Job Match and Housing Tenure

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Abstract

Homeownership, though it brings both private and social benefits, entails substantial fixed costs. Standard personal financial advice suggests that homeownership should only be undertaken when one's job situation is stable and job movement is not likely in the near future. Little research has asked whether this advice is followed, so our goal is to rectify that omission. We construct a theoretical model where the decision to become a homeowner only occurs when the householder is employed at a job with productivity that matches their ability. To test our model, we employ detailed information on workers and housing decisions from Danish administrative data. We construct a measure of job mismatch and find evidence suggesting that homeowners are indeed better matched at their jobs than renters, and that an improved match leads renters to become homeowners. An examination of job durations suggests that homeownership is correlated with longer job duration both because of a direct causal effect and also due to an indirect effect through selection into homeownership.

Keywords: Housing tenure, job match, search costs, labor market.

1 Introduction

It is well-established that homeowners have longer spells in their housing units than renters (Rohe and Stewart (1996), Van Ommeren and Van Leuvensteijn (2005)). Along with the ability to capture the returns from investment in both housing and social capital, long spells in owned housing are the source of the social benefits of homeownership, including improved physical appearance of homes and a better neighborhood environment (DiPasquale and Glaeser (1999), Coulson and Li (2013)).

Stability in housing originates from the higher entry and exit costs that are borne by homeowners as opposed to renters (Ioannides and Kan, 1996; Van Ommeren and Van Leuvensteijn, 2005). Selling a house is more expensive, in both time and money, than leaving a rental unit. However, while stability in housing incentivizes investment in property, it also reduces the mobility of home owners. Thus, the decision to become a homeowner is not a trivial one; a homeowner becomes "locked-in" to both their living arrangements and their location, with the need to spread the fixed costs of ownership over a sufficiently long spell. On that account, a household's decision to become a homeowner might reasonably be expected to be correlated with its current and expected labor market status – specifically, the expected length of the current job spell. It is a standard tenet of the personal financial advisor that buying a home is only advisable when one plans to stay in the home for at least a half-decade or so (for a recent example see Elkins (2018)). Although the idea that a household must amortize the entry and exit costs of ownership across a longer spell in the home seems plausible, evidence that households actually pay attention to expected spell length when making this decision is scant. The two studies most related to this direct question are Haurin and Gill (2002) who study expected length of stays and ownership acquisition for military families (a group known for frequent location changes) and Botsch and Morris (2020) who study assistant professors of economics, a group with measurable risk of job separation. Both of these groups have rather specialized experiences that may not be generalized to the broader population.[1]

[1]See also Halket and di Custoza (2015) who hypothesize that when households cannot credibly commit to long spells in a rental unit, the pooling equilibrium causes long-term tenants to choose ownership.

The purpose of this paper is to fill this gap in the literature. We create a measure of job mismatch, based on Groes et al. (2015). These authors note that exit rates from occupations are higher when one's wage is far from its expectation in either direction. We use this fact to motivate a simple theory model in which renters make a decision whether or not to become homeowners based on their current job mismatch. Workers who have greater levels of mismatch are more likely to detach from their job, and because homeownership is costly (though it increases utility) those with high levels of mismatch are less likely to choose homeownership. We perform calibrations of this model and find that for reasonable parameter values, there is a level of mismatch that precludes homeownership. It is this basic prediction that we take to the data.

Our empirical work uses the Danish Registry (also used by Groes et al. (2015)) to first create a measure of job mismatch, measured by the residual of a wage regression on occupation dummies and a rich set of controls. We then match this data with data from the Housing Census Register, which has annual data on the homeownership status of Danish households. Denmark's mortgage market is especially useful for US comparisons, as it is one of the few countries which commonly writes 30-year fixed rate mortgage contracts (Andersen et al., 2020; Gruber et al., 2021). We show, consistent with the cross-sectional implication of the theory, that owners have lower average levels of mismatch than renters. The dynamic implication of the model is that renters who find themselves with better job matches are more likely to become homeowners. We examine this hypothesis and find it confirmed by the data.

