly, successful and unsuccessful applicants can be compared. Results show large income gains for Tongans moving to New Zealand both in the short-term and long-term, but wellbeing outcomes are mixed. Happiness is no different in the first year of living in New Zealand and it declines after four years (relative to what it would have been). On another subjective measure – the sum of answers to questions about the amount of peacefulness, cheerfulness, nervousness and downheartedness – respondents are better off both on arrival and after settling in New Zealand for four years.

Impacts of migration may be also be well identified in panel datasets which include observations of migrants both before and after they move. Controlling for individual fixed effects enables researchers to eliminate time-constant unobserved differences between migrants and non-migrants and attribute changes to *within-person* variation. Changes in outcomes can be plotted over time around migration by controlling for the time that has passed since the event. Melzer (2011) uses this approach to observe the effect of migration on SWB over several years by using dummy indicators for the number of years since migration, while Frijters, Johnston, and Shields (2011) also include dummies for the years leading up to migration to measure anticipation effects. These studies control for time-varying individual characteristics which are likely to influence SWB together with year dummies to capture economy-wide shocks.[6] [7] Nowok et al. (2013) performs a similar analysis with British data.

Each of these studies shows that SWB tends to increase after moving. Results from Melzer (2011) show positive wellbeing outcomes for individuals as a result of moving from East to West Germany during 1990-2007. Ten years after the migration, positive effects remain significant for women, but for men they do not persist beyond six years. Using the same data as the present study (HILDA), Frijters, Johnston, and Shields (2008) find happiness decreases in the lead up to internal migration, increases at the time of migration and then returns to original

[6] Rather than including specific individual characteristics, Frijters, Johnston, and Shields (2008) use year dummies to capture changes in individual characteristics over time, as their migration dummies are at the quarterly level.
[7] While SWB measures are usually discrete variables, most studies use ordinary least squares (OLS) rather than ordered logit or probit for estimation because earlier work (e.g. Ferrer-i-Carbonell and Frijters (2004)) shows there is little effect on the results and they are easier to interpret.

levels after several years. Nowok et al. find similar results. The authors argue that moving could provide a "way out of unhappiness" caused by some other factor in the individual's life (Nowok et al. 2013, p.998). Fading impacts of migration on wellbeing in the long-term is consistent with set-point theory, which argues that individuals tend to return to a baseline level of happiness.

Other studies have used a fixed effects strategy to focus on particular types of migration or wellbeing outcomes among particular subgroups. Kettlewell (2010) considers the effect of *rural-to-urban* migration on life-satisfaction for males and females; Bradley and Van Willigen (2010) examine the effect of migration on symptoms of depression in older people; and Switek (2016) look at the effect of migration on life-satisfaction of young adults who move for work-related or other reasons.

Fixed effects methods have also been used for measuring changes in income around migration. Results generally lean toward positive economic outcomes of migration. Bartel (1979) finds that white male migrants within the U.S. experience higher wage growth than non-migrants, as do Böheim and Taylor (2007) for men in the UK. Yankow (2003) argue that for meaningful inference, the effect of migration needs to be separated from the effect of changing jobs. He finds a positive return to location mobility over and above the effect of job change, and it is larger for more educated individuals. Using propensity score matching to deal with selection effects, Ham, Reagan, and Li (2005) find a positive effect of migration for college graduates, a negative effect for high school dropouts, and no effect for other educational groups.

A further relevant study is Mitchell (2008) which uses the HILDA data to measure the effect of migration on wages in Australia by skill. The author finds that mobility increases the likelihood of receiving higher pay after controlling for selection bias with a simultaneous equation approach.

None of these studies of *ex post* payoffs to migration also analyse *ex ante* determinants of migration. The results of both approaches tend to show that economic determinants such as wages and unemployment affect, and (for the individual) are affected by, migration. However, there are very few studies that examine the roles of both SWB and wages in affecting, and being affected by, migration decisions – and none that does so with both *ex ante* and *ex post* analysis based on a consistent set of data. We do so after first setting out a theoretical model including both pecuniary and non-pecuniary determinants of migration within an intertemporal setting.

3 Theoretical Concepts

We conceptualise the effects of incomes, amenities and other factors on the individual's migration decision by considering an individual who lives for two generations (t=1,2) following graduation from education. In each generation, the individual can locate in one of two locations (j=A,B).

In each generation,[8] the individual earns real income (adjusted for local housing costs) of y^A (y^B) in location A (B), and has non-pecuniary amenities n^A (n^B). The individual's actual income in period 1 (2), y_1 (y_2), depends on her location and so equals y^A if located in A and y^B if located in B. Similarly, her non-pecuniary consumption of amenities (n_1 and n_2) equals n^A if located in A and n^B if located in B. We initially ignore moving costs[9] and assume that earnings in each location are constant across time. To keep the analysis concise, we consider an individual with a separable utility function of the form:

$$U = \log(c_1) + N_1 + (1+\rho)^{-1}[\log(c_2) + N_2] \qquad (1)$$

where: *log* denotes the natural logarithm, c_1 (c_2) is consumption of market goods and services in generation 1 (2), N_1 (N_2) is $\log(n_1)$ ($\log(n_2)$), and ρ is the (generational) rate of time preference. The utility function is maximised subject to the budget constraint:

$$c_2 = y_2 + (1+r)(y_1 - c_1) \qquad (2)$$

where: r is the generational real interest rate. Maximisation of (1) subject to (2) yields the Euler equation for consumption:

$$c_2 = \left(\frac{1+r}{1+\rho}\right) c_1 \qquad (3)$$

Equations (2) and (3) yield the following solutions for c_1 and c_2:

$$c_1 = \frac{(1+\rho)}{(2+\rho)} y_1 + \frac{(1+\rho)}{(2+\rho)(1+r)} y_2 \qquad (4)$$

$$c_2 = \frac{(1+r)}{(2+\rho)} y_1 + \frac{1}{(2+\rho)} y_2 \qquad (5)$$

which yields the optimised utility function:

$$U = (1+\rho)\log\left[\frac{1}{(2+\rho)} y_1 + \frac{1}{(2+\rho)(1+r)} y_2\right] + N_1 + (1+\rho)^{-1} log \left[\frac{(1+r)}{(2+\rho)} y_1 + \frac{1}{(2+\rho)} y_2\right] + (1+\rho)^{-1} N_2 \qquad (6)$$

In (6), the values of y_1, y_2, N_1 and N_2, are determined by the choice of location (A or B) in each period. To illustrate how the optimal location in each period depends on parameter values, we proceed numerically by substituting in values for the six parameters (ρ, r, y^A, y^B, N^A and N^B) and calculate the resulting utility for each combination of locations over the two generations: (A,A), (A,B), (B,A) and (B,B). The location pair which yields the highest utility for a given set of parameters is the chosen location pair for the individual over their (post-education) lifetime.

[8] In our numerical simulations, we assume each generation to be in the order of 25 years.
[9] Subsequently, we incorporate a non-pecuniary moving cost that is subtracted from utility if the individual migrates to a new location.

Table 1 shows the resulting simulations. Simulation 0 shows the base case in which parameters are set so that the individual is indifferent between any of the four location combinations. (A value of 0.5 for ρ corresponds to an annual rate of time preference of 0.0164 over a generation of 25 years, while a value of 0.7 for r corresponds to an annual real rate of interest of 0.0215; we initially ignore the column marked M.) The second block of the table (simulations 1 to 4) confirms expectations that an increase in each of y^A and N^A result in a preference to locate in (A,A) while an increase in each of y^B and N^B result in a preference to locate in (B,B).

In the third block of the table we begin in simulation 5 with a parameter combination of high wages in location A and high amenities in location B that favours location pair (A,A) given the other parameters. Simulation 6 then raises the real interest rate which results in a change in optimal location pair to (A,B). The reason for the change in optimal location is that the individual can earn high income in the first period by locating in A and use the higher investment return on their savings from that period to locate in an area with higher amenities later in life. Simulation 7 shows that the same (A,B) location pair arises with the original real interest rate (0.7) and a low rate of time preference (0.1).

Table 1: Simulations of Optimum Location Choice

	Parameters							Utility in each location pair				Optimum	
Simulation	**ρ**	**R**	**y^A**	**y^B**	**N^A**	**N^B**	**M**	**U(A,A)**	**U(A,B)**	**U(B,A)**	**U(B,B)**	**Location**	**U^1/U^2**
0	0.5	0.7	100	100	4.6	4.6	0	17.015	17.015	17.015	17.015	Indifferent	1.166
1	0.5	0.7	110	100	4.6	4.6	0	17.222	17.148	17.094	17.015	(A,A)	1.170
2	0.5	0.7	100	110	4.6	4.6	0	17.015	17.094	17.148	17.222	(B,B)	1.170
3	0.5	0.7	100	100	4.7	4.6	0	17.182	17.115	17.082	17.015	(A,A)	1.165
4	0.5	0.7	100	100	4.6	4.7	0	17.015	17.082	17.115	17.182	(B,B)	1.165
5	0.5	0.7	110	100	4.6	4.7	0	17.222	17.214	17.194	17.182	(A,A)	1.170
6	0.5	1.1	110	100	4.6	4.7	0	17.204	17.206	17.166	17.164	(A,B)	1.128
7	0.1	0.7	110	100	4.6	4.7	0	18.147	18.169	18.128	18.146	(A,B)	0.980
8	0.5	0.7	110	100	4.6	4.74	0	17.222	17.241	17.234	17.249	(B,B)	1.164
9	0.9	0.5	110	100	4.6	4.74	0	17.295	17.279	17.299	17.278	(B,A)	1.376
10	0.5	1.1	110	100	4.6	4.7	0.003	17.204	17.203	17.163	17.164	(A,A)	1.128

Notes: ρ is the (25 year) rate of time preference; r is the (25 year) real rate of interest; y^A is income earned in location A; y^B is income earned in location B; N^A is non-pecuniary amenities experienced in location A; N^B is non-pecuniary amenities experienced in location B; M is non-pecuniary moving costs if location changes between young and old; **U(A,A)** is lifetime utility obtained if located in A in period 1 and located in A in period 2 [and similarly for **U(A,B)**, **U(B,A)** and **U(B,B)**]; **Optimum Location** is the location pair that delivers the highest lifetime utility for the individual; **U^1/U^2** is the ratio of first period utility to (undiscounted) second period utility for the optimum location pair.

In the fourth block of the table (simulations 8 and 9) we increase the amenity value of location B while holding constant the two wage payoffs and the amenity value of location A. This results in the optimal location pair in simulation 8 of (B,B); the shift from (A,A) in simulation 5 to (B,B) in simulation 8 is driven by the greater amenity-related attractiveness of B relative to A. In simulation 9, we increase the rate of time preference (ρ) to 0.9 and decrease the real interest rate (r) to 0.5. The resulting optimal location pair is now (B,A); i.e. the individual moves from the high amenity, low wage location to the low amenity, high wage location. The individual in this simulation 'lives for the present' and so enjoys the high amenities when young but must make up for that by earning higher wages when old in order to satisfy their lifetime budget constraint.

Together, blocks 3 and 4 show that an optimizing individual may, over her lifetime: (i) remain in a high wage, low amenity area (A,A); (ii) remain in a low wage, high amenity area (B,B); (iii) migrate from a high wage, low amenity area to a low wage, high amenity area (A,B); or (iv) migrate from a low wage, high amenity area to a high wage, low amenity area (B,A). A person who discounts the future highly is more likely to value non-pecuniary amenities highly early in life and so live in a high amenity, low wage area when young; conversely, a person who has a low rate of time preference is more likely to choose a location in which they can earn a high income when young that they can use for high amenity consumption when older. Thus a high amenity location may attract a disproportionate number both of young people who live for the present and of older people who have saved in their earlier lifetime.[10] By contrast, a lower amenity area with higher real wages is likely to attract younger people who live for the future and older workers who need to earn income for their retirement.

In simulation 10, we add one further complexity by allowing for a (non-pecuniary) cost of moving, M,[11] for the location pairs (A,B) and (B,A) involving inter-regional migration. We use the same parameters for this simulation as for simulation 6 which previously resulted in the optimal location pair (A,B). With the addition of the moving cost (M=0.003), the utility associated with each of (A,B) and (B,A) now falls by that amount while that associated with locations (A,A) and (B,B) remain unchanged from simulation 6. The result is that (A,A) is now the preferred location. Thus the individual remains in the high wage, low amenity location even though, in the absence of moving costs, she would have preferred to move in later life to a high amenity area. Similarly, for other parameter combinations, an individual may remain in a high

[10] For example, relative to Australia as a whole, the (high amenity) Gold Coast area has a higher proportion of its population in both the 20-44 age group and in the 60+ age group, and has a lower proportion of its population in the 45-59 age group (source: 2011 census).

[11] We expect that M will differ according to one's attachment to the area. For instance, older people (especially those with family and friends living locally) are likely to have higher non-pecuniary moving costs than younger people, while home owners are likely to have higher moving costs than renters (e.g. see DiPasquale and Glaeser 1999). It would be straight-forward to add a pecuniary cost of moving that enters the budget constraint with similar outcomes.

amenity area over both periods even though, in the absence of moving costs, she would prefer to shift to a higher wage area later in life.

One other point to note from Table 1 is the column marked U^1/U^2 where U^1 is utility in the first generation of life and U^2 is (undiscounted) utility in the second. Depending on the relationship between ρ and r, and on the opportunities afforded by each location, individuals may either increase their utility at the time of migration (simulation 7) or reduce their utility (simulations 6, 8 and 9).

From this simple, but powerful, theoretical model we can conclude that simply observing people moving to either high or low wage places, or to high amenity or low amenity places does not, by themselves, contradict optimising behaviour. Similarly, observations of people migrating and simultaneously reducing their utility can be consistent with optimising behaviour.[12] Optimal migration choices will depend on the individual's own preferences (e.g. rate of time preference), the choices available in different locations, the real rate of interest and the magnitude of moving costs. We therefore expect to see considerable heterogeneity in migration choices reflecting heterogeneous preferences and opportunities. Nevertheless, from the simulations reported in Table 1, we expect that individuals who have a low rate of time preference are more likely to migrate from high wage to high amenity areas later in life while those with a high rate of time preference are more likely to migrate in the opposite direction. Applying the same insights, if we were to extend the model to include retired people, we would expect that amenities will become more important than earned income opportunities in influencing location choice for that stage of life.

4 Empirical Model

We use the theoretical model of section 3 to guide our empirical work that estimates both the *ex ante* determinants of migration and the *ex post* payoffs to migration. We investigate the *ex ante* question using discrete choice analysis, with emphasis on the roles of incomes, wellbeing (SWB) and other location attributes in decision-making. We then track the changes in both SWB and wage measures of individuals who migrate. In this *ex post* setting we test predictions of our theory of dynamic utility optimisation.

In both sections of the analysis, migration is defined as residing in a different Major Statistical Region (MSR) within Australia than the previous period. These MSRs are defined in Section 5. Individuals can freely choose to live in any of the 13 Australian MSRs.

[12] If we allow for rising incomes over time (e.g. for better educated individuals who are likely to have a strongly rising lifetime income path), the potential for a wide range of outcomes is further increased.

4.1 Ex Ante: Location Choice

Our *ex ante* location choice analysis investigates three distinctly framed questions:

1. Which location attributes are associated with outward migration;
2. Which location attributes attract individuals who decide to move; and
3. Which location attributes determine location choice overall?

The first of these questions focuses on *push-factors* of migration and the second on *pull-factors*. However assuming that the decisions of *whether to move* and *where to move* are separate is open to criticism (e.g. Davies, Greenwood, and Li 2001). Individuals face a choice set of residential locations which includes the option of remaining in the location in which they currently reside. This approach is pursued in the third question, in which the two former questions are incorporated into a single equation. The first two approaches concentrate on population *flows* whereas the third approach addresses the population *stock*, analysing where people reside at a point in time.

Each of the three questions can be modelled using discrete choice models. We include *location-year-specific* SWB and wages (in logs) as independent variables in each *ex ante* choice model to understand the role of each factor in location choice.[13] Other location attributes we control for are a quadratic in distance from one's location in the previous period, the population (in logs), the unemployment rate, and the average housing rent (in logs). In some specifications we also consider the role of individual characteristics or life circumstances. All location attributes and individual characteristics enter the models with a one period lag since a move represents a change in location at some point *in the past year*.

4.1.1 Push-Factors of Migration

Push-factors of migration are estimated with a binary logit model for whether one decides to move in a period, conditional on attributes of the MSR in which they were living in the most recent period. We use an individual fixed-effects specification to eliminate any time-constant unobserved factors relating to individuals.[14] Due to the requirement of fixed-effects for there to be variation over time in the dependent variable for individuals, many individuals are dropped from the estimation sample. All results, therefore, should be inferred as informative only about the sub-group of the population that moves at least once within the sample period.

Let us assume $m_{i,t}^{*}$ represents the net benefit to individual *i* at time *t* of leaving his or her location, which we cannot observe. We can observe whether or not the individual chooses to

[13] Wages are used instead of total incomes because the wage component (unlike other income components) is specific to where one lives.
[14] We also tried a random effects specification but it was rejected against the fixed effects model by the Hausman test.

migrate, which we can represent in a binary dependent variable $M_{i,t}$ equal to 1 if individual *i* chooses to migrate at time *t*, and 0 otherwise. The logit model is as follows:

$$m_{i,t}^{*} = \boldsymbol{\beta} \boldsymbol{Z}_{i,t-1}^{j} + \boldsymbol{\delta} \boldsymbol{X}_{i,t-1} + Y_t + \mu_i + \varepsilon_{i,t} \qquad (6)$$

where we assume $M_{i,t} = 1$ if $m_{i,t}^{*} > 0$ and $M_{i,t} = 0$ otherwise. The vector $\boldsymbol{Z}_{i,t-1}^{j}$ represents attributes of the location *j* in which individual *i* lived at *t-1*, *relative* to a population weighted average of the attribute in all other locations.[15] These variables represent potential *push-factors* of migration and $\boldsymbol{\beta}$ are the corresponding marginal effects of these attributes to be estimated. The vector $\boldsymbol{X}_{i,t-1}$ summarises characteristics of individual *i* at time *t-1* that could affect the propensity to move and $\boldsymbol{\delta}$ is the corresponding vector of marginal effects associated with these variables. Year fixed effects are captured in Y_t to absorb any nation-wide variation over time in the propensity to migrate, μ_i is the individual fixed effect and $\varepsilon_{i,t}$ is an independent and identically distributed (IID) error term, clustered at the individual level.

We estimate the model using four distinct definitions of the vector $\boldsymbol{X}_{i,t-1}$ which vary from including only the most clearly exogenous variables to including variables with greater potential for endogeneity. In the initial version we treat the vector as empty, then successively add groups of variables which may affect propensity to migrate. The first set of added variables is a vector of individual characteristics; we then also include a range of dummies for having experienced certain life events in the past year as well as self-reported health status; and finally, we add a dummy indicating whether one is a labour force participant.

4.1.2 Pull-factors of Migration

Next, we estimate the location attributes which attract an individual to select a location, conditional on having chosen to move. We start with McFadden's (1973) conditional logit model which models a choice from a discrete set of alternatives. We can consider the model as operating under a random utility framework in which the utility someone derives from choosing a particular location depends on its attributes.

The utility that individual *i* would derive from living in location *j* at time *t* can be represented by $U_{i,j,t}$:

$$U_{i,j,t} = \boldsymbol{\beta} \boldsymbol{Z}_{i,j,t-1} + \alpha_j + \varepsilon_{i,j,t}. \qquad (7)$$

The vector $\boldsymbol{Z}_{i,j,t-1}$ are attributes of location *j* in the previous period, which may also be specific to the individual, and $\boldsymbol{\beta}$ are the corresponding marginal effects to be estimated.[16] The

[15] Constructing the variables as *relative* to other locations captures the fact that individuals deciding where to live can compare the current location against all possible locations.