Finally, we note that this set of ideas may have implications for the tests of the so-called "Oswald hypothesis." The Oswald hypothesis suggests that homeownership may have causal implications for homeowners' labor market outcomes because of their reduced mobility (Oswald (1997), Munch et al. (2006), Coulson and Fisher (2009)). Real estate market frictions cause "housing mismatch" between homeowners and labor markets. We examine this relationship by modeling the determinants of employment durations (Brunet et al. (2012), Ringo (2014)). The Oswald hypothesis would suggest that homeowners' employment spells are longer because their lower mobility reduces the return to on-the-job search. Our theory would suggest that they are longer because owners are better matched in their current employment. We model employment durations as a function both of housing tenure status and job mismatch and find that there is a role for both, although the impact of homeownership is reduced when job mismatch is included in the model. Homeowners may not be able to change jobs so easily, but they also have less desire to do so.

The paper proceeds as follows. The next section describes the housing tenure based model and predictions, followed by corresponding empirical tests in Section 3. Finally, we discuss the implications of our work and conclude in Section 4.

2 The Model

In this section, we develop a labor search model in which the decision to buy a home interacts with job stability. Workers are characterized on two dimensions: their "skill" level, a, and their current housing tenure, owning or renting. Unemployed workers are randomly matched with firms, which are indexed by j.[2] This matching of firms and unemployed workers takes place with probability λ. Workers are paid a regardless of the firm type, but face detachment probabilities that depend on the distance $s(a, j)$ between the worker's skill and the firm type. We refer to this distance (however measured) as the *mismatch*. Firms release workers with high mismatch either because they are overpaying for skill levels that are not required (if $a > j$) or because the employee's skill level is not high enough for efficient levels of output (if $a < j$). The behavior of firms and workers described by these assumptions is extensively documented in Groes et al. (2015) in the context of occupational mobility. Unemployed renters receive benefits at replacement rate B. That is, their unemployment compensation is Ba.

Workers are either homeowners (H) or renters (R) at the time of the match. Owners receive multiplicative compensation from ownership at rate M. That is, employed owners have compensation Ma, and unemployed owners have compensation BMa, which provides utility with decreasing returns to the compensation. Sekkat and Szafarz (2011) provide a discussion of the private benefits of ownership, including psychological motivations that include "control"

[2] Note that while a distribution of skill levels is necessary to motivate job detachment, it is unnecessary to model this directly, as we are only interested in the incentives facing a working with a specific skill level.

and "comfort". This paper measures (see below) the benefits of ownership as a percentage of home value, which we interpret here as a percentage of income.

Renters can become owners, and obtain the benefits thereby accrued, by paying a one-time fixed cost of F. The search and acquisition cost of homeownership, compared with the cost of obtaining a rental unit, are well documented (Krysan (2008)). When owners become separated from their employment they not only face a reduction in compensation, but they also face the possibility of losing ownership, with probability δ, at which point the household reverts to rentership. To re-enter the ownership class they must repay the fixed cost F. Thus, the tradeoff to current renters is clear: benefits of increased utility from ownership must be balanced both against the fixed cost of ownership and against the probability of having to pay this fixed cost again upon reemployment if the home is lost. The loss of home, of course, increases with probability of detachment – that is to say, the level of mismatch. Note that owners, employed or unemployed, do not have the incentive to become renters, given that F is sunk.

We write the lifetime utility of agents of type a, employed in firm of type j, as $V_m^a(j,t)$, where $m = E$, U designates employed or unemployed, and $t = H$, R represents the household tenure status of a homeowner or renter. Note that the j argument is not included when $m = U$. The per period utility is described by a concave utility function $u(.)$ where the argument of u is the compensation levels of the various types described above.

Equations (1) through (4) describe the lifetime utility for each type of agent, owning or renting, employed or unemployed. Note that β is the per period discount factor in each case. Equations (1) and (2) are for employed and unemployed owners, respectively. These are straightforward since owners make no decisions:

$$V_E^a(j,H) = u(Ma) + \beta \left(s(j,a) V_U^a(H) + \left(1 - s\left(j,a\right)\right) V_E^a\left(j,H\right)\right) \tag{1}$$

Equation (1) simply states that employed owners receive utility given their compensation Ma, and continuation value based on the probability $s(j,a)$ of becoming detached and $(1-s(j,a))$ staying in their current employment.

$$V_U^a(H) = u(MBa) + \beta\Big(\delta\big[\lambda EV_E^a(j,R) + (1-\lambda)V_U^a(R)\big] + (1-\delta)\left[\lambda EV_E^a(j,H) + (1-\lambda)V_U^a(H)\right]\Big) \tag{2}$$

Equation (2) states that an unemployed owner has compensation MBa, and a continuation value based on the probability δ of losing her home. There is a probability λ of employment, with an expected value based on the distribution of firm types, and a probability $(1-\lambda)$ of remaining unemployed. With $B < 1$ and no utility from leisure job searchers never turn down job matches, regardless of the mismatch. Thus our model does not have anything to say about the length of unemployment spells, unlike the literature on the Oswald hypothesis cited above.

Equations (3) and (4) invoke the policy variable k, which equals 1 if the agent purchases a home, and zero if she stays a renter.

$$\begin{aligned} V_E^a(j,R) = \max_{k\in\{0,1\}} & \; u(a-kF) + k\beta\left[s(j,a)V_U^a(H) + (1-s(j,a))V_E^a(j,H)\right] \\ & + (1-k)\beta\left[s(j,a)V_U^a(R) + (1-s(j,a))V_E^a(j,R)\right] \end{aligned} \tag{3}$$

Equation (3) nests the choices of becoming a homeowner or continuing to rent while currently employed. In the former case, F is subtracted from the current period's compensation, at which point there is detachment from the job, or not, after becoming a homeowner. Note that if it is optimal to become a homeowner at any point in the employment spell, it is optimal to do so in the first period of employment. This ensures that F is indeed a one-time, immediate fixed cost. The homeownership tradeoff is therefore ultimately between the benefit of homeownership on the one hand, and the cost of purchasing a home on the other. Note that a renter has the same probabilities of job separation, but does not pay the fixed cost.

$$V_U^a(R) = u(Ba) + \beta\left[\lambda(EV_E^a(j,R)) + (1-\lambda)(V_U^a(R))\right] \tag{4}$$

Equation (4) simply states that an employed renter has compensation based on unemployment benefits with a continuation value based on the probability of attachment. Since we are interested in how the decision to purchase a home depends on a worker's job match, we assume that unemployed renters do not purchase a home. In principle, some skill levels of worker may choose to purchase homes when unemployed. Since these types of worker will always be home owners, their presence will not change our empirical predictions below about the relationship between home ownership and job match.

The following proposition describes the way that the decision to become a homeowner depends on a steady job:

Proposition 1 *If:*

1. $u(Ma) - u(a) >= u(BMa) - u(Ba)$

2. $(1 - \beta(1 - \delta))\,(u(Ma) - u(a - F)) > (u(Ma) - u(a))$,

then the relative benefit of buying a home is increasing in the stability of the match.

The proof is in the appendix.

Proposition 1 provides sufficient conditions for the benefit of buying a home to be increasing in the stability of the job match. The first condition posits that owning a home is at least as attractive when the worker is employed as it is when she is unemployed.[3] Of course an increase in job stability increases the probability that she is employed.[4] We need a second condition because the proposition is about buying a home, not only owning a home. The second condition requires that the fixed cost of buying a home is large enough, and the probability of losing the home when unemployed is high enough. If losing a home is unlikely, or it is cheap to buy a new one, having a stable job is not important for home ownership.