[16] Unlike the emigration (push) model, we no longer define location characteristics *relative* to the characteristics in other locations because the choice model compares values across all potential pairs of locations.

term α_j represents location-specific fixed effects, which are included to control for unobserved time-invariant attributes of the potential choices, such as climate. Identification therefore comes from within-location variance over time. For identification it is necessary to set the location-specific constant of one location alternative to zero, and we do this for Sydney. It is assumed that in each period t, individuals i can choose to live in one location j from a choice set C, which includes all MSRs in Australia *except for* the one that they have chosen to leave. The final term $\varepsilon_{i,j,t}$ is a random error term term, which we allow to be clustered at the individual level.[17]

Let $Y_{i,j,t}$ be an indicator variable equal to 1 if individual i chooses to live in location j at time t. Then the probability that individual i chooses location k is equal to the probability that the utility they derive from that location is greater than the utility they could enjoy in any other alternative. That is,

$$\Pr\left(Y_{i,k,t} = 1\right) = \Pr(U_{i,k,t} > U_{i,j,t}) \text{ for all } j \neq k. \quad (8)$$

If $\varepsilon_{i,j,t}$ are IID residuals following a Type I extreme value distribution, we can estimate the unknown parameters in the utility function with a discrete choice conditional logit model as shown by McFadden (1973). However, validity of the conditional logit approach requires independence of the unobserved components of utility across individuals, locations and time. Independence across time is likely violated because multiple observations are included of individuals who moved more than once. Furthermore, independence of errors across locations implies that the cross-elasticities of the probability of choosing between two locations, given a change in the characteristics of a third location, must be equal, i.e. the independence of irrelevant alternatives (IIA). The implied substitution patterns are unrealistic in the context of location choice because they do not account for similarities and dissimilarities of unobserved location features.

These two issues with conditional logit can be overcome with a mixed logit approach, in which unobserved taste heterogeneity is captured in the model (Train, 2009). The mixed logit allows individual-specific coefficients on the location attributes and constants. In practice, we choose a distribution for which the coefficients on each variable are assumed to vary across individuals. Allowing the coefficients to vary across individuals while remaining constant within individuals over time and alternatives both allows for the panel structure and relaxes the restrictive IIA property.[18]

[17] We apply the clustering method to all subsequent models described for discrete choice.
[18] The use of panel data is made appropriate because random coefficients are fixed within individuals across time periods, inducing correlation in unobservables over time. In fact, unobserved individual heterogeneity will be even better identified with the use of panel data. The common influence of individual-specific coefficients in the unobserved utility derived from each location induces correlation across locations, relaxing IIA.

In the mixed logit model, the coefficients $\boldsymbol{\beta}$ and location-specific constants α_j in equation (8) are replaced with individual-specific coefficients: $\boldsymbol{\beta} = \boldsymbol{\beta}_i$, and $\alpha_j = \alpha_{i,j}$. We assume that $\boldsymbol{\beta}_i$ and $\alpha_{i,j}$ are randomly distributed among the population of individuals *i*. Thus $\boldsymbol{\beta}_i$ reflects the individual-specific coefficients on the location attributes in vector $\boldsymbol{Z}_{i,j,t-1}$. Similarly, $\alpha_{i,j}$ indicates each individual's preference for time-constant location attributes. This incorporation of heterogeneity in location-specific fixed effects is desirable because valuations on time-constant location attributes such as climate may be highly subjective.[19]

We collect unknown parameters in a single term which is indexed for individual variation, $\boldsymbol{\eta}_i$. It is assumed that random coefficients have the density $f(\boldsymbol{\eta}_i\,|\boldsymbol{\theta})$ where $\boldsymbol{\theta}$ represent the distribution parameters. In our application, we assume a multivariate normal distribution such that the distribution parameters to be estimated are the means and standard deviations of each random coefficient.

An issue in estimating the mixed logit model is that it requires simulation,[20] which is highly taxing with regards to computation time.[21] For each variable that has random coefficients, an additional parameter (the standard deviation) has to be estimated, adding to the time burden. Due to computational restrictions, and to our focus on SWB and wages, we did not include random coefficients on all variables and instead hold coefficients fixed on the population and distance terms implying that preferences for these are equal across the sample.

4.1.3 Combined Push and Pull-factors of Migration

The third approach to location choice is to assume individuals constantly face a choice set of all locations including the option to remain in the same location as they were in at the previous period. We again employ the mixed logit model but now include all individuals in the sample, regardless of their migration status, and we allow them to choose from all 13 MSRs. In this case, both push and pull-factors of migration are captured together with factors that may cause location to remain unchanged.[22]

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[19] Ideally we would allow correlation among random coefficients to induce correlation between preferences for time-constant location characteristics across alternatives. However, the added computation burden of this is too great.

[20] See Revelt and Train (1998) for an explanation of why simulation is necessary to solve the mixed logit and see section 6.6 of Train (2009) for an explanation of the simulation procedure.

[21] In our application we use 100 replications in the simulation process. Rather than using standard pseudo-random draws in the simulation process, we employ Halton sequences which are more effective (Train 2009). We use a burn-in of 15, i.e. we discard the first 15 Halton draws, which helps to remove correlation between sequences of draws. Train (2009) recommends that that the burn-in used should be at least as large as the largest prime used to generate the Halton sequences. In our full sample mixed logit, the largest prime is 61 (since our Stata program uses the first k primes for k variables with random coefficients and we have k=18). We therefore estimated a version of the full sample mixed logit with 146 replications and a burn-in of 61, which retains the same number of used replications as the version with 100 replications and a burn-in of 15. Results were largely unchanged.

[22] It is possible to allow the data to speak to push and pull-factors separately but this requires an interaction of each explanatory variable with a dummy for whether one lived in the alternative in the previous period (Steele et al. (2016)), adding to the computational burden.

We begin our empirical modelling for this approach with equation (8) above with random parameters. Because we are now applying the model to the full sample, we must consider that due to the financial and psychic costs of moving, a large portion of individuals will choose to stay in the same place as they were in at the previous period. Ignoring this *state dependence* can result in biased estimates (Heckman 1981) so we include the lagged dependent variable, $Y_{i,j,t-1}$. Because the lagged choice is likely to be correlated with both unobserved differences and the current choice, the need to control for unobserved heterogeneity is amplified. The mixed logit continues to be an effective way around this problem.

However, even if we deal with individual heterogeneity, we are faced with an initial condition problem because we do not observe each individual's initial location choice in the data. Hence, the influence of earlier choices remain in the error term which affects both the dependent variable and the first observation of the lagged dependent variable; ignoring this leads to inconsistent estimates.

We employ a solution to the initial conditions problem provided by Wooldridge (2005) which involves controlling for the initial observed choice, $Y_{i,0}$, and the within-person means of the exogenous variables over time, $\overline{\boldsymbol{Z}}_{i,j}$.[23] [24] We also include the first observed value of each exogenous variable $\boldsymbol{Z}_{i,j,0}$ as controls because assuming they have the same coefficient as all other years can bias results (Rabe-Hesketh and Skrondal 2002).

To define our dynamic model of overall location choice, we add the lagged dependent variable and the Wooldridge adjustment variables to our definitions of $U_{i,j,t}$. The model to be estimated as a mixed logit is therefore:

$$U_{i,j,t} = \boldsymbol{\beta_i}\boldsymbol{Z}_{i,j,t-1} + \delta_i Y_{i,j,t-1} + \mu Y_{i,j,0} + \boldsymbol{\theta}\overline{\boldsymbol{Z}}_{i,j} + \boldsymbol{\sigma}\boldsymbol{Z}_{i,j,0} + \alpha_{ij} + \varepsilon_{i,j,t} \qquad (9)$$

In equation 10, as well as allowing for individual heterogeneity through $\boldsymbol{\beta}_i$ and $\alpha_{i,j}$, we also allow for heterogeneity in the propensity to move through δ_i.

Any of the utility functions for mixed logit can be extended to include controls for characteristics of the individuals by interacting variables for individual characteristics ($\boldsymbol{X}_{i,j,t-1}$) with location attribute variables in $\boldsymbol{Z}_{i,j,t-1}$ or with the location-specific constants α_j. In general, we refrain from doing so because the computational time required for the original version is already long and heterogeneity is captured by random coefficients. However in the combined model we do interact a homeownership variable with the lagged dependent variable (i.e. lagged MSR) since homeownership is hypothesised to increase the cost of moving MSR (Oswald 1996).

[23] Wooldridge (2005) initially advised including a separate value of $\boldsymbol{X}_{i,j}$ for each period t, but using within-means is more parsimonious and allows us to use an unbalanced panel. Values from the initial year should be included in the average, whereas they are not included in the constrained model (Rabe-Hesketh and Skrondal 2002).
[24] Examples of extensions of the Wooldridge solution to multinomial choice models include Bjørner and Leth-Petersen (2007); Haan (2005); and Cai, Mavromaras, and Sloane (2016).

4.1.4 Measuring Location-Specific SWB

One of the explanatory variables we incorporate is the SWB of a location; however the only information on wellbeing we have is at the individual level. Averaging this over individuals in each location for each time period may provide a distorted measure of the contribution each location makes to individual wellbeing because it is likely that some locations attract happier individuals. For instance, a location with a disproportionally high ratio of retired people may have high average SWB but this may be attributable to retired people having more leisure time than the rest of the population.

To isolate the location-specific component of SWB, we regress SWB on a dummy indicator for whether one lived in each MSR in each time period together with controls for other factors which could influence SWB: socio-demographic characteristics; individual fixed effects which absorb time-invariant unobservable factors; and year fixed effects which capture events across the whole nation in different periods.[25] The coefficients on the location-year dummies represent the added value to SWB that individuals receive on average from the place in which they live. These benefits may come from amenities, institutions and the social context of the location in that period. For identification, we set the location-year coefficient for Sydney in the first year to zero, such that all other coefficients are relative to this reference category.[26]

4.2 Ex Post: Payoffs to Migration

We now focus on what happens to the wellbeing and wages of individuals who move, *ex post*. We follow a similar method to Clark et al. (2008) who measure anticipation and adaptation of individuals' SWB to life and labour market events, and Nowok et al. (2013) who apply the same technique for moving residence. The empirical strategy we employ estimates changes in outcomes for those who move over time.

While our main interest is in how wellbeing and wages change after migration, it is valuable to consider several years before the move to check for trends in SWB and wages in pre-migration years. Pre-migration patterns may change our perspective of the post-migration outcomes. For example, if wages are on a rising path before migration, an increase in the year of migration is less likely to be attributed to the migration event itself. Rather, plotting out changes over time both before and after migration allows us to discern any sharp deviations in trend. The trajectory of outcomes prior to migration could also be related to the migration event itself.

[25] Following Ferrer-i-Carbonell and Frijters (2004) we use an OLS regression rather than an ordered logit or probit model since the interpretation is much easier and results are not materially affected for models of SWB.
[26] Using a generated regressor potentially downward biases our standard errors in the mixed logit model. The standard correction for this using bootstrapping is not computationally feasible given the already intensive simulation process. Haucap et al. (2013) encounter this same problem in their mixed logit model and argue it is not a serious concern if the estimated standard errors are small. The argument for adjusting location-year-specific SWB for the characteristics of the residents could also apply to wages and the unemployment rate. However, we do not apply a regression adjustment to these variables because they are sourced as aggregate variables from official statistics.

For example, migration could be triggered by declining wages or SWB. Alternatively, wages or (more likely) SWB could be affected by the anticipation of the approaching move.

For this analysis we use the sample of individuals who move across MSRs in our observed period, including observations of those movers in years before and after their move. The empirical setup involves modelling the outcome variable (i.e. SWB or wage income) of movers in a fixed effects OLS regression conditional on the number of years before or after migration, personal circumstances, and year fixed effects.[27] The fixed-effects approach enables us to measure within-person effects and controls for all time-constant individual factors which may affect the outcome.

To track the outcome variable relative to the time of migration, the number of years before or after migration is included as a set of dummy indicator variables which indicate the number of waves it has been since the individual migrated.[28] The timing dummies cover four waves (years) before and after migration plus the year of migration itself. The coefficients on these timing dummies represent the average difference in the outcome (wages or SWB) at each wave around migration relative to an allocated base period, conditional on the other controls.

Formally, following Nowok et al. (2013), we estimate the equation:

$$W_{i,t} = \alpha + \sum_{l=-L}^{l=\mathrm{L}} \beta_{M,t-l} M_{i,t-l} + \boldsymbol{\beta}'_X \boldsymbol{X}_{i,t} + Y_t + I_i + \varepsilon_{i,t} \quad (10)$$

where $W_{i,t}$ is the outcome measure (SWB or weekly wage income) for individual i in year t, and l represents the number of years before migration. The migration dummies are denoted by $M_{i,t-l}$, and equal 1 if individual i migrated in year $t-l$, and 0 otherwise, where l represents the period t in which the individual migrated. These migration dummies have coefficients $\beta_{M,t-l}$. We set the coefficient on M_{t-1} to zero so that all other coefficients on the migration dummies can be interpreted as the expected deviation in the outcome variable relative to the year before moving, conditional on other factors.

The vector $\boldsymbol{X}_{i,t}$ contains a set of control variables which we discuss below. Year fixed effects, Y_t allow for particular effects on the whole economy in a given year and I_i represent individual fixed effects. The random error term $\varepsilon_{i,t}$ is clustered at the individual level.

A particular issue in the model is how to deal with individuals who move multiple times. Restricting the sample to only one-time movers would be likely to introduce selection bias (Nowok et al. 2013). We make an assumption similar to Nowok et al. that only one timing effect takes place at a time, and that post-migration effects (i.e. where $(t-l) \geq 0$) dominate pre-migration effects $((t)-l<0)$. After those assumptions are taken into account, for any period

[27] Again, we use linear estimation for SWB, as well as for wages, for the reasons discussed earlier.
[28] Note that while we refer to migration as occurring at l=0, it really occurs at some point between l=-1 and l=0.

which still exhibits more than one pre- or post-migration effect, the effect relating to the most recent move dominates.

In implementing the regression, we estimate several different specifications which sequentially add more control variables in $\boldsymbol{X}_{i,t}$ in order to observe whether the changes in SWB or wages around migration are explained away by changes in individual circumstances which may be associated with moving. For example, it is plausible that individuals may be likely to move around the time of retiring, and we want to separate changes associated with migration from changes associated with such events. We report a basic model with no controls, then add individual characteristics and then life events and health status. In a final specification, we control for whether one is a labour force participant.

We are wary of potential endogeneity of explanatory variables in our various specifications, particularly of life events and labour-force related covariates. Therefore, our preferred specification is the one which only includes personal characteristics. We do not control for income in models of SWB because it is especially likely to be endogenous.

We compare results across a variety of sub-samples in the data. This is executed by adding a categorical variable for group membership to equation (11) and an interaction of this variable with each of the migration timing dummies. Controlling for group membership absorbs the average differences between the two groups. The interaction terms with the timing dummies then track the different pathways of each sub-sample. In particular, we consider the different pathways of groups defined by an interaction of age and time preference, in order to explore the relevance of dynamic utility maximisation to location choice.[29]

5 Data

Most data used in this study are sourced from the Household Income and Labour Dynamics in Australia (HILDA) individual-level unbalanced panel dataset which is designed to be a nationally representative sample. HILDA includes almost 20,000 individuals in each wave (19,914 in the first wave, replenished with 5,477 in wave 11) from around 7,500 households (7,682 in wave 1). We incorporate 14 waves from 2001 – 2014.

We drop defence personnel from our sample because their location choices are unlikely to be completely voluntary. We limit our sample to individuals at least 25 years of age to narrow our focus predominantly to individuals who have completed education. Also omitted are

[29] In specifications with interactions of migration timing dummies and some other characteristic e.g. age, we also include the characteristic itself as a control. This means that coefficients on the interaction terms are informative of the change in wellbeing over time relative to the omitted time (one year before migration). We do not need to do this when we examine differences by gender because it is fixed over time for all individuals in our sample and is therefore captured by the individual fixed effects.

temporary sample members – those who did not belong to the original household and were not new children of the original members or parents of those new children.

In the *ex ante* estimation the explanatory variables are lagged by one period. This means the first observation of each individual, and any other for which the previous wave is missing, is dropped. All measures of income and rents used in this study are adjusted for CPI inflation as reported by the Australian Bureau of Statistics (ABS) relative to a base year of 2012.

Migration is defined as a change in residence from one MSR to another, as defined by the ABS and described in Table 2 below.[30] We observe the MSR in which each individual lives at each observed period. There are 13 MSRs covered in our data, and we assume all 13 are available to all individuals in each period.[31] The abbreviations given in Table 2 are used throughout this document. The map in Figure 1 demonstrates how these MSRs are spread across Australia.

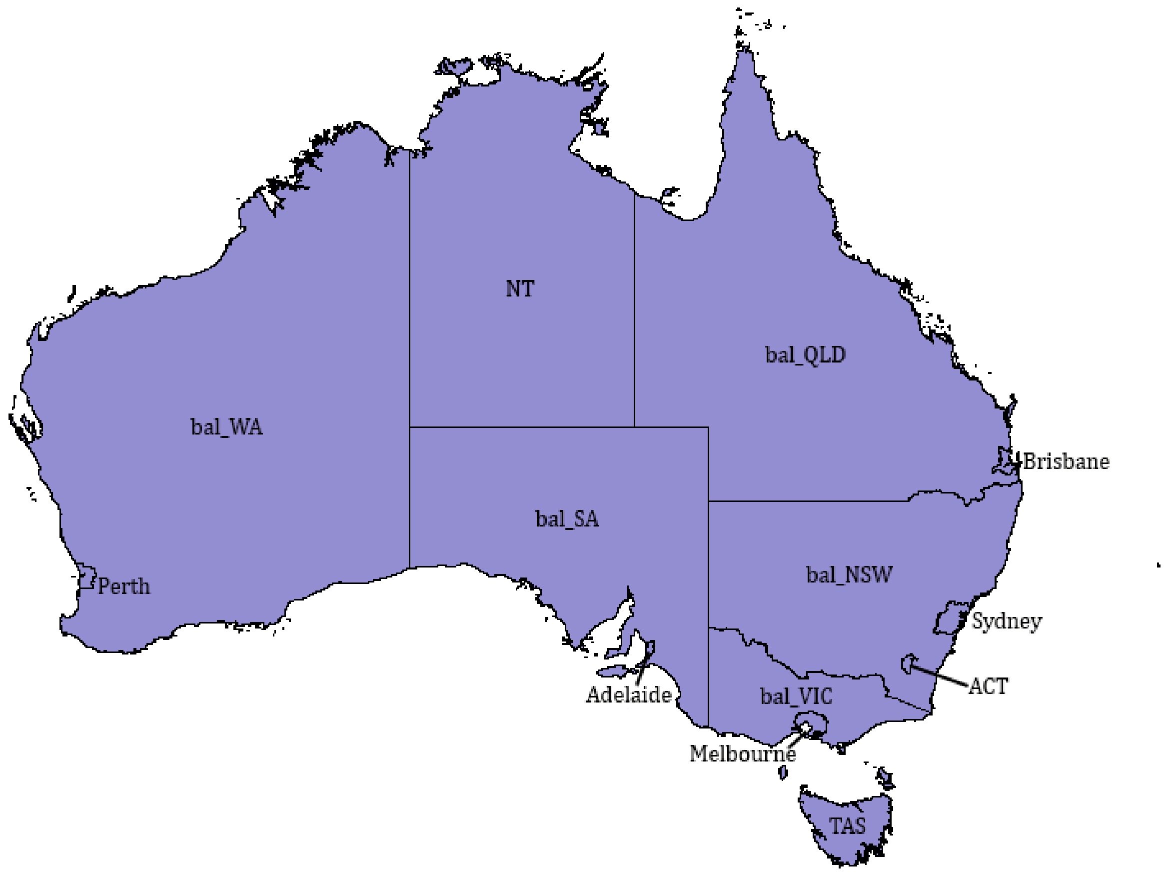
Table 2: Ex Ante MSR Location Definitions

Abbreviation	**Location**	**Type**	**State/Territory**
Sydney	Sydney	Capital of s/t	New South Wales
bal_NSW	Balance of New South Wales	Rest of s/t	
Melbourne	Melbourne	Capital of s/t	Victoria
bal_VIC	Balance of Victoria	Rest of s/t	
Brisbane	Brisbane	Capital of s/t	Queensland
bal_QLD	Balance of Queensland	Rest of s/t	
Adelaide	Adelaide	Capital of s/t	South Australia
bal_SA	Balance of South Australia	Rest of s/t	
Perth	Perth	Capital of s/t	Western Australia
bal_WA	Balance of Western Australia	Rest of s/t	
TAS	Tasmania	Entire s/t	Tasmania
NT	Northern Territory	Entire s/t	Northern Territory
ACT	Australian Capital Territory	Entire s/t	Australian Capital Territory

Notes: s/t = state or territory

[30] MSRs group Australia by the capital city statistical divisions of the five larger states, the remainder of each of these states, and the entire region for each of the smaller states and territories (see the ABS report by Trewin 2005).
[31] There is one more MSR, *Other Territories*, for which we have no observations in the HILDA data. The regions within this MSR make up an extremely small portion of Australia's population.