[3]The condition is satisfied with utility functions in the CRRA family, for example.

[4]Imagine that this condition did not hold, so that owning a home was more attractive when unemployed. Then increases in job stability might *decrease* the relative benefit of buying a home, since owning a home would be insurance against losing one's job.

Although it is not the focus of our empirical exercise, with log utility, higher ability (richer) workers will also be more likely to buy conditional on job stability. In a word, this is because of the curvature of utility, which causes buying a home to be more painful for low ability workers:

Corollary 1 *Conditional on job stability, if utility is log the relative benefit of buying a home is weakly increasing in ability a.*

The proof is in the appendix.

2.1 Calibrated simulation

To build intuition, we simulate the model developed in Section 2. We assume log utility,

$$u(x) = \ln(x),$$

and that the separation probability is given by:

$$s(j, a) = 1 - e^{-|a-j|}$$

We normalize the worker's skill a to unity, and assume that her job offers are drawn from a uniform distribution of firm types with support $[0.85, 1.15]$. This parameterization implies that mismatch is bounded above by 0.15, so that the maximum separation probability is 13% per period.

Given that there are no available empirical equivalents of the spread of job types, our simulation of the model can be no more than suggestive of real life phenomena. Nevertheless, we attempt to ground the remaining parameters in a realistic way. Where possible we use Danish data. Where Danish data is unavailable, we use American data as the United States is the foreign country with the mortgage market most similar to Denmark.[5] In particular, we set

[5] In a recent comparison of the Danish and American mortgage markets, Berg et al. (2018) find that, "The Danish mortgage finance system is a salient reference point because in several respects it is the international model most similar to the United States." These similarities include the capital market funding of mortgages backed by a specialized mortgage bank which bears credit risk. The United States and Denmark are to our

B, the replacement rate of unemployment compensation, to 0.85, congruent with labor policy in Denmark. The job finding rate out of unemployment is given for Danish workers as 0.55 in Svalund (2013). Gerardi et al. (2018) find that the marginal impact of unemployment on the probability of default in the subsequent year is between five and six percent in the United States, so we use a value of 6% for δ in our benchmark calculation. Sekkat and Szafarz (2011) find that the premium assigned by US consumers to home ownership is approximately 9% of home value, so we set M to 1.09. Our calculation of F is guided by estimates of the search and transaction costs of home buying in the US market. Piazzesi et al. (2020) deduce that this is approximately 14% of home value. We do not model home prices directly, so we must express this in terms of income. The average home price in Denmark is roughly 2 million DKK (Statista (2019)), which gives 280,000 DKK for the acquisition cost (if US and Denmark costs are comparable) or about US $40,000. Median family disposable income in Denmark in 2019 was just a bit higher, at 297,700 DKK (*Denmark Statistics Family Income Main Table*, 2019). We therefore set F to 90% of annual income. Finally, we set the discount factor β to 0.97. At these parameter values and with log utility, both conditions of Proposition 1 are satisfied.

Figure 1 contains the policy function for employed renters indicated by a dotted vertical line. Type on the x-axis refers to job type. Renters only buy if mismatch is low enough. Figure 2 contains similar information presented another way. The blue line is the value to an employed renter of continuing to rent, and the red line is the value if the renter buys. The value of buying is higher than the value of renting when mismatch is low. To give a sense of the magnitudes involved, we simulate 10,000 workers for 100 years.[6] In the final year of our simulation, the average mismatch of homeowners $|j-1|$ is 0.04, and the average mismatch of renters is 0.12. This implies that a homeowner with average mismatch faces a 4% chance of losing her job each year, while a renter with average mismatch has an 12% chance of losing her job.

knowledge the only countries in the world where consumers regularly take out 30-year, prepayable fixed-rate mortgages. The most important difference between the two markets is perhaps in the importance of subprime mortgages. In Denmark, the wide availability of subsidized public housing and less overall income inequality contribute to a much smaller high-credit-risk mortgage market.