Figure 1: Location of MSRs in Australia



5.1 Ex Ante: Location Choice Variables

In our *ex ante* location choice equations, we omit observations for which home ownership is unobserved because it is an explanatory variable in all models; the proportion of observations missing this information is small (less than 0.1%). All samples employ 13 years of data which feature location choices of individuals made from 2002 to 2014 with location attributes and individual characteristics from 2001-2013. We describe the variables pertaining to the binary choice model and mixed logit models separately below.

5.1.1 Binary Choice Model

The binary logit model can only be estimated for individuals with variation in the dependent variable over time. Hence, the sample for estimating the push-factors of migration includes individuals who migrate at least once, but not in all observed periods. Most of the individuals in our data never move, leaving a sample of 2,072 individuals. For those individuals, we observe 20,081 choice occasions over time.

The dependent variable is a binary indicator for whether the individual migrated from one MSR to another since the previous period, or not. This is the case for 2,928 out of 20,081 choice occasions, or 14.6%.

Explanatory variables

The main explanatory variables in the binary choice model are attributes of the MSR in which each individual lived in the previous period, defined relative to the population weighted average of the value in all other locations. Our two main variables of interest are *ln(Wage)* and *SWB_adjusted*, which are described in Table 3 below alongside definitions of other variables.

Table 3: Binary Logit Location Variable Definitions

Variable	Definition	Source
	Dependent Variable	
Migrate	1 if individual *i* migrated since previous period, 0 otherwise	HILDA
	Independent Variables	
ln(Wage)	Natural log of average yearly wage income	ABS
SWB_adjusted	Estimated contribution of location to its residents' SWB	HILDA
ln(Pop)	Natural log of total population	ABS
UE Rate	Unemployment rate in previous period	ABS
ln(Rent)	Natural log of the 2% trimmed mean usual monthly household rent payments	HILDA

Notes: In the fixed effects binary logit model independent variables are defined *relative* to a population weighted average of the value in all other locations. All independent variables are for the previous period.

Other included variables are the total population (logged), the unemployment rate, and average house rents (logged). The location attributes are equal for all individuals who lived in a particular location during a particular year. Population is an important control because, all else equal, one is more likely to find a labour market match in a larger location or have ties to people living in that location. The unemployment rate reflects the likelihood of obtaining work, complementing the wage variable which represents the return if in work. Rents reflect the cost of non-tradeable goods and services.

Data on location attributes are linked to our dataset from national-level data from the ABS, except for *SWB_adjusted* and *ln(Rent)* which are derived from the HILDA survey dataset. The construction of *SWB_adjusted* is explained in Section 4.1.4. The individual-level measure of SWB in the HILDA survey, used to derive the area-level measure, is a person's answer to the question on a 0 to 10 scale of:

> All things considered, how satisfied are you with your life?[32]

The variable *SWB_adjusted* is constructed so that it reflects the contribution of an MSR to its residents' wellbeing, avoiding selection effects. Appendix Figure 1 provides an illustration of the variation in this variable for each of the potential location choices.

House rents are taken as the mean of rents reported by individuals in the HILDA survey in each MSR for each time period, trimmed by 2% to reduce the influence of outliers. Average wage income for each MSR is provided by ABS for each financial year. To merge this information to our dataset, we associate the income of the most recent financial year with each year of data; therefore there is an extra lag on this variable. For example, in 2013, our average income measure is from the 2011-2012 financial year.[33]

5.1.2 Mixed logit models

Modelling multinomial choice (mixed logit models) requires that for each person-year we include a separate data-point for each location alternative within that person's choice set i.e. each data-point is a unique *person-location-year*. An indicator for whether that particular location was chosen or not is then used as the dependent variable, and attributes associated with each location can be included as explanatory variables. Each explanatory variable can be at a *location-year* level, i.e. all values for observations over individuals in the same location and same year are equal, or *person-location-year* level i.e. values are also individual specific.

We are interested in two distinct choices which correspond to different samples, where one is a subset of the other. The first sample includes migrants only, and only in the periods in which they move. For this sample, the migrants are assumed to choose from all MSRs *except* the one they left; hence in each period they face a choice set containing 12 location alternatives. The second sample includes all individuals in all periods, and it is assumed that those individuals choose from all 13 MSRs in each period. The composition of these two samples is summarised in

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[32] This question is asked in HILDA after the survey has just finished asking about particular aspects of one's life. That is, the survey first asks about peoples' satisfaction with their health, family relationships, employment, etc. Since these particular aspects are near-term properties of a person's life (i.e. your employment this year, your health now etcetera) it is natural to suppose that people answer the aggregate life satisfaction question in a way that reflects the totality of their current circumstances, not so much their expected future circumstances.

[33] The wage data was not complete for the period of our study and therefore we imputed it for MSRs in 2012 and 2014 years given the information available. This was done by increasing the wages in ABS data in the previous period by the growth rate in average income for that MSR observed in the HILDA data.

Table 4. We note that in the full sample, the first observation of each individual is excluded because of the Wooldridge adjustment as explained in Section 4.1.3.

Table 4: Multinomial Choice Estimation Samples

	Individuals *i*	**Choice Occasions *i,t***	**Locations *j* in choice set $C_{i,t}$**	**Total Obs.**
Migrants	2,141	3,001	12	36,012
Full Sample	16,231	119,298	13	1,550,874

Location alternatives

Table 5 contains the frequency that each MSR is chosen in in the full sample and among migrants only. It also shows the location of migrants in the previous year i.e. the places they leave. Some locations are more popular among migrants compared to the full sample, and vice versa. It appears that migrants are disproportionately drawn to bal_NSW, bal_VIC, Brisbane, bal_QLD, bal_SA, bal_WA, NT and ACT. However, a comparison of the first and third columns shows that people tend to leave disproportionally often from many of those same locations.

Table 5: MSR Frequencies

	Full Sample		**Migrants (New)**		**Migrants (Previous)**	
MSR	**Freq.**	**%**	**Freq.**	**%**	**Freq.**	**%**
Sydney	20,228	17.0	299	10.0	443	14.8
bal_NSW	16,608	13.9	449	15.0	404	13.5
Melbourne	20,508	17.2	280	9.3	393	13.1
bal_VIC	9,109	7.6	316	10.5	190	6.3
Brisbane	10,436	8.8	350	11.7	354	11.8
bal_QLD	13,467	11.3	487	16.2	406	13.5
Adelaide	7,327	6.1	133	4.4	168	5.6
bal_SA	3,577	3.0	101	3.4	102	3.4
Perth	8,354	7.0	189	6.3	186	6.2
bal_WA	3,197	2.7	145	4.8	139	4.6
TAS	3,626	3.0	85	2.8	65	2.2
NT	757	0.6	70	2.3	68	2.3
ACT	2,104	1.8	97	3.2	83	2.8
Total	119,298	100.0	3,001	100.0	3,001	100.0

Notes: s/t = state or territory

Year-Specific Location Attributes

Most of the location attributes used to explain choice are constant across individuals for a given time period. We use the same location attributes as in the binary choice model, but we no longer adjust them to be relative to all other locations because the multinomial model captures differences along all possible pairs of locations.

Individual-Year-Specific Location Attributes

In the multinomial choice models we include a set of location attributes that can vary not only across time but across individuals. One of these attributes is the distance of the alternative MSR from the individual's previous location. This variable captures the costs of moving to a new location, as well as uncertainty of potential outcomes in that location, which may increase with the distance from one's previous location. We include a quadratic distance term to account for potential non-linearity of this relationship. The between-MSR distances we use are lengths of the shortest curve across the earth's surface between their centre-points, measured in kilometres.[34]

A summary of the variables used in the multinomial choice models is provided in Table 6 below.

Table 6: Multinomial Choice Location Variable Definitions

Variable	Definition	Source
	Dependent Variable	
MSR	1 if location chosen, 0 otherwise	HILDA
	Independent Variables	
Year-Specific Location Attributes		
ln(Wage)	Natural log of average yearly wage income	ABS
SWB_adjusted	Estimated contribution of location to its residents' SWB	HILDA
ln(Pop)	Natural log of total population	ABS
UE Rate	Unemployment rate	ABS
ln(Rent)	Natural log of the 2% trimmed mean usual monthly household rent	HILDA
Individual-Year Specific Location Attributes		
Distance	km between location and individual's previous location choice	ABS
Distance^2	km^2 between location and individual's previous location choice	ABS

Notes: All year-specific location attributes are for the previous period.

[34] The shape files used to find the coordinates of MSR centre-points were downloaded from the ABS website.

5.1.3 Summary Statistics of Location Attributes

Table 7 presents means of the main location attributes included in the model of location choice for each MSR in 2013 to provide an overview of the cross-sectional data variation.[35] We present both the average of unadjusted SWB and of the adjusted SWB measure, *SWB_adjusted*, which is the variable employed in the empirical model. *Distance* is the only variable shown which is individual-specific. All other variables presented in the table are constant across individuals for the year displayed (but differ across years).

Table 7: Area Characteristic Means in 2013

	Wage ($)	**SWB**	**SWB_adjusted**	**Pop**	**U Rate**	**Rent ($)**	**Distance (km)**
Sydney	62,246	7.698	-0.020	4,756,398	4.9%	1,391	895
bal_NSW	51,949	8.013	0.062	2,652,939	5.9%	963	815
Melbourne	56,963	7.827	-0.025	4,344,673	5.6%	1,235	891
bal_VIC	47,929	8.070	0.000	1,390,334	5.7%	891	861
Brisbane	58,540	7.879	0.093	2,236,044	5.8%	1,222	1,233
bal_QLD	54,581	7.933	0.092	2,415,868	6.1%	1,170	1,387
Adelaide	53,216	7.771	0.154	1,291,377	5.8%	1,013	1,047
bal_SA	46,981	7.931	0.044	379,121	5.5%	694	1,273
Perth	67,130	7.900	0.008	1,972,849	4.2%	1,322	2,668
bal_WA	61,923	7.823	-0.211	546,158	5.1%	972	2,388
TAS	48,756	7.997	0.082	513,100	6.5%	854	1,249
NT	60,012	8.169	0.010	242,541	4.4%	1,422	2,044
ACT	66,153	7.918	0.067	381,291	4.1%	1,195	875
Weighted avg.	57,400	7.87	0.025	2,931,156	5.4%	1180	1,188

Average wage incomes in 2013 range from $46,981 per year in bal_SA to $67,130 in Perth. Deviations from the base SWB (i.e. that of Sydney in 2001) represented by *SWB_adjusted* appear relatively small, ranging from -0.211 points to 0.154. However, this is not surprising given the highly centred unadjusted SWB measures from which they are computed. Note that NT has the highest raw average *SWB* in 2013, but only the eighth highest *SWB_adjusted*, showing the difference that the adjustment makes.

[35] In the *ex ante* estimations, this data on 2013 is linked to location choices in 2014 because of the lag imposed on location attributes.

Average wages in the capital cities are, in all cases, higher than those in the balance of the corresponding state, as are populations, employment rates and rents. Conversely, there is no such pattern for wellbeing.

There is a wide range in the MSR populations. NT has the fewest inhabitants, with 242,541, while Sydney has the most, with 4.76 million. Most of Australia's population is concentrated on its east coast, so the distance variable ranges from 815km for bal_NSW, on the eastern side of Australia, to 2,668km for Perth, which lies on the west coast.

Within each MSR the characteristics we describe will vary widely. For instance, the contribution of a place to individual SWB could be much higher in some parts of Sydney than other parts of the city, or rent prices could be much higher in one neighbourhood than another. In another example, the distance between two possible locations is represented by the kilometres between MSR centre-points, but non-urban MSRs cover large areas. Hence our distance measures should serve as proxies for the true factors involved in location decisions. The inevitable approximations involved in the construction of these proxies is likely to lead to attenuation bias in our *ex ante* estimates, with inflated standard errors. Conversely, the finding of significant results in the face of this issue provides greater confidence that the relevant variable is an important determinant of the location choice decision.

Individual Characteristics

We compare summary statistics of individual characteristics across our three samples: migrants, migrants in the year of moving, and the full sample. Table 8 below summarises the frequencies within each sample of various characteristics. All variables are categorical except for *No. of children* which is discrete. In the empirical models, these variables only enter the binary model, for which the sample in the first column (Migrants) is used.

Migrants are notably younger than the complete sample, less often married, and on average have fewer children. They are also more likely to have a higher level of education and are slightly more likely to be Australian-born than born overseas. It is considerably less common for migrants to own their own home than the full sample. Most of these differences are stronger when considering migrants only in the year of moving relative to the full sample rather than migrants across all years.

Table 8: Ex Ante Individual Characteristics Summary Statistics

	Migrants		**Migrants in year move**		**Full Sample**	
	Freq.	**%**	**Freq.**	**%**	**Freq.**	**%**
Gender						
Male	9,326	46.4	1,428	47.6	56,372	47.3
Female	10,755	53.6	1,573	52.4	62,926	52.7
Age						
25 to 34	5,679	28.3	1,256	41.9	20,247	17.0
35 to 49	7,361	36.7	943	31.4	41,433	34.7
50 to 64	4,602	22.9	539	18.0	33,163	27.8
65 +	2,439	12.1	263	8.8	24,455	20.5
Marital status						
Married	10,504	52.3	1,338	44.6	70,823	59.4
De facto	3,159	15.7	535	17.8	11,830	9.9
Separated/divorced	2,558	12.7	397	13.2	12,761	10.7
Widowed	645	3.2	83	2.8	7,481	6.3
Never married/not de facto	2,746	13.7	561	18.7	12,108	10.1
Missing	469	2.3	87	2.9	4,295	3.6
Family type						
Couple w child	6,599	32.9	888	29.6	40,913	34.3
Couple no child	7,310	36.4	1,019	34.0	44,677	37.4
Single w child	1,130	5.6	170	5.7	5,387	4.5
Single no child	5,042	25.1	924	30.8	28,321	23.7
No. children*	0.76		0.67		0.77	
Highest education						
Postgrad	1,238	6.2	156	5.2	5,105	4.3
Grad diploma/certificate	1,472	7.3	207	6.9	7,106	6.0
Bachelor/honours	3,243	16.1	561	18.7	15,764	13.2
Adv diploma, diploma	2,063	10.3	266	8.9	11,401	9.6
Cert III or IV	4,402	21.9	662	22.1	24,553	20.6
Year 12	2,122	10.6	349	11.6	12,931	10.8
Year 11 and below	5,089	25.3	714	23.8	38,141	32.0
Missing	452	2.3	86	2.9	4,297	3.6
Place of birth						
Australia	15,445	76.9	2,322	77.4	86,869	72.8
Foreign born	4,177	20.8	591	19.7	28,151	23.6
Missing	459	2.3	88	2.9	4,278	3.6
Own home						
Yes	11,744.00	58.5	1,347	44.9	89,649	75.1
No	8,337.00	41.5	1,654.00	55.1	29,649	24.9

* No. Children is shown as the average for each sample.

5.2 Ex Post: Payoffs to Migration Variables

The *ex post* analysis uses all 14 waves of the HILDA panel. The sample is reduced to include only individuals who are observed to transition from one MSR to another at least once. Of the movers, observations more than four waves before or after a move are dropped, leaving 15,769 observations. Our SWB measure is missing for 395 of these observations of movers and, to keep our samples for the SWB and the wage estimations comparable, we drop those 395 observations.[36]

Next, we apply the assumptions described in Section 4.2 about which migration timing effects dominate each other, so that for individuals who have moved more than once, we see them as experiencing only one effect at a time. To be included in the estimation, one must be observed in the remaining data at least the year before and of migrating even after accounting for domination of some effects over others. Data from any other wave is only included if it follows consecutively, i.e. to include an observation three years before moving, we must also have included the observation two years before moving.[37] The final *ex post* sample includes 12,508 observations covering 2,054 individuals. The number of migrations observed in this sample is 2,145 , which is greater than the total number of individuals because some move more than once.

The dependent and independent variables used in the *ex post* analysis are defined in Table 9. We describe each of these variable groups in the sections that follow.[38]

[36] We also estimated the wage outcomes for the full sample and the difference in results was trivial.
[37] The intuition behind this is that if there is missing information between two observations, we cannot be sure that there has been no change in location in the missed year.
[38] Note that for the *ex post* analysis, SWB is not adjusted since the variable refers to the individual's own wellbeing rather than being a regional average. Similarly, wages and all other variables are for the individual.

Table 9: Ex Post Variable Definitions

	Variable	Definition	Type
		Dependent Variables	
	SWB	Self-reported life satisfaction, discrete scale from 0 to 10	Categorical
	Wages	Weekly personal wage or salary income	Continuous
		Independent Variables	
(I)	Migration	Number of waves since the person migrated	Categorical
	Year	Year of interview	Categorical
(II)	Age	25 to 34, 35 to 49, 50 to 64, or 65+	Categorical
	Marital status	Married, De facto, Separated/divorced, Widowed, Never married/not de facto	Categorical
	Family type	Couple w. child, Couple no child, Single w. child, Single no child	Categorical
	No. children	Number of dependent children in household aged 0 to 24	Continuous
	Highest education	Post grad, Grad diploma/certificate, Bachelor/honours, Adv diploma/diploma, Cert III or IV, Year 12, Year 11 and below	Categorical
	Home ownership	Owns home, does not own home	Categorical
(III)	Married	Got married in past year, missing	Categorical
	Separated	Separated from partner in past year, missing	Categorical
	Back together	Got back together with spouse in past year, missing	Categorical
	Pregnancy	Pregnancy in past year, missing	Categorical
	Birth	Birth/adoption of new child in past year, missing	Categorical
	Death spouse/child	Death of spouse/child in past year, missing	Categorical
	Self-reported health	Excellent, Very good, Good, Fair, Poor, missing	Categorical
(IV)	Lab force	Labour force participant, not labour force participant	Categorical

5.2.1 Dependent Variables

Our SWB measure at the individual level is the 0 to 10 measure of life satisfaction described in Section 5.1.1. The measure we use for wages is the gross weekly wage or salary income in Australian dollars at the time of the interview, adjusted to the 2012 price level. Summary statistics for these dependent variables are laid out in Table 10 for the *ex post* estimation sample. Note that many of the individuals earn no wage income at the time they are surveyed which pulls down the average wage; the average wage of those with positive earnings is $1,221.

Table 10: Ex Post Dependent Variable Summary Statistics

	Mean	SD	Min	Max
SWB	7.78	1.52	0	10
Wages ($)	735	907	0	12,932

5.2.2 Independent variables

We estimate our *ex post* model using four different specifications as described in Section 4.2. The first specification includes the variables in group (I) of Table 9 as independent variables. Subsequent specifications add the variables in groups (II) to (IV). The migration timing dummies range from -4 to 4 years since migration, with -1 selected as the omitted category. Year fixed effects control for nation-wide changes that could affect SWB or wages in each period. Summary statistics are provided in Table 11.

In our estimation sample there is missing data on marital status (0.06% of the sample), home ownership (0.10%), each life event (~15.5%), and health status (11.1%). For the life events and health status, where there is missing information, we enter this as a separate 'missing' category so as not to lose all other information on that observation, and so that we control for any patterns related to non-reporting or invalid responses. For marital status and home ownership the number of missing values is so small that it is not feasible to create a separate category. Instead, individuals for which there is missing information on these explanatory variables (in *any* year) are dropped, amounting to 125 observations.[39]

5.2.3 Sub-Samples

We assess variation in SWB and wage trajectories for particular sub-groups, including various age categories, time preference and an interaction of age and time preference categories. In the SWB and wage trajectory estimation, we keep individuals in the same group over time based on the wave in which they move. Statistics relating to the sub-samples are presented in Table 12.