[6]In our simulation, we assume that a worker dies with probability 0.01, and is replaced with an unemployed renter of the same skill level. Since in principle a worker could be matched with a job with zero separation probability, this keeps the simulation ergodic.

3 Empirical findings

We turn to the Danish administrative data to test the main predictions of the housing tenure model. The dataset is comprised of annual information on socioeconomic variables of the population during the years 2008 to 2016. Following Groes et al. (2015) we measure job mismatch by comparing a worker's wage with the average wage in her occupation at a given point in time. Groes et al. (2015) argue that the wage of a worker proxies for the worker's ability in the occupation, and the gap between her wage and the average wage measures her level of mismatch relative to the standard occupational requirement.[7]

We access various registers from Denmark Statistics to test our theoretical predictions. The Employment of Wage Earners Register (BFL) contains detailed data on wages, hours worked and industry/occupation classifications, which we use in our construction of job mismatch for individuals in the sample. The Housing Census Register (BOL) contains annual housing information for the population of Denmark. From this database we gather data on housing tenure and transitions between renting and owning. The Population Register (BEF) provides demographic information for persons such as age, gender and municipality, while the Family Relationship Register (FAM) provides details on the family structure and size. Lastly, the Education Register (UDDA) provides information on educational attainment. These last three databases provide information for control variables used in the regression models. We merge these datasets using a unique masked individual identifier.

We limit our sample to working age individuals of ages between 25 and 65 years. Our analysis proceeds in two steps. In the first step, we estimate job mismatch using the entire sample of employed individuals in this age range. This is over 16.1 million individual-year observations. In the second set of regressions we use this mismatch estimate in regression models that estimate housing tenure. Since housing tenure is a household level variable, we use the individual characteristics, including the mismatch measure, of the 2008 household head in estimating our models. We use the Denmark Statistics definition of household head, which

[7] Groes et al. (2015) show that workers with higher occupational mismatch have shorter spells within their occupations. Besides presenting empirical results on occupation mobility, Groes et al. (2015) provide a theoretical basis for observed wages serving as a proxy for ability.

is defined as the oldest woman in the household if the household consists of at least one adult man and one adult woman. In all other households, it is the oldest household member. The measure of income in our regressions remains the total income of all household members.

Table 2 provides some summary statistics on this merged data set of household heads. The mean hourly wage is 199 Danish kroner and the mean household monthly income is 50,853 kroner. The average age in our sample is 45. The average number of children in each household is around one.[8] The mean spell at a job is 3.9 years. Table 3 presents frequency distributions of several variables. The sample sizes for some variables naturally differ when considering changes in either housing tenure, occupations or firms.[9] Since we use the individual characteristics of household heads only, 83% of the individuals are female. 66.1% of the households are couples. We break highest education attainment into four categories. 19% of individuals in our data have a high school degree or less education, 32% have an undergraduate equivalent, and 10% have a masters degree or more. The plurality at 39% in this categorization have a trade degree, either trade school or a formal apprenticeship.[10] The homeownership rate is 68.7%, with 5.2% transitioning from renting to owning and 1.3% from owning to renting in any given year. Table 3 also presents summary data on labor market transitions. Most individuals remain at the same firm and occupation (76%) from year to year. 13.1% change occupation within the same firm, and 6.2% change firm but remain in the same occupation. 4.7% change both firm and occupation. Even without a change in firm or occupation, the measure of mismatch can change due to an individual wage's convergence to, or divergence from, the mean wage which we calculate annually. Over the entire sample, we have a total of 179,525 firms and 205 occupations.

We measure mismatch as the residual of the following regression model:

$$\ln w_{it} = \alpha + X_{it}\beta + \epsilon_{it} \tag{5}$$

[8]We cap the number of children in the sample at 5 to account for potential measurement error.