[39] This information is dropped from the sample only for estimations including marital status and home ownership as explanatory variables.

Table 11: Ex Post Explanatory Variable Summary Statistics

	Freq.	%		Freq.	%
Year since migration			**Highest education**		
-4	911	7.4	Postgrad	708	5.7
-3	1,173	9.5	Grad diploma/certificate	955	7.7
-2	1,574	12.7	Bachelor/honours	2,114	17.1
-1	2,123	17.1	Adv diploma, diploma	1,239	10.0
0	2,123	17.1	Cert III or IV	2,798	22.6
1	1,543	12.5	Year 12	1,426	11.5
2	1,198	9.7	Year 11 and below	3,143	25.4
3	950	7.7	**Home ownership**		
4	788	6.4	Does not own home	5,647	45.6
Year			Owns home	6,736	54.4
2001	662	5.3	**Got Married**		
2002	786	6.3	Didn't marry	10,122	81.7
2003	868	7.0	Got married	336	2.7
2004	948	7.7	Got married missing	1,925	15.5
2005	1,027	8.3	**Separated**		
2006	1,039	8.4	Didn't separate	9,918	80.1
2007	979	7.9	Separated	534	4.3
2008	949	7.7	Separated missing	1,931	15.6
2009	931	7.5	**Got Back Together**		
2010	920	7.4	Didn't get back together	10,295	83.1
2011	977	7.9	Back together	157	1.3
2012	898	7.3	Back together missing	1,931	15.6
2013	780	6.3	**Pregnancy**		
2014	619	5.0	No pregnancy	9,561	77.2
Age			Pregnancy	901	7.3
25 to 34	4,267	34.5	Pregnancy missing	1,921	15.5
35 to 49	3,896	31.5	**Birth/Adoption**		
50 to 64	2,710	21.9	No birth	9,870	79.7
65 +	1,510	12.2	Birth	583	4.7
Marital status			Total	1,930	15.6
Married	6,542	52.8	**Death of Spouse/Child**		
De facto	2,055	16.6	No death	10,351	83.6
Seperated/divorced	1,455	11.7	Death spouse/child	100	0.8
Widowed	430	3.5	Death spouse/child missing	1,932	15.6
Never married/not de facto	1,901	15.4	**Health status**		
Family type			Excellent	1,476	11.9
Couple w child	3,824	30.9	Very good	4,082	33.0
Couple no child	4,665	37.7	Good	3,785	30.6
Single w child	685	5.5	Fair	1,306	10.5
Single no child	3,209	25.9	Poor	369	3.0
No. children		0.7	Health missing	1,365	11.0
			Lab force		
			No	3,787	30.6
			Yes	8,596	69.4

Notes: Frequencies are shown for the estimation sample when individual controls are included (N=12,383). Gender is not included owing to the inclusion of individual fixed effects. Within the sample, 54.1% (6,700) of individuals are female.

Table 12: Ex Post Sub-Sample Definitions and Frequencies

	Definition	Freq.	%
Age			
25 to 34	Age 25 to 34	4,157	33.9
35 to 49	Age 35 to 49	3,875	31.6
50 to 64	Age 50 to 64	2,683	21.9
65+	Age 65+	1,534	12.5
Age and Time Preference			
high_under50	High time preference and age under 50	5,629	48.0
low_under50	Low time preference and age under 50	1,951	16.6
high_50plus	High time preference and age 50 or over	2,515	21.5
low_50plus	Low time preference and age 50 or over	1,626	13.9
Missing		528	0.0
Gender			
Male	Male	5,653	45.7
Female	Female	6,716	54.3
Main Reasons for Moving (MRfM):			
Work Related			
No	MRfM was not work related	9,406	78.9
Yes	One of MRfM was work related	2,512	21.1
Missing		331	0.0
New Job			
No	MRfM did not include a new job	10,245	89.6
Yes	One of MRfM was for a new job	1,183	10.4
Missing		821	0.1
Work Transfer			
No	MRfM did not include a work transfer	10,665	93.3
Yes	One of MRfM was for a work transfer	763	6.7
Missing		821	0.1
Better Area			
No	MRfM did not include to live in a better area	10,661	93.3
Yes	One of MRfM was to live in a better area	767	6.7
Missing		821	0.1
Friends/Family			
No	MRfM did not include to live closer to friends/family	8,732	76.4
Yes	One of MRfM was to live closer to friends/family	2,696	23.6
Missing		821	0.1
New Lifestyle			
No	MRfM did not include seeking a change of lifestyle	8,200	71.8
Yes	One of MRfM was seeking a change of lifestyle	3,228	28.2
Missing		821	0.1

Notes: Definitions are based on survey answers in the year of moving (except time preference information which is lagged by one year if missing). In practice we do not include missing categories in estimations.

5.2.4 Time Preference

Migrants are assigned to have high or low time preference according to their answer to the following HILDA survey question in the year of moving:

> In planning your saving and spending, which of the following time periods is most important to you?

Six discrete options were offered to respondents (the next week; the next few months; the next year; the next 2 to 4 years; the next 5 to10 years; and more than 10 years ahead). Time preference information is missing for some observations, predominantly because the question was not asked in waves 5, 7, 9, 11 and 13 of the survey, but also due to some cases of non- or invalid response. We use a lag of time preference from the previous year if it was missing to reduce the amount of missing information.

The frequencies of time preference categories among migrants in the ex post sample are displayed in Table 13. More than two thirds of migrants (in the year of migrating) report that they focus no further than one year ahead. We define these individuals as having a high rate of time preference and the rest as having a low rate of time preference.

Table 13: Time Preference in Ex Post Sample

		Freq.	**%**	**Cum. %**
High	The next week	463	23.13	23.13
	The next few months	541	27.02	50.15
	The next year	388	19.38	69.53
Low	The next 2 to 4 years	252	12.59	82.12
	The next 5 to 10 years	248	12.39	94.51
	More than 10 years ahead	110	5.49	100.00
Total		2,002		

6 Descriptive Analysis

Before turning to the econometric results, we present a descriptive analysis of the data. We consider features and patterns both among location alternatives and individuals.

6.1 Location-to-Location Mobility

Table 14 presents the unconditional probability of change in MSR over time in a transition matrix. Each cell in the table contains the likelihood of someone choosing the MSR in the corresponding top row, given that they lived in the MSR in the corresponding left column in the previous period. The probability is calculated over 2002 to 2014, the same information used in the full sample location choice analysis.

Table 14: Probability of an Individual Choosing an MSR in one Period Given Location in the Previous Period for 2002 to 2014 (%)

Choice: **Previous MSR**	**Sydney**	**bal_NSW**	**Melbourne**	**bal_VIC**	**Brisbane**	**bal_QLD**	**Adelaide**	**bal_SA**	**Perth**	**bal_WA**	**TAS**	**NT**	**ACT**	**Total**
Sydney	**98.11**	0.80	0.19	0.04	0.23	0.26	0.07	0.00	0.13	0.01	0.03	0.01	0.13	100
bal_NSW	0.64	**97.92**	0.08	0.16	0.27	0.49	0.02	0.02	0.03	0.05	0.09	0.10	0.14	100
Melbourne	0.19	0.13	**98.30**	0.79	0.11	0.16	0.03	0.01	0.10	0.01	0.08	0.03	0.05	100
bal_VIC	0.07	0.32	0.82	**98.19**	0.02	0.23	0.08	0.06	0.07	0.04	0.04	0.02	0.03	100
Brisbane	0.22	0.27	0.22	0.01	**97.08**	1.75	0.09	0.02	0.11	0.08	0.09	0.01	0.06	100
bal_QLD	0.18	0.50	0.15	0.12	1.03	**97.58**	0.09	0.01	0.07	0.07	0.05	0.12	0.04	100
Adelaide	0.10	0.10	0.20	0.11	0.07	0.18	**98.08**	0.80	0.10	0.08	0.04	0.05	0.10	100
bal_SA	0.03	0.08	0.08	0.31	0.06	0.11	1.42	**97.54**	0.00	0.11	0.08	0.14	0.03	100
Perth	0.24	0.08	0.20	0.13	0.08	0.10	0.00	0.00	**98.08**	0.91	0.10	0.05	0.02	100
bal_WA	0.12	0.25	0.00	0.09	0.25	0.37	0.12	0.16	2.28	**95.97**	0.22	0.16	0.00	100
TAS	0.17	0.36	0.28	0.25	0.22	0.11	0.06	0.06	0.06	0.03	**98.36**	0.03	0.03	100
NT	0.26	1.32	0.26	0.53	1.06	2.25	0.26	0.79	0.66	0.40	0.26	**91.79**	0.13	100
ACT	0.91	1.29	0.48	0.14	0.43	0.24	0.10	0.00	0.19	0.00	0.00	0.05	**96.19**	100
Unconditional probability	17.05	13.89	17.28	7.55	8.76	11.21	6.16	3.00	6.99	2.68	3.03	0.63	1.76	100

The cells in bold represent probabilities that someone from each MSR will remain there in the next period. Retention of residents is high, with more than 91% of each MSR's population expected to stay put. People in NT are the least likely to stay in the following year (91.79%). In contrast, TAS is expected to retain the highest portion (98.36%) of its residents from one year to another. Intra-state movements are more common than inter-state movements.

6.2 Location Age Distributions

A key part of our analysis involves considering how migration patterns differ by age. Table 15 presents the age structures for our ex ante sample of individuals aged 25 or over across 13 years. We observe that capital cities have younger populations than their balance of state counterparts, while NT is an outlier, exhibiting a much younger population than any other MSR.

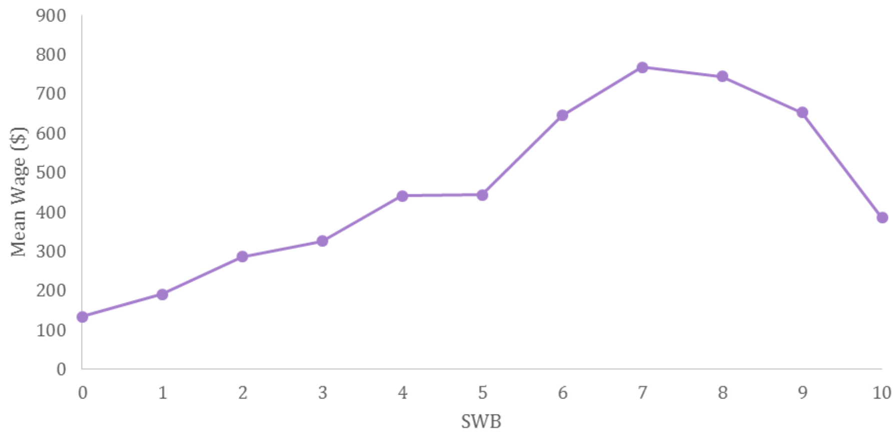
Table 15: Person-Year Frequencies of Individuals in Each Age-Group by MSR (%)

MSR	25 to 34	35 to 49	50 to 64	65 +
Sydney	21.6	33.5	26.4	18.5
bal_NSW	15.1	31.8	29.0	24.1
Melbourne	21.0	35.1	25.7	18.2
bal_VIC	15.3	31.9	28.8	24.0
Brisbane	22.0	36.9	24.9	16.2
bal_QLD	19.9	36.7	25.0	18.4
Adelaide	18.3	33.1	28.7	19.9
bal_SA	14.9	32.3	31.2	21.6
Perth	19.7	33.4	26.1	20.8
bal_WA	16.2	32.5	30.1	21.1
Tasmania	17.8	39.0	23.2	20.0
NT	30.6	39.3	25.8	4.3
ACT	22.7	34.2	28.6	14.6
Australia	19.3	34.2	26.8	19.7

6.3 Wage and SWB Relationship

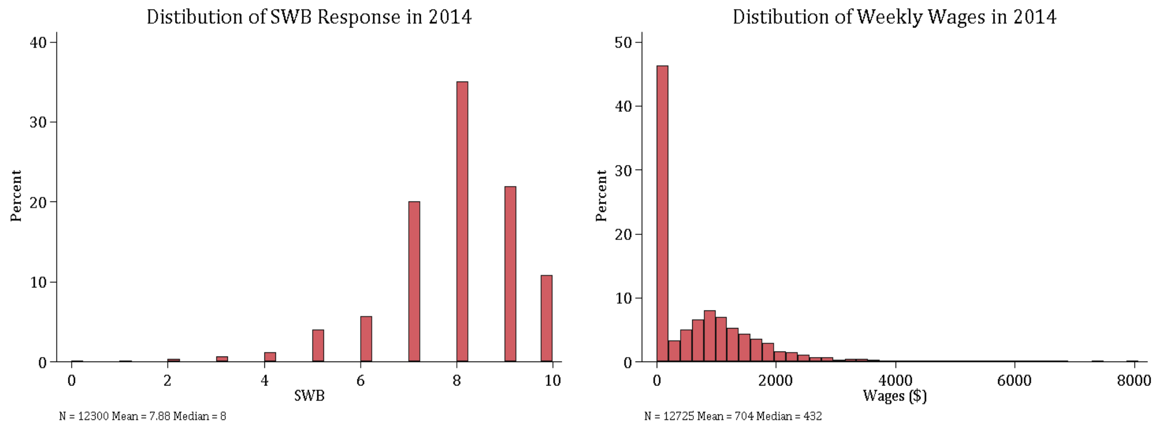
We inspect our data for the raw relationship between SWB and wages. A graph of the average wage for individuals at each discrete point on the scale of SWB is presented in Figure 2. Wages and SWB are positively related up to an SWB value of 7. Thereafter, wages decline as SWB rises. A key reason for this pattern is that older people tend to have both high SWB and low wage income.

Figure 2: Mean Wage of Individuals Reporting Different Levels of SWB



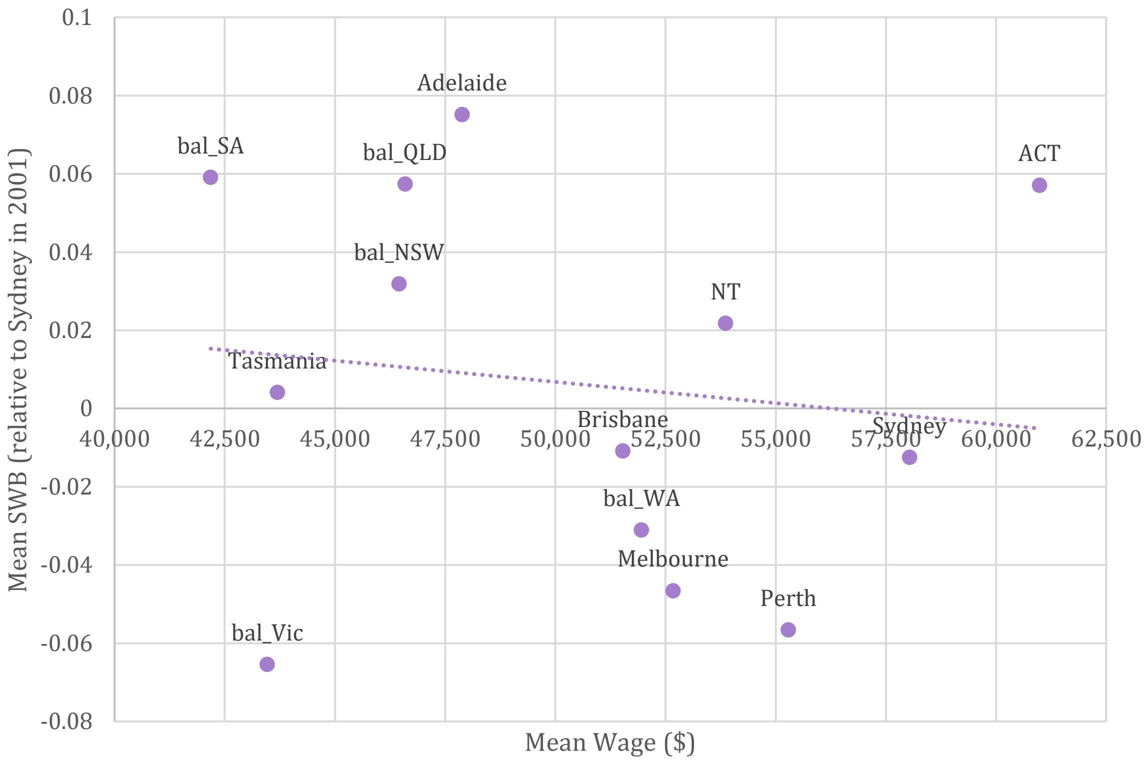
SWB and wage histograms for 2014 are shown in Figure 3. SWB is negatively skewed with a mode of 8. The histogram for wages shows that almost half of the sample earn very little or zero.

Figure 3: SWB and Wages in 2014



We also compare our wage and SWB measures across MSRs. *SWB_adjusted* should reflect the contribution of a place to its residents' happiness, which may include both pecuniary and non-pecuniary factors. We plot average wage incomes over all years of data against average *SWB_adjusted* over all years for each MSR in Figure 4. The downward slope of the line of best fit suggests higher wages are associated with lower wellbeing measures. However, the points are dispersed widely from the line of best fit suggesting any relationship is not strong. ACT (that includes Canberra, the capital city), for example has the highest average wage but also ranks relatively highly on the wellbeing measure. Furthermore, while there is stability in relative wages by MSR across time, there is much less consistency in SWB across years.

Figure 4: MSR Time-Averaged SWB and Wages 2002-2014



Mean wages and SWB are presented for a range of categories in Table 16. We also include the average wage of those who earn a positive amount. There is a large discrepancy in the mean wage of females versus males, even for those with positive wages possibly (in part) reflecting different average hours worked. Wages, if positive, are fairly similar over different age groups except for the oldest age group which takes home much less per week (in fact, less than 7% of this age group report positive wage income). Women have slightly higher mean reported wellbeing than men and the oldest group report the highest wellbeing.

We present the data according to time preference (high/low) interacted with age. Low time preference is associated with higher incomes while wellbeing is also higher for low time-preference groups. Migrants (in the year of moving) receive higher wages than the average person, but report lower SWB on average.

Table 16: Ex Ante Sample Mean Wages and SWB by Sub-Groups

	Wages ($)	Wages ($) if > 0	SWB	No. individuals
Males	874.44	1,429.56	7.84	64,930
Females	462.19	907.55	7.94	72,160
25 to 34	845.07	1,132.31	7.82	26,392
35 to 49	901.09	1,227.23	7.68	46,889
50 to 64	653.74	1,173.67	7.89	36,786
65+	56.49	824.68	8.34	27,023
high_under50	801.93	1,100.90	7.66	45,303
low_under50	1,071.47	1,382.74	7.90	19,661
high_50+	302.50	1,017.04	8.02	37,783
low_50+	571.29	1,279.04	8.22	21,146
Migrant	782.92	1,259.13	7.56	3,001
All	657.45	1,178.69	7.89	137,090

Notes: SWB values are missing for 3.79% of the ex ante sample and Wages ($) are positive for 55.78% of the sample.

6.4 Change in SWB and Wages around Migration

Figure 5 illustrates how average SWB and wages change for migrants in years relative to when they migrate. There is a downwards trend in wellbeing in the lead up to migration, followed by a sharp increase in the year of moving that is sustained thereafter.

On average, wages tend to trend down slightly over the three years prior to moving, and average wage changes thereafter are noisy. However, these averages hide considerable heterogeneity associated, in particular, with retirement and other labour force participation decisions. Table 17 summarises the proportion of migrants (in total and by sub-group) who experience a positive, negative, or zero change in each of the outcomes.