[9]For instance, the dataset comprises of 1,806,551 renters and 4,263,545 owners for which we track housing tenure changes. Occupation and firm changes are tracked across 6,022,449 observations.

[10]The Danish education data naturally break educational attainment down into ten categories, which we aggregated for the purpose of these summary statistics. In our empirical exercise below we will sometimes include all categories with dummies. The ten categories are: primary school, preparatory school, high school, trade high school, trade apprenticeship, short further education, bachelors, medium further education, long further education, and research education.

The index i refers to a worker, and t indexes years. We report results for three specifications. In the first specification, X_{it} is a set of the following controls: age, number of children and fixed effects for family type, gender, education, year, and city. The regression models are estimated across each occupation separately. In the second specification, the set of controls include number of children, fixed effects for family type, and a 5-way interaction for age group, gender, education, job year, city. Here too, the regression is estimated separately for each occupation category. Finally, the third specification involves the following controls: number of children, fixed effects for family type, and 6-way interaction for age group, gender, education, job year, city, and occupation. The absolute residual from each of the estimated model specifications $|\hat{\epsilon}_{it}|$ is our measure of job mismatch.

Table 4 presents the summary statistics for this exercise. Note that the mean of each of the mismatch measures are not zero as we consider the sub-sample based on head of household status, whereas the wage residual is based on all the observations. The mean of the residual based on the first specification is -0.003 and its standard deviation is 0.3, skewness is 0.9 and kurtosis is 22.4.[11] Deviation from the mean, on either side, captures the level of mismatch. The mean of the absolute residual is 0.2 and the standard deviation is 0.2. The residuals based on the second and third specifications exhibit a similar pattern. Table 5 presents the correlation coefficients of the residuals across the three model specifications. We note that all three residuals are highly correlated as the correlation coefficients are over 0.96. As a check of our measure of mismatch, Table 6 presents the regression results that models job change as a function of mismatch and relevant controls. The results imply that the absolute residual does indeed predict job separation.[12]

Figure 3 displays a kernel density of the residuals from our first specification, separately calculated for owners and renters.[13] Owners have more concentrated residuals than renters, implying that owners overall have less occupational mismatch.[14] Figures 4, 5, and 6 provide

[11] We easily reject the null that the residual is normally distributed.

[12] Groes et al. (2015) verify that their mismatch measure is correlated with occupational mobility, whereas we are most concerned with job mobility.

[13] Due to disclosure rules, these are not kernel densities over raw residuals, but rather over a running 10-observation mean of residuals with the largest and smallest 10 observations by category dropped.

[14] The Kolmogorov - Smirnov test for the equality of the distributions of the two samples of residuals (for owners and renters) suggests that the distributions are statistically different at the 1% level.

empirical kernel densities on gender, age, and education respectively; it can be seen that men have more mismatch than women, those in the youngest age group have more mismatch than older cohorts, and those with less education have more mismatch than those with more.

We come now to the heart of our empirical work relating homeownership to mismatch. Our theoretical model has both cross-sectional and dynamic predictions we can take to the data. A cross-sectional prediction is that a lower level of mismatch will be associated with a higher probability of homeownership. A dynamic prediction is that, ceteris paribus, a renter with a better job match will be more likely to become a homeowner. In Table 7 we present tests of the first hypothesis. We estimate linear probability models of the homeownership dummy on the absolute value of the mismatch residual. The table presents the estimated regression coefficients for two models for each of the three residuals obtained earlier. In Column 1, the model is estimated with an exhaustive set of covariates that include gender, education, family structure, occupation, municipality and year fixed effects. We also include income, a quadratic in age and number of children.[15] All of these have the expected sign and magnitude: higher income and a greater number of children increase ownership probability, as does age, but at a decreasing rate. The coefficient of the absolute residual is statistically significant, and of the expected negative sign. A one standard deviation decrease in the absolute residual (0.224) is associated with a 0.42 percentage point increase in the probability of being a homeowner. The effect should be considered relative to the probability of a change in homeownership, which is quite small overall. As a comparison, an increase in the family size by one (increase in the number of children) is associated with a 1.40 percentage point increase in the probability of being a homeowner. Thus, while the magnitude of an increase in the likelihood of being a homeowner associated with a decrease in mismatch is small, it is comparable with that of other factors that have a marginal impact on the housing tenure decision. In Column 2 we add an interaction between the absolute residual and number of occupations in the municipality. The number of occupations in the municipality serves as a proxy for job options in the area. The coefficient for the interaction term is positive and statistically significant. While a larger