Figure 5: Mean SWB and Wage Incomes around Migration

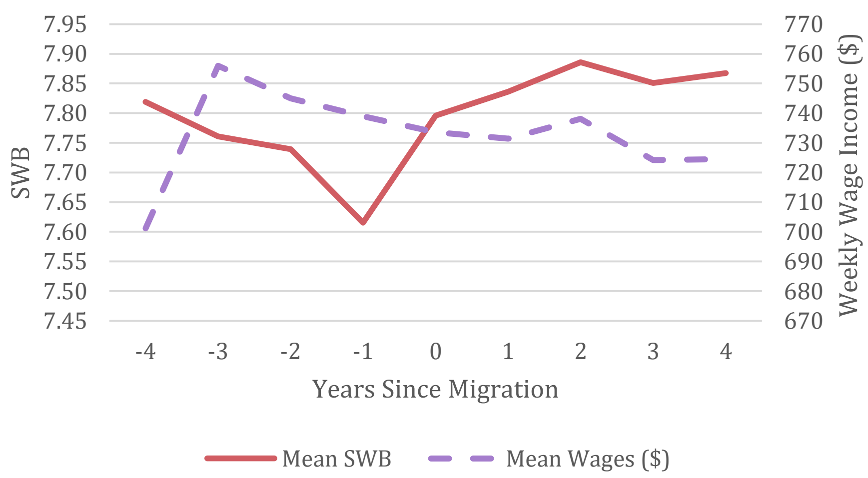


Table 17: Frequency of Positive, Negative, or No Change in Wage and SWB in Year of Migration (%)

	Positive	No Change	Negative	Net Positive
		Change in Wages		
Age				
25 to 34	46.5	15.7	37.8	8.7
35 to 49	40.6	20.8	38.6	2.0
50 to 64	19.5	39.9	40.6	-21.1
65 +	2.1	88.9	8.9	-6.8
Age and Time Preference				
high_young	42.9	19.2	37.9	5.0
low_young	44.9	13.9	41.3	3.6
high_old	12.1	63.9	24.0	-11.9
low_old	15.0	48.4	36.6	-21.6
Gender				
Male	41.3	24.0	34.7	6.6
Female	28.8	35.1	36.1	-7.3
		Change in SWB		
Age				
25 to 34	37.8	34.0	28.2	9.6
35 to 49	36.1	33.0	30.9	5.2
50 to 64	38.7	34.3	27.0	11.7
65 +	40.4	33.6	26.0	14.4
Age and Time Preference				
high_young	36.2	34.1	29.7	6.5
low_young	36.3	34.1	29.6	6.7
high_old	40.1	32.7	27.2	12.9
low_old	39.4	35.8	24.8	14.6
Gender				
Male	34.8	35.1	30.1	4.7
Female	40.2	32.5	27.3	12.9

All sub-groups experience a net positive change in wellbeing at the time of migration. People under the age of 50 tend to increase their wages, while those over 50 tend to receive decreased wage income in the year of migration indicating that migration for many in the latter group may coincide with changes in the degree of labour force participation. Older people with low time preference more often experience a drop in wage income than those with high time preference, consistent with our theoretical model in which the former group saves more when young to use for non-pecuniary sources of wellbeing later in life. Wages are more likely to increase for males than for females. Conversely, SWB is more likely to increase for females than for males.

6.5 Validity of Time Preference Measure

With stable preferences, individuals' measures of time preference should be stable over time. If our measure of time preference (i.e. from the question on planning ahead when it comes to spending and saving) is robust, this stability should be reflected in the data. Table 18 shows the probability of an individual reporting high or low time preference given that they reported high or low time preference in the previous period. This estimate is based on consecutive observations of time preference which the survey included each year from 2002 to 2005. The results indicate that individuals are at least 80% likely to report the same rate of time preference (i.e. high or low) as they reported in the previous year.

Table 18: Probability of an Individual Reporting High or Low Time Preference in one Period Given Time Preference in the Previous Period (%) for Consecutive Obs.

Previous Time Pref. \ Time Pref.	Low	High	Total
Low	**80.03**	19.97	100
High	9.98	**90.02**	100
Unconditional Probability	33.25	66.75	

Notes: Consecutive obs. are for the years 2002 to 2005.

7 Results

7.1 Ex Ante: Location Choice

Coefficient estimates of location attributes on the log-odds of choosing to move out of the individual's existing location are presented in Table 19.[40] Column (1) is the most basic specification, column (2) adds individual characteristics as controls, (3) adds life events and self-reported health status, and (4) adds a control for labour force participation. A full set of results is reported in Appendix Table 1.

The effects predicted for location attributes are relatively stable across the four models. Column (1) shows that individuals are less likely to leave their current MSR if it has a relatively large population and more likely to leave if their MSR has a relatively high unemployment rate. These results are statistically significant at the 10% level. No other location attributes have coefficients significantly different from zero, but signs indicate people are less likely to leave places with relatively high levels of wellbeing and high wages and more likely to leave those with relatively high rents. These directions of effect are as expected from theory.

[40] The coefficients represent the rate of change of the log-odds of migrating as the independent variable changes.

Table 19: Fixed Effects Logit Estimates of Propensity to Move

	(1)	(2)	(3)	(4)
SWB_adjusted rel	-0.253	-0.3016	-0.2815	-0.3047
	(0.4473)	(0.4504)	(0.4515)	(0.4586)
ln(Wage) rel	-1.1712	-1.5937*	-1.6308*	-1.5712*
	(0.8784)	(0.8826)	(0.8823)	(0.9000)
ln(Pop) rel	-2.0148*	-1.2005	-1.2028	-1.4476
	(1.1672)	(1.1762)	(1.1783)	(1.1929)
U Rate rel	7.4146*	7.4779*	7.1951*	5.0183
	(4.2786)	(4.3082)	(4.3123)	(4.3670)
ln(Rent) rel	0.7041	0.6808	0.6804	0.7098
	(0.4565)	(0.4522)	(0.4524)	(0.4603)
Indiv. characteristics	No	**Yes**	**Yes**	**Yes**
Life events	No	No	**Yes**	**Yes**
Lab force participant	No	No	No	**Yes**
Obs.	20,081	20,081	20,081	19,484
Clusters	2,072	2,072	2,072	2,021
Pseudo-R^2	0.0207	0.0318	0.0328	0.0330

Notes: Clustered standard errors in parentheses. Stars denote * 0.10 ** 0.05 *** 0.01. All specifications contain individual fixed effects and MSR fixed effects. A random effects specification was also estimated but was rejected by the Hausman test. The model would not converge when including a dummy for missing labour force status, so in column (4) individuals with missing labour force status were dropped from the sample.

Adding individual characteristics (column (2)) sees the significance of the effect of population fall away, but now wages have a weakly statistically significant negative effect on moving, while unemployment remains significant at the 10% level. The results are similar when adding controls for life events. When we control for labour force participation, the magnitude and significance of the unemployment rate falls. The marginal effect of labour force participation indicates that non-participants are more likely to move (see Appendix Table 1).

Overall, while results are not strongly statistically significant, the findings are consistent with the theory that individuals are more likely to leave a place in which labour market conditions are poor relative to opportunities elsewhere. Individuals may also be more likely to leave locations with relatively low wellbeing, but this is not precisely estimated. We stress that these results are based only off individuals who move at some point, and ignore those who never move.

Table 20 presents results from the mixed logit for multinomial choice. Column (1) provides results for the location choice of migrants in the year of moving. Column (2) provides results for location choice of individuals in the full sample.[41]

Table 20: Mixed Logit Estimates of Location Choice

	Migrants (1)		Full Sample (2)	
	Mean	**SD**	**Mean**	**SD**
Mean				
SWB_adjusted	1.6894***	4.0762***	0.5677	4.2657***
	(0.5531)	(1.2101)	(0.4374)	(0.5361)
ln(Wage)	-1.7098*	3.8943***	1.6701*	-0.0279
	(1.0144)	(1.0677)	(0.9236)	(0.0579)
Previous MSR			3.4150***	0.1608
			(0.1100)	(0.1114)
Previous MSR * Own Home			0.7272***	0.0443
			(0.0746)	(0.0712)
Distance	-0.0046***		0.0016***	
	(0.0002)		(0.0002)	
Distance^2	0.0000***		-0.0000***	
	(0.0000)		(0.0000)	
ln(Pop)	1.136		1.5392	
	(1.1855)		(1.0379)	
U Rate	0.6686	-2.5744	-11.327***	-2.1904
	(5.0703)	(26.5612)	(4.1310)	(2.2566)
ln(Rent)	0.3767	0.004	0.1711	-0.0223
	(0.5232)	(0.5323)	(0.4106)	(0.0705)
Wooldridge adjustment	No		Yes	
Individual characteristics	No		No	
Obs.	36,012		1,550,874	
Cases	3,001		119,298	
Clusters	2,141		16,231	

Notes: Clustered standard errors in parentheses. Stars denote * p<0.10, ** p<0.05, *** p<0.01. Both simulations used 100 replications.

These results were estimated using 100 replications in the simulation process. The full set of results for the models in columns (1) and (2) are provided in Appendix Table 2 and Appendix Table 3, respectively. We also estimated the mixed logit models with 50 replications (also shown in the appendices). The stability of the results from 50 to 100 replications suggests the true maximum of the log likelihood has been located.

[41] We also tried estimating choices separately for our four age-time-preference groups, but the results were not robust to small changes in specification. We believe that splitting the sample into small groups is asking too much of the data because there is not much variation in location attributes once location fixed effects are controlled for.

The parameter estimates reported in the table are the coefficients at the mean of the distribution and the estimated standard deviations of their distribution. Coefficients on *Distance*, *Distance*^{2} and *ln(Pop)* are held fixed across individuals. For the remaining variables, the mean and standard deviation estimates enable us to predict the share of population with positive or negative coefficients.

We find a positive and highly statistically significant effect of SWB on the likelihood of choosing a location for the average migrant. The predicted standard deviation of coefficients on SWB is also significant at the 1% level. Given these parameter estimates, we can expect two thirds of migrants to be positively attracted to places with higher levels of location SWB. Consistent with our theoretical model, this still leaves a large group (one third) of migrants who choose to live in an area with relatively low SWB. In our *ex post* estimates, we examine the actual SWB (and wage) changes for migrants with differing characteristics.

Interestingly, we estimate a negative coefficient on (place-based) wages for the average migrant which is marginally significant. The standard deviation estimate for the coefficients on wages are highly statistically significant. The estimated parameters imply one third of migrants place positive value on choosing a location with high wages and the other two thirds have a negative taste for areas with high wages. The strong heterogeneity associated with the wage variable is again consistent with differing motivations for migration as per our theoretical model. For instance, young adults may seek out areas with high wages while those retiring may wish to migrate to areas with low wages and hence lower prices of non-traded goods and services.

The highly significant coefficients on *Distance* and its quadratic term for the average migrant combine to give a negative effect for all values of distance in our data. There is no statistically significant effect of population, unemployment, or rents.

In column (2), which estimates determinants of location choice for the full sample, we see that the coefficient on SWB for the average individual is positive but not significantly different from zero. A highly significant standard deviation for SWB implies variation in responses across the sample for this location attribute. Based on the point estimates, 55% of the sample choose to locate in areas with higher SWB.

Wages have a marginally significant positive effect on location choice for the average individual in the full sample. The variation in the distribution of the coefficients on wages is not statistically significant. In our theoretical model, wage income can be saved for the future whereas enjoyment of amenities cannot be stored. This is consistent with wages being significantly positive for location choice in the full sample but not for the migrant sample, while SWB is significantly positive for the migrant sample but not in the full sample.

Unsurprisingly, having lived in an MSR in the previous period increases the probability of living there again and this result is significant at the 1% level. The strong tendency for individuals not to move is reflective of moving costs and unobserved attributes which they value of their current locations. Moreover, the coefficient on the interaction of *Previous MSR* and *Own Home* suggests that people who own their own home are significantly more attached to their previous location. Otherwise, we do not find evidence that there is heterogeneity in preferences for staying in the same MSR.

As for migrants, the predicted coefficients of *Distance* and its quadratic for the full sample combine to give a negative effect for all values of distance in our data. Population and rents have positive but non-significant estimates. The predicted effect of the unemployment rate is negative and does not vary within individuals given the non-significance of the standard deviation parameter.

Predicted Probabilities

To compare the effect of SWB and wages in our mixed logit model for the full sample, we estimate the predicted change in probability of choosing each MSR if it experiences an increase in its *SWB_adjusted* or *ln(Wage)* by one standard deviation (1SD) (of the full sample SWB and wages) respectively.[42] Table 21 shows the estimated response to a 1SD change in SWB and wages in each MSR. The first column reports the predicted probability of choosing each MSR using the actual data; the second (fourth) column reports the predicted probability of choosing each MSR if there is a SWB (Wage) increase in that MSR, all else constant; and the third (fifth) column presents the *percent change* in likelihood of living in each MSR given it experiences a 1SD increase in SWB (Wage).

[42] For *SWB_adjusted* a 1SD increase is 0.0816 (relative to its mean of 0.0063) and for *ln(Wages)* it is 0.1474 (relative to its mean of 10.7772) or $7,610 of annual wage income.

Table 21: Mixed Logit Predicted Probabilities for Full Sample

MSR	Prob	Prob|↑SWB	%ΔProb|↑SWB	Prob|↑Wage	%ΔProb|↑Wage
Sydney	0.1695	0.1697	0.1096	0.1705	0.5521
bal_NSW	0.1393	0.1396	0.1918	0.1403	0.7159
Melbourne	0.1719	0.1721	0.0988	0.1730	0.6387
bal_VIC	0.0763	0.0765	0.2151	0.0773	1.2798
Brisbane	0.0876	0.0878	0.1429	0.0883	0.7090
bal_QLD	0.1129	0.1131	0.1617	0.1137	0.6990
Adelaide	0.0615	0.0616	0.1195	0.0618	0.5318
bal_SA	0.0300	0.0300	0.1889	0.0302	0.7325
Perth	0.0699	0.0700	0.0795	0.0702	0.4827
bal_WA	0.0269	0.0270	0.1573	0.0271	0.8839
TAS	0.0303	0.0304	0.2933	0.0306	0.8685
NT	0.0061	0.0062	0.7715	0.0063	2.5686
ACT	0.0176	0.0178	1.0924	0.0181	2.5014

Note: The %Δ in probability is calculated as the probability of choosing the MSR with the 1SD change less the initial probability of choosing the MSR, divided by the initial probability, expressed as a percentage.

The results reveal that a 1SD increase in logged wages results in greater population change than a 1SD increase of wellbeing. In fact, the population change associated with the wage increase is 2.2 to 6.3 times larger than that of *SWB_adjusted* for all MSRs. Our predicted changes in populations are substantially different across the MSRs. For example, the SWB increase results in a 0.08% population change for Perth but a 1.10% increase for ACT. Smaller regions experience greater percentage changes than larger regions since if the same number of people were to move from the rest of Australia to a particular MSR then that will constitute a larger proportionate increase in the population of the smaller MSR compared with the larger MSR.

The magnitudes of the percentage changes reflect moderate population changes. For example, the population of Sydney in 2013 was 4,756,398 (though our estimates are actually specific to the population of 25-year-olds and over, not the total population). Should a population of this size grow by 0.11%, as predicted by the model due to a 1SD rise in *SWB_adjusted*, all else constant, it would gain 5,213 people. By the same interpretation, should Sydney's average yearly wages increase by 1SD ($7,610), *ceteris paribus*, an extra 26,160 people would be expected to live there.[43]

[43] Of course, any increase predicted for one location choice will coincide with a predicted decrease in probability of living in the other locations.

These results contrast with the choices of migrants, who are more strongly affected by SWB than by wages. We therefore observe a different estimated outcome if we concentrate on population *flows* as opposed to the population *stock*. The stock shows high persistence in location reflecting high moving costs but once people decide to leave an area, placed-based SWB provides a strong drawcard for migrants. Thus it is important to define an appropriate sample for addressing a specific location question. If the question relates to overall location choice, including retention of existing residents, then (if it were feasible) an increase in local wages would be favoured over an increase in SWB. By contrast, if the question relates to what attracts people who have decided to migrate, then an increase in local SWB would be favoured over an increase in wages. As we see in the next section (and as reflected by the significant heterogeneity in our *ex ante* estimates) actual *ex post* effects show strong (individual) SWB returns from migrating, but outcomes do differ according to migrant category.

7.2 Ex Post: Payoffs to Migration

We report results of predicted wellbeing and wage trajectories around the time of migration in graph form for ease of interpretation, following (Clark et al. 2008; Nowok et al. 2013). In all cases, the coefficient on the dummy variable for one year before migration (l=-1) is the omitted reference category so that coefficients on all other timing dummies reflect the average deviation in SWB or wages relative to this time. Note that it is important to pay attention to graph axes because they change according to sample.

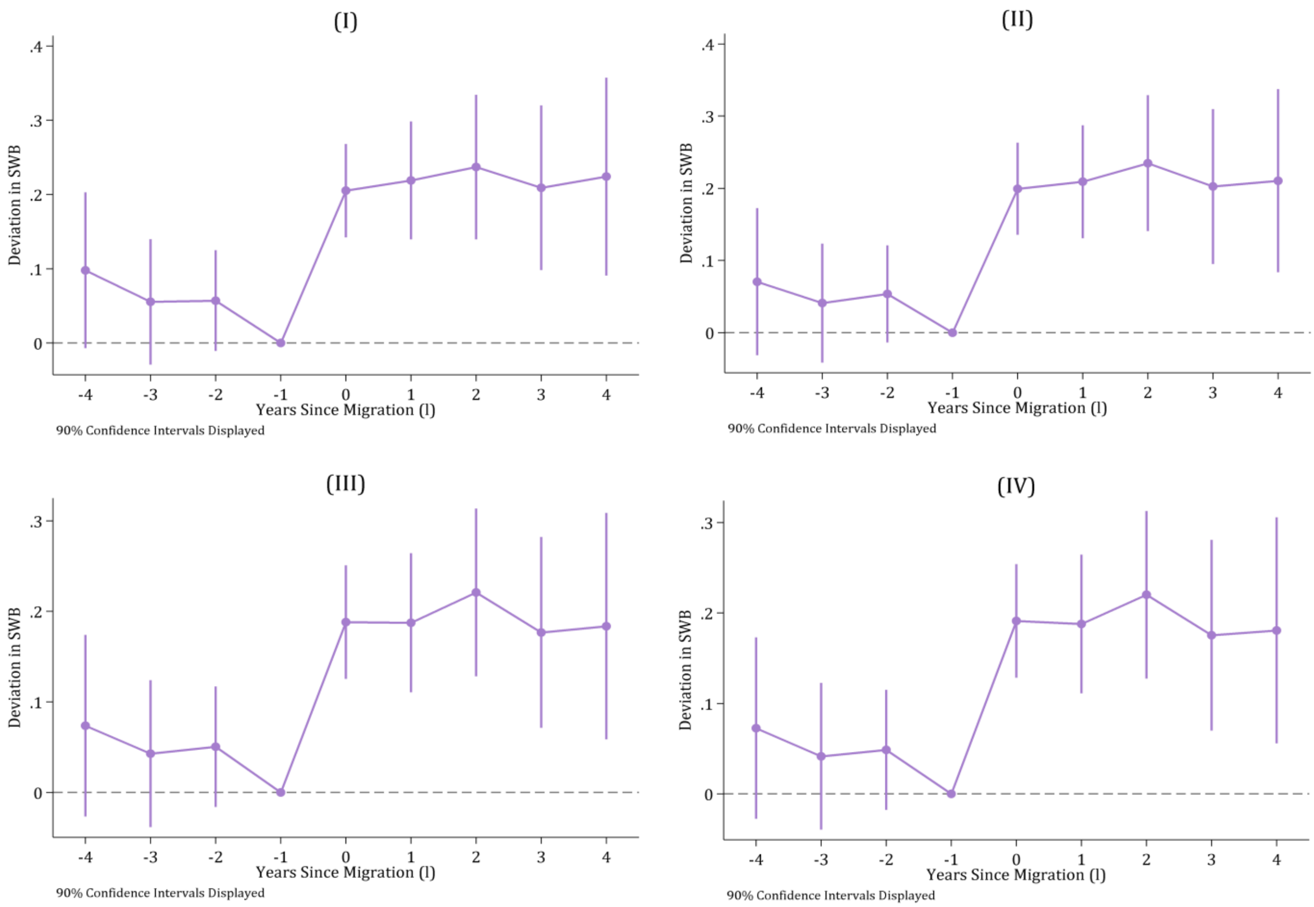
Results from four specifications of the main results are presented, labelled (I) to (IV). The most basic version includes only individual and year fixed effects (I) as controls. Model (II) adds controls for personal characteristics, (III) subsequently adds life events and health status, and (IV) adds a dummy indicator for labour force participation. Each coefficient features spikes which represent the 90% confidence interval of the estimate.

7.2.1 SWB Payoffs

Results for the models which have SWB as the dependent variable are shown in Figure 6 for the sample of all migrants. A full table of estimates is laid out in Appendix Table 4. Our estimates are robust across specifications, indicating that changes in individual characteristics, life events and labour force participation do little to affect the change in wellbeing around migration.

In general, wellbeing drops in the year prior to moving compared to earlier years, though this fall is not statistically significant. There are several potential explanations for such a finding: migration could be triggered by a fall in wellbeing associated with some unobserved events; the anticipation of an improved situation could alter one's satisfaction with what the individual has now; or the lead up to migration may be stressful, resulting in a decrease in wellbeing.

Figure 6: Changes in SWB around Migration



In the year of migration (*l*=0) there is a clear wellbeing increase relative to the year before, of much larger magnitude than the earlier drop. The increase is statistically significant at the 1% level in all four specifications and is around one fifth of a point on the SWB scale (which compares with one standard deviation of the SWB measure of 1.52). The predicted increase relating to migration is roughly equivalent to the predicted effect of getting married as estimated in models (III) and (IV).

The model predicts that the new level of wellbeing is broadly sustained over the following four years. Coefficients on these timing dummies from *l*=1 to *l*=4 are all positive and statistically significant at the 5% level across all model specifications. The precision of estimates decreases in years further from the time of migration which may reflect smaller sample sizes.

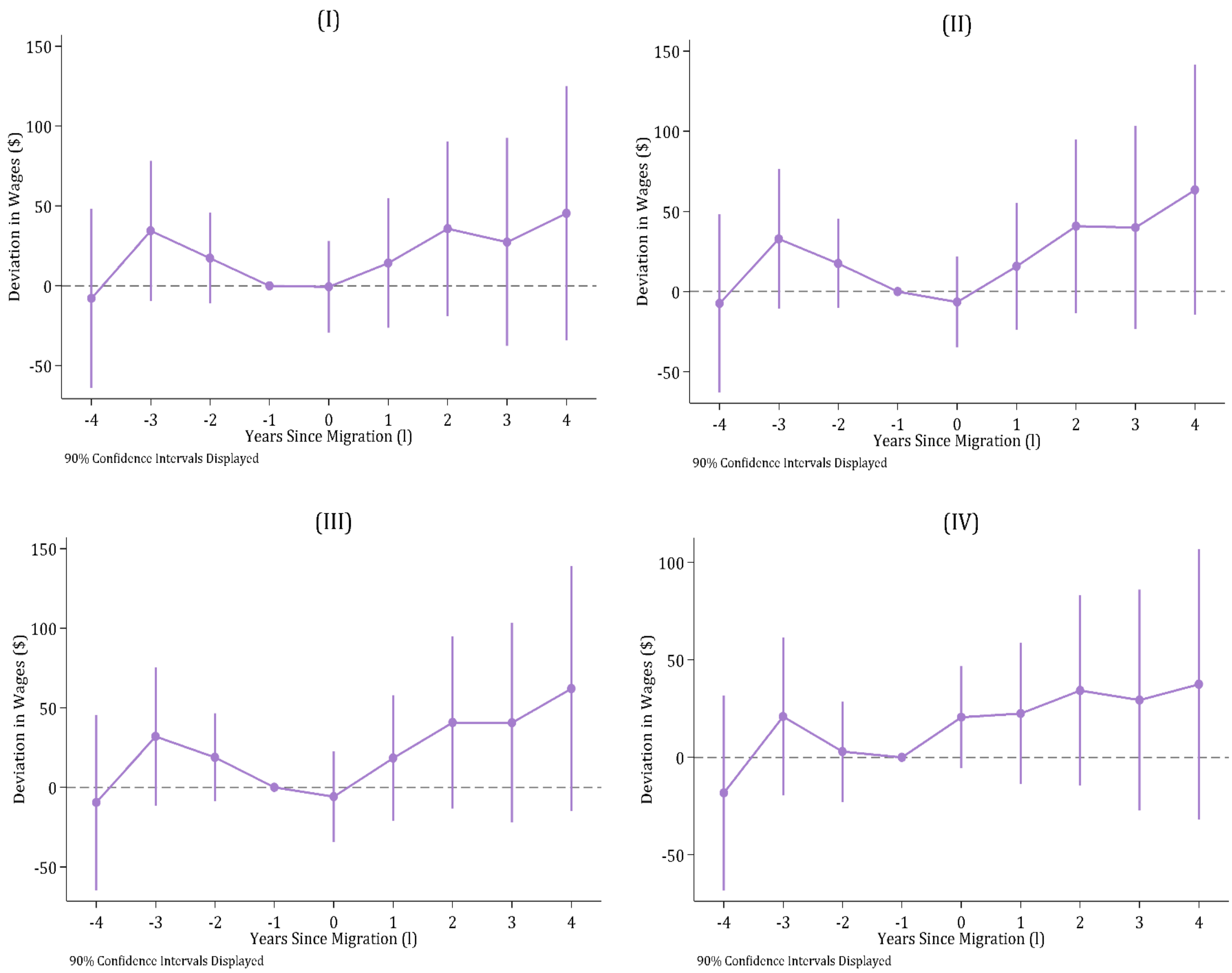
7.2.2 Wage Payoffs

Wage outcomes of migration for the sample of all migrants are shown in Figure 7, with a full set of coefficient estimates provided in Appendix Table 5. The general pattern in models (I) to (III) shows wages on average falling slightly in the two years before migration, and falling again slightly in the year of moving, then rising fairly persistently in subsequent years. When controlling for labour force participation as in model (IV), wages increase slightly in the year before and the year of moving. This indicates that moving may be associated with leaving the labour force which in turn is associated with a decrease in wage earnings.

However, none of the migration timing coefficients in any of the four models of wages is significantly different from zero. It is likely that a high level of variation in wage experiences around migration leads to these imprecise estimates.

Overall, the findings suggest that wage paths of migrants, controlling for other factors, are an individual-specific phenomena. This is in contrast to results for SWB, for which there is a clear positive post-migration jump for the full sample.

Figure 7: Changes in Wages around Migration



7.2.3 Sub-sample results

We present SWB and wage trajectories for different sub-samples of our data in Figure 8 to Figure 11. The same controls are used as in model (II) above.[44] Experiences are compared by age, gender, an interaction of age and time preference, and various reasons for moving. Because of space restrictions we do not provide full tables of results for these estimations, but we do provide the P-values of tests that migration timing coefficients for different groups are equal in Table 22.

Observations for a particular migration by an individual are assigned to a group according to the individual's status in the year of moving. We focus in this section mainly on post-migration effects, but it is important to check pre-migration trends in order to compare the years after the event. Note that the age and time preference interactions are included in a single estimation but reported in two separate graphs for ease of interpretation.

The sub-sample results confirm what we find for the full sample: that SWB tends to increase after moving. Point estimates vary for different groups, and the confidence intervals are wide for some, which is likely due to small sample sizes in some cases (e.g. for older age groups). There is one exception to this general conclusion, and that is for those who move because of a work transfer. This small sub-sample on average experiences an initial decrease in wellbeing after moving, though not significantly different from zero. A reason for this exception may be that a work transfer is not an entirely voluntary move.

In contrast to the SWB results, wages can be on very different pathways for different groups. This is reflected in Table 22 which shows there are more significant differences in outcome pathways across sub-samples for wages than for SWB. For the groups that we consider, a sharp increase in wages *relative to the trend before moving* is only clear for those who move for work-related reasons or specifically for a new job. Consistent with the *ex ante* estimation results for the migrant sample, this evidence supports the relevance of measures of life-satisfaction over wages for the migration decision of those who choose to migrate. In addition, consistent with the *ex ante* results for the migrant sample, we see considerable heterogeneity – particularly for wages – across different migrant sub-samples.

Disparities in the trajectories by time preference and life-stage are mostly consistent with the life-cycle theory presented earlier in this paper, albeit without statistically significant differences. Using the point estimates, wellbeing increases more for young people if they have high (relative to low) time preference, and it increases slightly more for the senior group if they have low (relative to high) time preference. For the older cohort, there is a decrease in wages for both high and low time preference groups. The predicted fall in wages is however larger,

[44] Model (II) is chosen because controls in (III) and (IV) are potentially endogenous to wage and SWB outcomes.

significantly so in some years, for the low time preference (older age) group, consistent with this group being more able to transition into retirement if their prior savings behaviour reflected their respective time preference profiles. These results are each consistent with our theory. However, contrary to the theory, for younger people, wages rise similarly immediately upon migration for high and low time preference individuals, and wages then rise less rapidly for those with low time preference.

An important result across these various sub-samples is that life-satisfaction improvements tend to be larger in cases where wage gains are relatively smaller. This result is consistent with our theoretical model. In particular, those who move for work-related reasons to have smaller wellbeing gains despite a large jump in income post-migration, compared to the remaining sample. On the other hand, individuals moving because of a non-pecuniary motivation (new lifestyle; to be closer to friends/family; to live in a better area) experience larger wellbeing improvements despite initial falls in wages.

Figure 8: Changes in SWB around Migration by Sub-Sample (A)

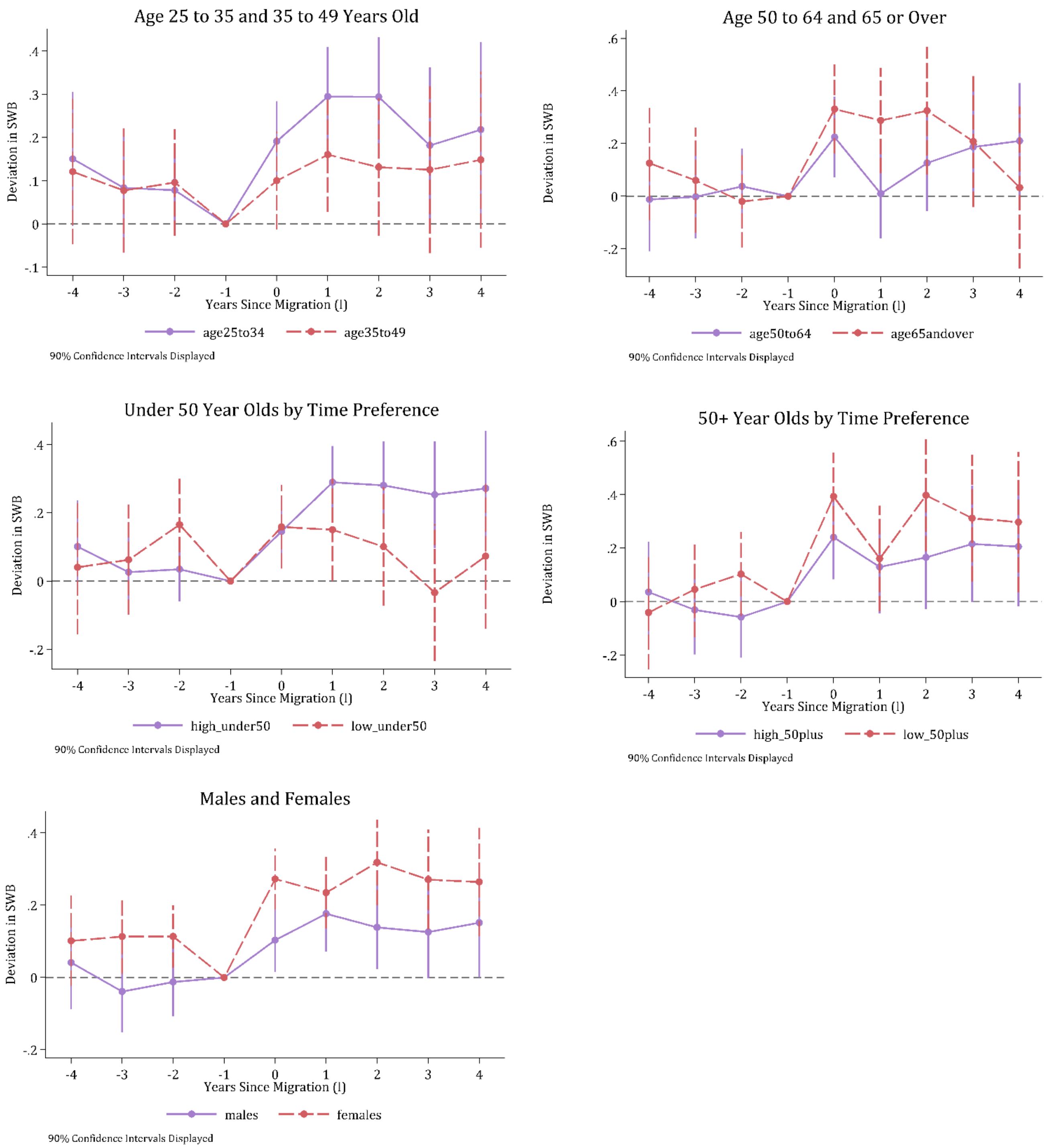


Figure 9: Changes in SWB around Migration by Sub-Sample (B)

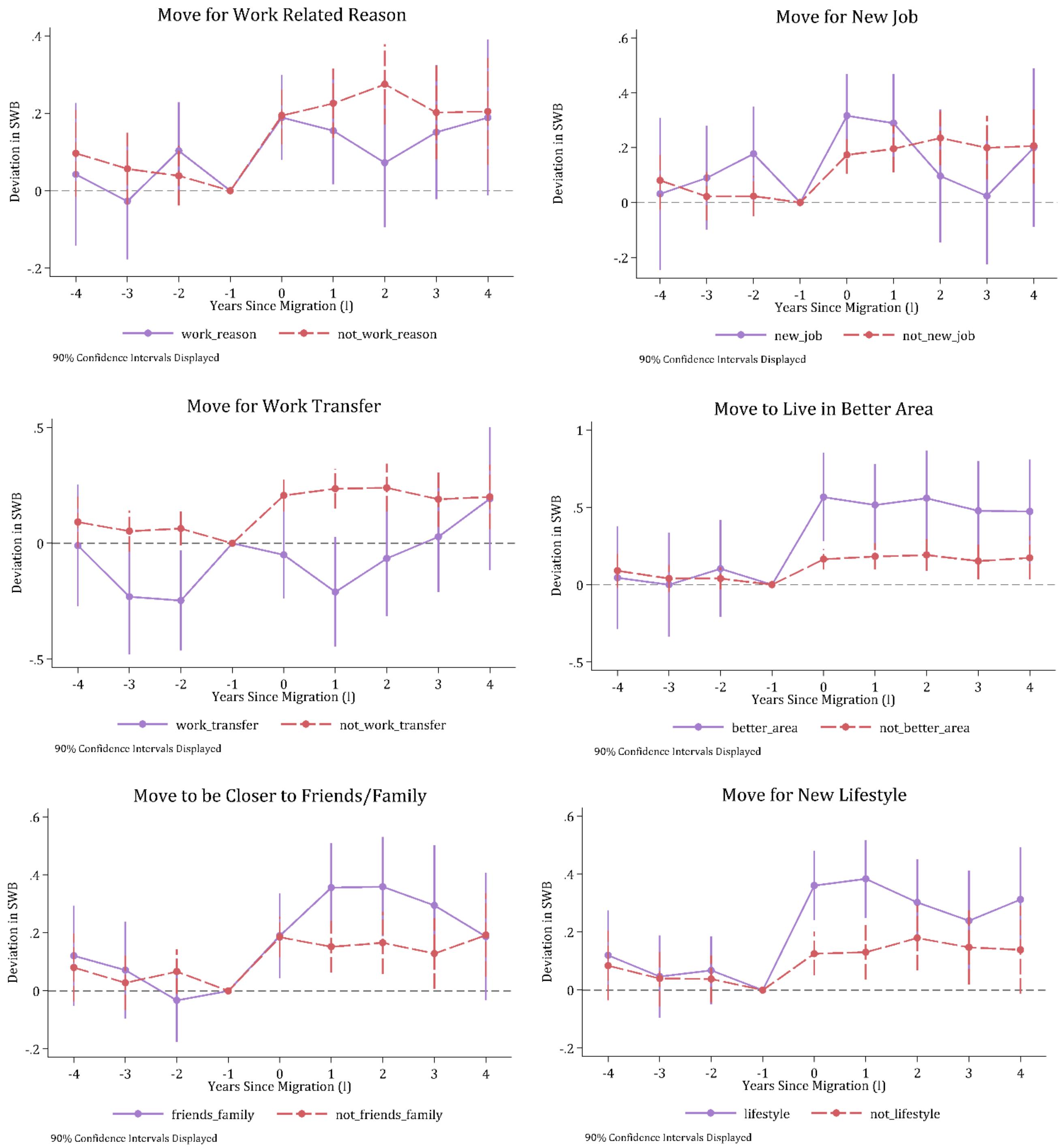


Figure 10: Changes in Wages around Migration by Sub-Sample (A)

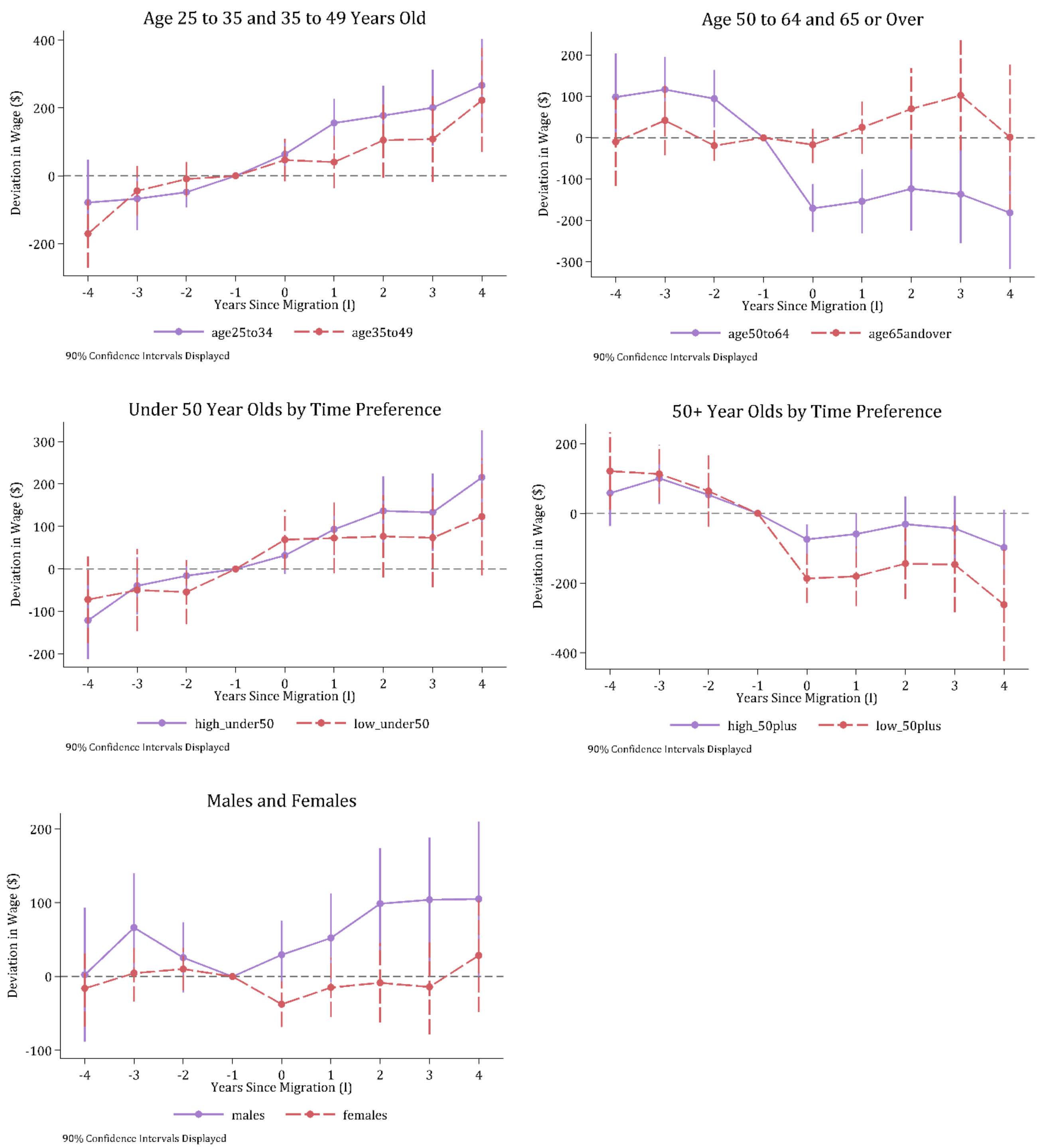


Figure 11: Changes in Wages around Migration by Sub-Sample (B)

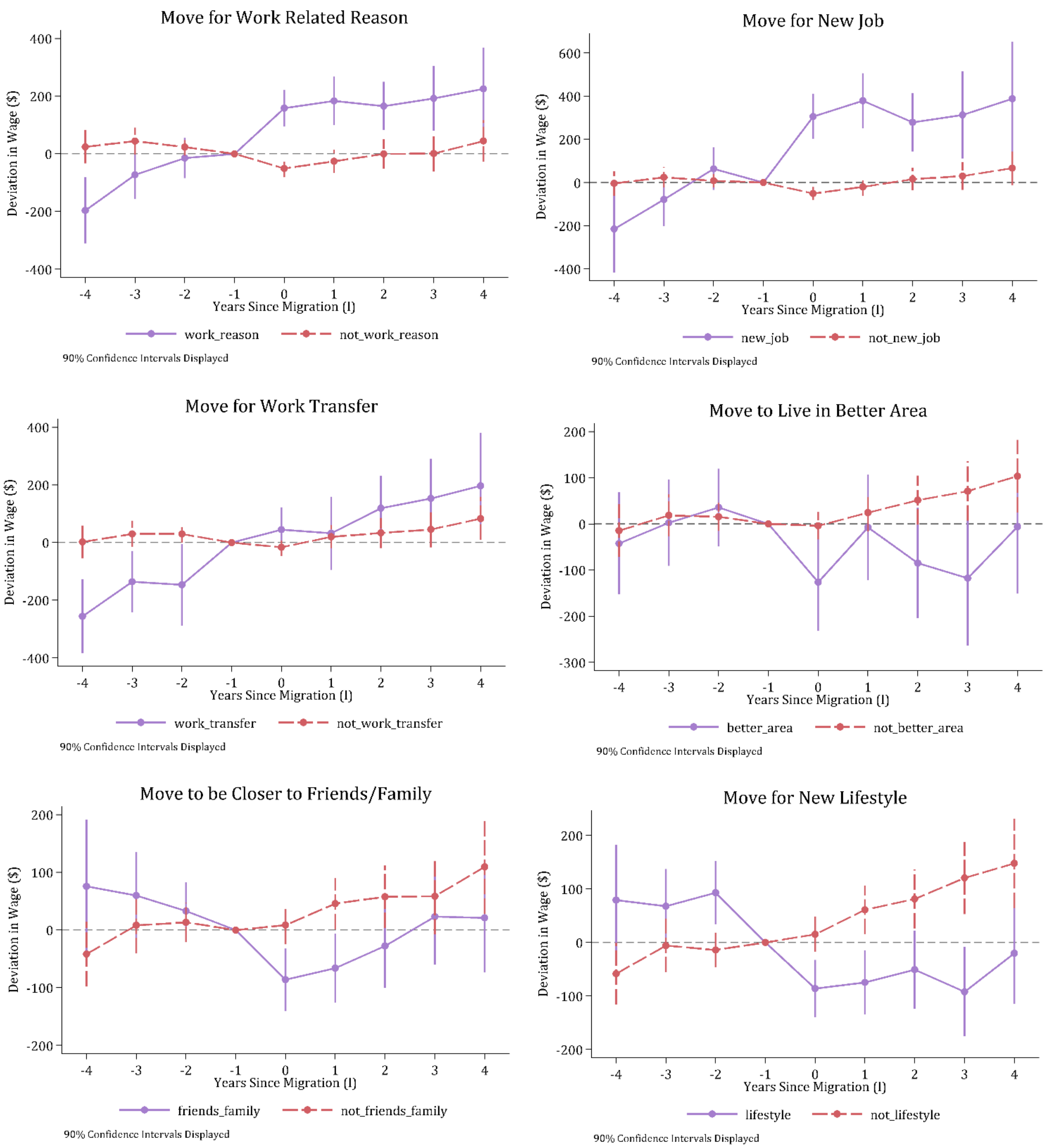


Table 22: Tests for Equality of Migration Timing Dummy-Interaction Coefficients

	SWB								Wages							
Test	-4	-3	-2	0	1	2	3	4	-4	-3	-2	0	1	2	3	4
25 to 34 = 35 to 49													**			
25 to 34 = 50 to 64					**				**	***	***	***	***	***	***	***
25 to 34 = 65+												**	***	**		***
35 to 49 = 50 to 64									***	***	**	***	***	***	***	***
35 to 49 = 65+				*					**							**
50 to 64 = 65+					*						**	***	***	***	***	**
male = female		*	*	**		**							*	**	**	
high_under50 = low_under50							**									
high_under50 = high_50plus									***	***	**	***	***	***	***	***
high_under50 = low_50plus				**					***	***		***	***	***	***	***
low_under50 = high_50plus			*						*	**	**	***	**	*	*	***
low_under50 = low_50plus				*		*	**		**	**		***	***	***	**	***
high_50plus = low_50plus												**	**	*		*
Work Reason (Yes = No)						*			***	**		***	***	***	***	**
New Job (Yes = No)									*			***	***	***	**	**
Work Transfer (Yes = No)		*	**	**	***	**			***	**	**					
Better Area (Yes = No)				**	**	*						*		*	**	
Closer to Friends/Family (Yes = No)					**	*						**	***	**		*
New Lifestyle (Yes = No)				***	***				**		***	***	***	***	***	***

Notes: Stars denote: * p<0.10, ** p<0.05, *** p<0.010. Blank cells indicate p>0.10 i.e. we cannot reject equality of the coefficients at the 10% level.

8 Conclusions

In our theoretical model we showed that a well-informed rational individual may choose to move to an 'unhappy place' in order to optimise their lifetime utility. In our empirical work based on Australian longitudinal panel data, we find that labour market factors dominate SWB as determinants of the choice to emigrate and for overall location, although high moving costs and unobserved attributes of one's initial location dominate the latter resulting in most people staying in the same area from one year to the next.

High moving costs may therefore result in many people remaining in an unhappy place. However, for those who choose to migrate (internally within Australia), place-based subjective wellbeing is the dominant factor in predicting where people choose to move. Furthermore, when we examine the *ex post* outcomes for this group we find a consistent pronounced upturn in individuals' SWB in the year of migration that is sustained for at least four years. This upturn is estimated to be present across virtually all our sub-samples – by age, gender, time preference, and across various reasons for moving. Relative to other determinants of wellbeing, the jump in individual SWB following migration is material, being roughly equivalent to the jump experienced upon marriage.

Consistent with our theoretical model which predicts that migration decisions are considered within a life cycle process reflecting individual characteristics, we observe considerable heterogeneity in migration decisions. This is apparent both in our *ex ante* predictive models (for migrants and for the full sample) and in *ex post* outcomes. Our *ex post* results across sub-samples show that life-satisfaction improvements tend to be larger in cases where wage gains are relatively smaller. For instance, those who move for work-related reasons or for a new job tend to have smaller wellbeing gains despite a large jump in income post-migration, compared to the remaining sample. Conversely, individuals moving because of a non-pecuniary motivation (new lifestyle; to be closer to friends/family; to live in a better area) experience larger wellbeing improvements despite initial falls in wages. These predictions are consistent with the implications of our theoretical model. When we split our sample by age and time preference, the results are mostly consistent with our theory, especially in relation to SWB outcomes. In particular, we observe that younger people with high time preference have a greater SWB boost upon migration than do younger people with low time preference, while the opposite pattern holds for older people. However these differences are not statistically significant.

The consistent SWB effects that we see – both in our predictive model of migrant location and for actual migrant outcomes – indicate that migrants do make location choices based on prospective wellbeing in different locations and that they achieve sustained SWB increases upon migration. These findings substantiate the use of SWB as a useful concept for policy-makers to target. In particular, the findings indicate that local policy-makers who wish to attract migrants should consider targeting improvements in outcomes that will lead to high SWB of prospective migrants. For instance, they may act to improve non-pecuniary amenities in an area. However, if they wish to retain existing residents, our findings show that they also need to adopt policies that foster local employment and wages. Both labour market and subjective wellbeing variables are therefore important indicators of policy success at the local level.

From a broader perspective, this study shows that measures of SWB do have real content since they influence one of the most major decisions that people make in their lives – their choice of where to live. This consistency between an important revealed preference (migrant location choice) and SWB indicates that wellbeing measures – such as the life satisfaction measure used here – should be included amongst target outcomes for policy-makers.

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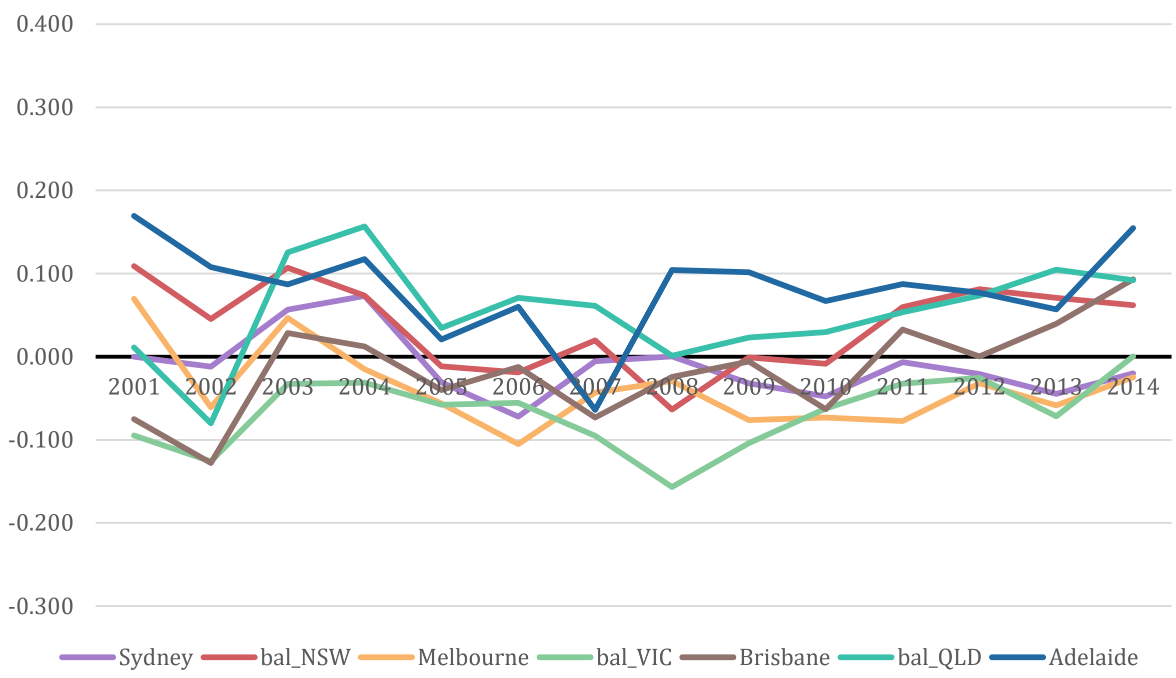
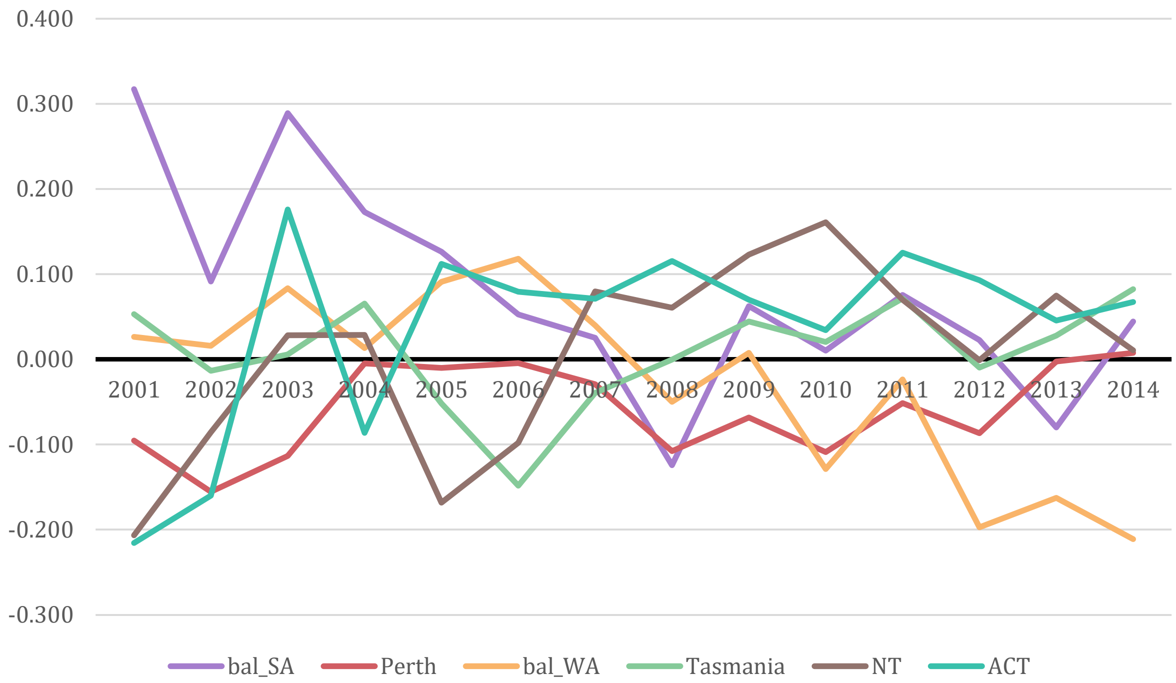
Appendices

Appendix Figure 1: SWB_adjusted over Time for MSRs





Appendix Table 1: Fixed Effects Logit Estimates of Propensity to Move

	(1)	**(2)**	**(3)**	**(4)**
SWB_adjusted rel	-0.253	-0.3016	-0.2815	-0.3047
	(0.4473)	(0.4504)	(0.4515)	(0.4586)
ln(Wage) rel	-1.1712	-1.5937*	-1.6308*	-1.5712*
	(0.8784)	(0.8826)	(0.8823)	(0.9000)
ln(Pop) rel	-2.0148*	-1.2005	-1.2028	-1.4476
	(1.1672)	(1.1762)	(1.1783)	(1.1929)
U Rate rel	7.4146*	7.4779*	7.1951*	5.0183
	(4.2786)	(4.3082)	(4.3123)	(4.3670)
ln(Rent) rel	0.7041	0.6808	0.6804	0.7098
	(0.4565)	(0.4522)	(0.4524)	(0.4603)
Age				
25 to 34				
35 to 49		-0.2970***	-0.3004***	- 0.3076***
		(0.1068)	(0.1070)	(0.1080)
50 to 64		-0.1942	-0.194	-0.2371
		(0.1883)	(0.1883)	(0.1897)
65+		-0.0125	-0.0085	-0.1307
		(0.2716)	(0.2719)	(0.2752)
Marital Status				
Married				
De facto		-0.1830*	-0.1578	-0.1237
		(0.1084)	(0.1126)	(0.1155)
Separated/Divorced		-0.2708	-0.2845	-0.251
		(0.2440)	(0.2440)	(0.2658)
Widowed		0.257	0.202	0.1706
		(0.3710)	(0.3656)	(0.3823)
Never married/Not de facto		-0.3386	-0.3266	-0.2698
		(0.2509)	(0.2521)	(0.2773)
Missing		-1.5411	-1.5318	-1.461
		(1.1331)	(1.1240)	(1.1267)
Family Type				
Couple w child				
Couple no child		0.0349	0.0111	0.0451
		(0.1313)	(0.1307)	(0.1350)
Single w child		0.2736	0.2663	0.2794
		(0.2547)	(0.2541)	(0.2710)
Single no child		0.3516	0.337	0.3609
		(0.2446)	(0.2440)	(0.2669)
No. Dependent Children		-0.1821***	-0.1785***	- 0.1678***
		(0.0598)	(0.0601)	(0.0606)

	(1)	(2)	(3)	(4)
Education				
Postgrad				
Grad diploma/certificate		0.1882	0.1895	0.0658
		(0.2960)	(0.2966)	(0.2946)
Bachelor/honours		0.3151	0.3214	0.2777
		(0.2660)	(0.2673)	(0.2605)
Adv diploma/diploma		-0.0719	-0.0653	0.0674
		(0.4036)	(0.4050)	(0.4268)
Cert III or IV		0.167	0.1761	0.2984
		(0.3633)	(0.3639)	(0.3840)
Year 12		0.4151	0.4179	0.3396
		(0.3653)	(0.3662)	(0.3819)
Year 11 or below		0.3198	0.3273	0.4128
		(0.3920)	(0.3939)	(0.4214)
Missing		2.0272*	1.9786*	
		(1.1838)	(1.1762)	
Own Home		-0.4002***	-0.3970***	-0.3985***
		(0.0666)	(0.0667)	(0.0675)
Missing				
Got married			0.0967	0.1058
			(0.1440)	(0.1451)
Missing			0.2584	0.2746
			(0.5999)	(0.5860)
Separated			0.0869	0.0772
			(0.1153)	(0.1153)
Missing			-0.5072	-0.5488
			(0.4845)	(0.5046)
Got back together			-0.0276	-0.0308
			(0.1958)	(0.1969)
Missing			-0.1121	-0.0784
			(0.6207)	(0.6150)
Pregnancy			0.0701	0.0652
			(0.1013)	(0.1020)
Missing			0.6543	0.6682
			(0.5477)	(0.5514)
Birth/adoption			-0.0974	-0.1167
			(0.1268)	(0.1277)
Missing			-0.2796	-0.2854
			(0.4523)	(0.4439)
Death of spouse/child			0.2214	0.2305
			(0.2599)	(0.2611)
Missing			0.0134	0.0213
			(0.5088)	(0.4876)

	(1)	(2)	(3)	(4)
Self-assessed Health				
Excellent				
Very good			-0.0579	-0.0541
			(0.0899)	(0.0901)
Good			-0.0853	-0.0846
			(0.1027)	(0.1032)
Fair			0.0158	0.0054
			(0.1272)	(0.1281)
Poor			0.2974	0.2494
			(0.1900)	(0.1900)
Missing			0.0165	-0.0073
			(0.1657)	(0.1728)
In Lab Force				-0.2268***
				(0.0786)
MSR				
Sydney				
bal_NSW	-2.0663***	-1.5654**	-1.5822**	-1.6998**
	(0.7831)	(0.7852)	(0.7865)	(0.7966)
Melbourne	-0.5419**	-0.4369*	-0.4416*	-0.4651*
	(0.2534)	(0.2513)	(0.2522)	(0.2568)
bal_Vic	-3.9380**	-2.8673*	-2.8926*	-3.1736**
	(1.5332)	(1.5445)	(1.5478)	(1.5673)
Brisbane	-2.6738**	-1.8927*	-1.9070*	-2.1347*
	(1.1390)	(1.1465)	(1.1482)	(1.1628)
bal_QLD	-2.8106***	-2.1595**	-2.1795**	-2.3802**
	(0.9875)	(0.9923)	(0.9940)	(1.0072)
Adelaide	-3.2605**	-2.1225	-2.1422	-2.4295
	(1.6567)	(1.6694)	(1.6724)	(1.6927)
bal_SA	-5.6132*	-3.6129	-3.6514	-4.2548
	(2.9577)	(2.9788)	(2.9841)	(3.0169)
Perth	-2.6207**	-1.6487	-1.662	-1.9733
	(1.3256)	(1.3348)	(1.3378)	(1.3562)
bal_WA	-4.7168*	-2.7798	-2.7948	-3.3224
	(2.7095)	(2.7312)	(2.7363)	(2.7712)
Tasmania	-5.7012**	-3.8688	-3.8898	-4.4194
	(2.6515)	(2.6695)	(2.6738)	(2.7058)
NT	-6.5575*	-4.0451	-4.0549	-4.8478
	(3.6993)	(3.7262)	(3.7320)	(3.7801)
ACT	-5.8604*	-3.5912	-3.6048	-4.2547
	(3.1933)	(3.2193)	(3.2251)	(3.2665)

	(1)	(2)	(3)	(4)
Year				
2002				
2003	0.0205	0.0279	0.0424	0.088
	(0.0984)	(0.0997)	(0.1733)	(0.1863)
2004	-0.0849	-0.0723	-0.0586	-0.0228
	(0.1061)	(0.1085)	(0.1798)	(0.1932)
2005	0.0859	0.0958	0.1097	0.1551
	(0.1031)	(0.1057)	(0.1732)	(0.1848)
2006	-0.0666	-0.0458	-0.0298	0.0181
	(0.1068)	(0.1107)	(0.1798)	(0.1922)
2007	0.0984	0.1317	0.1466	0.1679
	(0.1042)	(0.1099)	(0.1810)	(0.1933)
2008	-0.2412**	-0.2026*	-0.1877	-0.1438
	(0.1108)	(0.1182)	(0.1839)	(0.1953)
2009	-0.1802	-0.1161	-0.1008	-0.0559
	(0.1099)	(0.1188)	(0.1822)	(0.1947)
2010	-0.3893***	-0.3160**	-0.3047	-0.2504
	(0.1129)	(0.1247)	(0.1885)	(0.2007)
2011	-0.3055***	-0.2140*	-0.193	-0.1614
	(0.1127)	(0.1262)	(0.1875)	(0.2001)
2012	-0.4186***	-0.3087**	-0.2912	-0.2658
	(0.1119)	(0.1278)	(0.1911)	(0.2031)
2013	-0.5012***	-0.3917***	-0.3718*	-0.3378*
	(0.1117)	(0.1313)	(0.1919)	(0.2039)
2014	-0.3931***	-0.2778**	-0.2602	-0.2322
	(0.1137)	(0.1339)	(0.1930)	(0.2046)
Obs.	20,081	20,081	20,081	19,484
Obs. dropped	117,009	117,009	117,009	112,495
Clusters	2,072	2,072	2,072	2,021
Pseudo-R^2	0.0206539	0.03177769	0.03279577	0.032964

Notes: Clustered standard errors in parentheses. Stars denote * 0.10 ** 0.05 *** 0.01. All specifications contain individual fixed effects. A random effects specification was also estimated but was rejected by the Hausman test. The model would not converge when including a dummy for missing labour force status, so in column (4) individuals with missing labour force status were dropped from the sample.

Appendix Table 2: Mixed Logit Estimates of Location Choice for Migrants

	50 reps		**100 reps**	
	Mean	**SD**	**Mean**	**SD**
Mean				
ln(Wage)	-1.4715	2.3786*	-1.7098*	3.8943***
	(0.9402)	(1.3341)	(1.0144)	(1.0677)
SWB_adjusted	1.5463***	4.0891***	1.6894***	4.0762***
	(0.4962)	(1.4023)	(0.5531)	(1.2101)
Distance	-0.0043***		-0.0046***	
	(0.0002)		(0.0002)	
Distance^2	0.0000***		0.0000***	
	(0.0000)		(0.0000)	
ln(Pop)	1.0227		1.136	
	(1.1073)		(1.1855)	
U Rate	1.2677	-8.7559	0.6686	-2.5744
	(4.6513)	(8.5737)	(5.0703)	(26.5612)
ln(Rent)	0.4592	0.7537	0.3767	0.004
	(0.4926)	(0.5449)	(0.5232)	(0.5323)
MSR				
Sydney				
bal_NSW	0.5263	-0.8343**	0.6786	-0.393
	(0.5566)	(0.3270)	(0.5920)	(0.7520)
Melbourne	-0.6579*	1.8707***	-0.7957***	2.1740***
	(0.3751)	(0.4661)	(0.3053)	(0.3474)
bal_VIC	0.4688	0.9263*	0.3805	1.2057***
	(1.2363)	(0.5126)	(1.2997)	(0.4008)
Brisbane	1.4919*	0.1549	1.3565	1.1539***
	(0.8507)	(0.3484)	(0.8962)	(0.2362)
bal_QLD	2.2575***	-0.7132*	2.3661***	-1.0008***
	(0.7324)	(0.4325)	(0.7672)	(0.3575)
Adelaide	0.7212	-0.3326	0.9073	0.1764
	(1.3462)	(0.3386)	(1.4328)	(0.2682)
bal_SA	1.778	-0.0381	1.9592	-0.2049
	(2.5696)	(0.1596)	(2.7556)	(0.2929)
Perth	2.2622**	0.6039	2.1218*	1.3650***
	(1.0559)	(0.5390)	(1.1502)	(0.4731)
bal_WA	2.9247	0.21	3.0426	0.8635***
	(2.3503)	(0.2482)	(2.5039)	(0.3040)
Tasmania	-5.1746	5.6503***	-11.2859***	9.0685***
	(4.1618)	(2.0965)	(3.2931)	(1.1473)
NT	-0.7019	3.6752***	1.8671	2.1709***
	(3.4933)	(0.7501)	(3.7206)	(0.7911)
ACT	0.5082	-0.8842	-1.0512	-2.5900***
	(2.8465)	(1.0159)	(3.0576)	(0.5451)
Obs.	36,012		36,012	
Cases	3,001		3,001	
Clusters	2,141		2,141	

Notes: Clustered standard errors in parentheses. Stars denote * p<0.10, ** p<0.05, *** p<0.01. All models use a burn-in of 15.

Appendix Table 3: Mixed Logit Estimates of Location Choice for Full Sample

	50 reps		**100 reps**	
	Mean	**SD**	**Mean**	**SD**
Mean				
ln(Wage)	1.8393**	-0.0131	1.6701*	-0.0279
	(0.9178)	(0.0647)	(0.9236)	(0.0579)
SWB_adjusted	0.5051	3.2512***	0.5677	4.2657***
	(0.4313)	(0.6262)	(0.4374)	(0.5361)
Previous MSR	3.4045***	-0.0866	3.4150***	0.1608
	(0.1083)	(0.1256)	(0.1100)	(0.1114)
Previous MSR * Own Home	0.7005***	0.0088	0.7272***	0.0443
	(0.0749)	(0.0560)	(0.0746)	(0.0712)
Distance	0.0016***		0.0016***	
	(0.0002)		(0.0002)	
Distance^2	-0.0000***		-0.0000***	
	(0.0000)		(0.0000)	
ln(Pop)	1.6552		1.5392	
	(1.0340)		(1.0379)	
U Rate	-11.0282***	-1.141	-11.3271***	-2.1904
	(4.1086)	(2.0839)	(4.1310)	(2.2566)
ln(Rent)	0.1802	0.065	0.1711	-0.0223
	(0.4004)	(0.0959)	(0.4106)	(0.0705)
Initial MSR	-0.4192***		-0.3980***	
	(0.0999)		(0.1008)	
Initial MSR * avg Own Home	0.6793***		0.7017***	
	(0.1233)		(0.1281)	
avg ln(Wage)	-8.9473**		-7.9803*	
	(3.9965)		(4.2148)	
avg SWB_adjusted	-0.2134		0.5181	
	(2.3046)		(2.4014)	
avg Distance	-0.0102***		-0.0103***	
	(0.0002)		(0.0002)	
avg Distance^2	0.0000***		0.0000***	
	(0.0000)		(0.0000)	
avg ln(Pop)	-3.9293		-3.9256	
	(3.1141)		(3.0531)	
avg U Rate	-8.2411		-3.4053	
	(22.2940)		(22.4579)	
avg ln(Rent)	2.4977		2.4547	
	(1.7693)		(1.7729)	

	50 reps		100 reps	
	Mean	**SD**		**Mean**
	(0.0949)		(0.0983)	
first ln(Wage)	0.5471		-0.4782	
	(2.4266)		(2.6630)	
first SWB_adjusted	0.4818		0.7059	
	(0.7186)		(0.7099)	
first Distance	0.0021***		0.0021***	
	(0.0002)		(0.0002)	
first Distance^2	-0.0000***		-0.0000***	
	(0.0000)		(0.0000)	
first ln(Pop)	1.9833		2.0237	
	(2.2706)		(2.2509)	
first U Rate	0.665		1.3461	
	(7.7506)		(7.8347)	
first ln(Rent)	-0.0964		-0.0569	
	(0.7113)		(0.6925)	
MSR				
Sydney				
bal_NSW	-0.3085	0.0806	-0.5546	-0.0699
	(1.3031)	(0.0761)	(1.3079)	(0.0860)
Melbourne	0.0283	0.027	0.0066	0.0138
	(0.4171)	(0.0235)	(0.4115)	(0.0181)
bal_VIC	-0.8793	0.0247	-1.0478	-0.0068
	(2.6875)	(0.0205)	(2.6543)	(0.0166)
Brisbane	-0.2438	0.4440***	-0.4223	0.6480***
	(1.7364)	(0.1689)	(1.7344)	(0.1166)
bal_QLD	-0.5551	1.9405***	-0.8395	2.0255***
	(1.6031)	(0.0707)	(1.6142)	(0.0723)
Adelaide	-0.8621	0.0673	-1.2112	0.3534*
	(2.7399)	(0.4105)	(2.7252)	(0.1912)
bal_SA	-1.6686	0.5475***	-2.0922	0.6268***
	(5.2930)	(0.1602)	(5.2446)	(0.1290)
Perth	0.3946	0.7886***	0.1998	1.4135*
	(2.0801)	(0.2061)	(2.0913)	(0.7569)
bal_WA	-0.4835	1.6856***	-0.3396	1.1534
	(4.6690)	(0.1523)	(4.5822)	(0.8818)
Tasmania	-1.2121	-0.6011***	-1.5713	-0.7167***
	(4.6735)	(0.1444)	(4.6296)	(0.1525)
NT	-1.021	1.1545***	-1.5656	1.3926***
	(6.4004)	(0.2298)	(6.3610)	(0.2428)
ACT	-1.4084	0.0592	-1.6234	0.0315
	(5.3021)	(0.0383)	(5.2701)	(0.0336)
Obs.	1,550,874		1,550,874	
Cases	119,298		119,298	
Clusters	16,231		16,231	

Notes: Clustered standard errors in parentheses. Stars denote * p<0.10, ** p<0.05, *** p<0.01. All models use a burn-in of 15.

Appendix Table 4: Fixed Effects OLS Estimates for SWB around the Migration Decision

	(I)	(II)	(III)	(IV)
Years since migration				
-4	0.098	0.0705	0.0737	0.0727
	(0.0638)	(0.0619)	(0.0610)	(0.0610)
-3	0.0554	0.0409	0.0428	0.0416
	(0.0514)	(0.0501)	(0.0494)	(0.0493)
-2	0.0571	0.0535	0.0505	0.0486
	(0.0412)	(0.0409)	(0.0404)	(0.0404)
-1 (omitted)				
0	0.2051***	0.1994***	0.1882***	0.1912***
	(0.0382)	(0.0388)	(0.0381)	(0.0381)
1	0.2190***	0.2090***	0.1874***	0.1879***
	(0.0483)	(0.0475)	(0.0467)	(0.0466)
2	0.2370***	0.2348***	0.2209***	0.2202***
	(0.0591)	(0.0572)	(0.0564)	(0.0563)
3	0.2091***	0.2025***	0.1767***	0.1754***
	(0.0673)	(0.0652)	(0.0641)	(0.0641)
4	0.2241***	0.2105***	0.1837**	0.1808**
	(0.0809)	(0.0771)	(0.0760)	(0.0760)
35 to 49		-0.0394	-0.0551	-0.0609
		(0.0615)	(0.0604)	(0.0603)
50 to 64		-0.0665	-0.0493	-0.0535
		(0.1182)	(0.1158)	(0.1159)
65 +		0.016	0.0014	0.0095
		(0.1498)	(0.1470)	(0.1469)
De facto		0.2086***	0.2819***	0.2825***
		(0.0638)	(0.0688)	(0.0690)
Separated/divorced		-0.4266***	-0.2705*	-0.2641*
		(0.1528)	(0.1551)	(0.1554)
Widowed		-0.2352	-0.1363	-0.1366
		(0.3001)	(0.2870)	(0.2869)
Never married/not de facto		0.0152	0.1872	0.1912
		(0.1622)	(0.1691)	(0.1688)
Couple no child		-0.1428*	-0.1431*	-0.1441*
		(0.0748)	(0.0746)	(0.0745)
Single w child		0.0096	-0.005	-0.0108
		(0.1810)	(0.1773)	(0.1769)
Single no child		0.4197***	-0.4338***	-0.4380***
		(0.1561)	(0.1577)	(0.1575)
No. children		-0.1179***	-0.1197***	-0.1174***
		(0.0380)	(0.0379)	(0.0380)
Grad diploma/certificate		0.113	0.088	0.0972
		(0.1678)	(0.1671)	(0.1682)
Bachelor/honours		-0.0486	-0.0813	-0.0697
		(0.1744)	(0.1760)	(0.1763)
Adv diploma, diploma		-0.1572	-0.1788	-0.1539
		(0.3092)	(0.3109)	(0.3119)

Cert III or IV	-0.2521	-0.2946	-0.263
	(0.2967)	(0.2988)	(0.2991)
Year 12	-0.2582	-0.2901	-0.2529
	(0.2803)	(0.2824)	(0.2836)
Year 11 and below	-0.0912	-0.1527	-0.099
	(0.3870)	(0.3784)	(0.3800)
Own Home	0.0437	0.0547	0.0557
	(0.0380)	(0.0367)	(0.0368)
Got married		0.2234***	0.2224***
		(0.0662)	(0.0662)
Got married missing		-0.5198**	-0.5152**
		(0.2580)	(0.2579)
Separated		-0.2809***	-0.2822***
		(0.0833)	(0.0832)
Separated missing		0.1148	0.112
		(0.2200)	(0.2189)
Back together		0.0213	0.0195
		(0.1192)	(0.1191)
Back together missing		-0.018	-0.0206
		(0.2992)	(0.3009)
Pregnancy		0.0525	0.0566
		(0.0493)	(0.0494)
Pregnancy missing		0.1725	0.1707
		(0.3561)	(0.3573)
Birth		0.1042*	0.1130**
		(0.0566)	(0.0566)
Birth missing		-0.0283	-0.0274
		(0.2441)	(0.2465)
Death spouse/child		-0.4641***	-0.4593***
		(0.1756)	(0.1753)
Death spouse/child missing		0.2558	0.2573
		(0.3419)	(0.3423)
Very good		-0.1211***	-0.1223***
		(0.0410)	(0.0409)
Good		-0.3975***	-0.3984***
		(0.0499)	(0.0498)
Fair		-0.7838***	-0.7823***
		(0.0733)	(0.0731)
Poor		-1.5858***	-1.5777***
		(0.1634)	(0.1635)
Health missing		-0.3464***	-0.3493***
		(0.0998)	(0.0996)

In Labour Force				0.0781
				(0.0504)
Constant	7.8443***	8.2236***	8.4826***	8.3914***
	(0.0994)	(0.2549)	(0.2722)	(0.2768)
N	12,508	12,383	12,383	12,383
No. individuals	2,054	2,034	2,034	2,034
Within R^2	0.0058	0.0238	0.0607	0.0611

Notes: Robust standard errors in parentheses. All models include year fixed effects. Stars denote: * p<0.10, ** p<0.05, *** p<0.01

Appendix Table 5: Fixed Effects OLS Estimates for Wages around the Migration Decision

	(I)	(II)	(III)	(IV)
Years since migration				
-4	-7.9256	-7.3259	-9.4878	-18.188
	(34.0226)	(33.7058)	(33.4859)	(30.3666)
-3	34.4025	32.8634	32.0498	20.9555
	(26.6650)	(26.4924)	(26.4109)	(24.5708)
-2	17.3417	17.5591	18.8901	2.9938
	(17.1625)	(16.8906)	(16.8484)	(15.6669)
-1 (ommited)				
0	-0.6164	-6.4945	-5.7872	20.6507
	(17.4449)	(17.2505)	(17.2984)	(15.9598)
1	14.1651	15.844	18.4746	22.5139
	(24.6322)	(24.0914)	(24.0051)	(21.9638)
2	35.6776	40.7837	40.7815	34.2997
	(33.2961)	(32.9557)	(32.7795)	(29.6554)
3	27.3675	39.9971	40.6174	29.4161
	(39.5544)	(38.5031)	(38.1669)	(34.4212)
4	45.3048	63.4124	62.1131	37.5498
	(48.4232)	(47.3638)	(46.7760)	(42.1070)
35 to 49		87.2501**	81.6478**	31.2295
		(35.6388)	(35.2167)	(33.3737)
50 to 64		79.5812	84.3438	48.4057
		(65.0087)	(64.4448)	(58.1145)
65 +		-134.4709	-130.0657	-59.6154
		(89.8121)	(89.3400)	(75.8829)
De facto		-58.3911	-56.9757	-52.4652
		(40.0619)	(41.5532)	(37.1582)
Seperated/divorced		-90.0396	-78.8273	-22.8873
		(67.0293)	(67.8367)	(64.7826)
Widowed		-49.5924	-33.5399	-36.1892
		(83.6624)	(84.4597)	(70.1872)
Never married/not de facto		-200.2140***	-196.0464**	-161.7705**
		(75.4595)	(77.2776)	(72.8837)
Couple no child		58.4329	32.6342	23.8223
		(47.5307)	(47.3941)	(42.6520)
Single w child		135.5500**	126.7514*	76.9711
		(67.4246)	(67.9373)	(65.4194)
Single no child		160.8843**	140.6831**	105.1075
		(67.8982)	(67.9275)	(65.1247)
No. children		-43.2924**	-40.5678*	-20.7553
		(21.4624)	(21.8563)	(20.4977)
Grad diploma/certificate		-330.3336**	-328.1602**	-248.3337*
		(133.5030)	(132.9234)	(135.7436)
Bachelor/honours		-362.5126***	-364.2064***	-263.5745***
		(104.2469)	(102.9662)	(97.2059)

Adv diploma, diploma	-712.2255***	-716.5980***	-501.2545***
	(155.4915)	(154.1123)	(147.2672)
Cert III or IV	-718.7603***	-721.4898***	-449.1202***
	(147.2085)	(147.2689)	(129.0661)
Year 12	-823.6781***	-814.9443***	-493.6289***
	(137.9804)	(137.3068)	(122.6811)
Year 11 and below	-922.3370***	-922.6680***	-459.4106***
	(171.4741)	(170.6781)	(146.2424)
Own Home	-36.0849*	-34.8153	-26.1333
	(21.3291)	(21.2924)	(19.3958)
Got married		17.3928	8.9268
		(47.8621)	(44.6005)
Got married missing		211.0939	250.7324
		(166.8592)	(160.1841)
Separated		-49.8397	-61.1663*
		(33.5235)	(31.5685)
Separated missing		-168.8781*	-192.6190**
		(97.6142)	(88.8767)
Back together		11.7427	-3.8122
		(55.7084)	(53.5474)
Back together missing		138.5042	115.6694
		(107.2376)	(99.4326)
Pregnancy		-25.5455	10.5102
		(26.6071)	(24.8267)
Pregnancy missing		60.0353	44.4757
		(111.7659)	(108.7918)
Birth		-90.3943***	-14.4721
		(33.3994)	(30.8931)
Birth missing		56.0543	63.7179
		(86.7085)	(96.3872)
Death spouse/child		-53.7035	-12.1441
		(37.0079)	(33.9134)
Death spouse/child missing		-307.6076***	-294.4831**
		(116.5141)	(119.1945)
Very good		2.4934	-7.6921
		(29.6975)	(28.3191)
Good		19.0757	11.4853
		(34.6692)	(32.8889)
Fair		-17.7937	-4.7291
		(39.1784)	(36.1197)
Poor		-128.4825*	-58.2454
		(65.6866)	(57.5737)
Health missing		78.2805	53.1044
		(63.9865)	(61.7991)

In Lab Force				673.5507***
				(25.5120)
Constant	750.9447***	1438.0783***	1456.6924***	670.1730***
	(52.4471)	(135.1185)	(147.9732)	(133.2908)
N	12,508	12,383	12,383	12,383
No. individuals	2,054	2,034	2,034	2,034
Within R^2	0.0011	0.0152	0.0204	0.1339

Notes: Robust standard errors in parentheses. All models include year fixed effects. Stars denote: * p<0.10, ** p<0.05, *** p<0.01

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