[15] Denmark Statistics masks the actual address of the worker but provides the municipality of the address. Family structure comprises of the following types: single, married, registered partnerships, co-resident couples, co-living couples, and non-resident children.

mismatch is negatively related to homeownership, the effect is less pronounced in areas that have many job options. Columns 3 through 6 present the regression coefficients based on inclusion of estimated residuals from the other two model specifications. Overall, the results are remarkably stable across different residual specifications. Table 8 presents the cross-sectional regression results across negative and positive residuals separately. It indicates that the effect of mismatch on homeownership is more pronounced for negative residuals, which is congruent with the idea that a higher income insulates the worker from the negative effects of mismatch.

We turn our attention to transitions to homeownership. We estimate the following specification,

$$\Delta R\_to\_O_{i,t} = \alpha + \eta_1 |\hat{\epsilon}_{i,t}| + \eta_2 \, Z_{i,t} + \zeta_{i,t} \tag{6}$$

Here, $\Delta R\_to\_O_{i,t}$ is an indicator characterizing transitions to homeownership. $|\hat{\epsilon}_{i,t}|$ is the absolute residual in year t. We include the same controls as in Table 7 and present the estimated regressions for each set of residuals in Table 9.[16] We also control for changes in the firm or occupation of the worker. In addition, we control for changes in location with a binary variable indicating a change in the municipality of the residence of the worker. Columns 1, 2 and 3 present the regression results based on the estimated residual from Specifications 1, 2 and 3. Overall, we estimate a statistically significant negative coefficient for $|\hat{\epsilon}_{i,t}|$, implying that renters transition to homeownership when the level of mismatch is smaller.

Having established that in both static and dynamic regressions that homeownership is negatively associated with job mismatch, we next study whether homeownership itself affects job duration independently from job mismatch. Theoretical models such as Ringo (2014) allow for (costly) on-the-job search by homeowners and renters. The reduced mobility of owners induces less intense job search, with the result that the employment spells of homeowners are longer than those of renters. Empirical studies have found correlation of job mobility and homeownership (Havet and Penot (2010)). In light of our theory and results, this correlation

[16] The sample size differs from prior tables as it tracks the housing tenure status of renters.

may be spuriously generated by job match quality. That is, the longer spells of homeowners may not be a result of differential search, but of superior job matches of homeowners.

To examine both our theory of the effect of labor mismatch on homeownership jointly with the theory of how homeownership affects job duration, we estimate a proportional hazard model of job terminations as a function of mismatch, homeownership and other controls. We test whether homeownership predicts a longer job duration after controlling for mismatch. The database that we have constructed does not contain start dates of existing jobs, so we only know the beginning of an employment spell if it occurs within the span of our panel. We use only these employments spells for our analyses. We use standard techniques to control for right-censored job spells which are not terminated in our sample period. We characterize the housing tenure of the spell as one of homeownership if at any time during the spell the household is a homeowner. Our measure of mismatch varies across years within a job spell, so we characterize a spell's mismatch as its mean over the entire job spell. Age, number of children in the household, and fixed effects for gender, education, family structure, municipality area and job spell at the start year are used as controls. Table 10 presents the estimated coefficients for the hazard model wherein two models are estimated for each of the three sets of residuals obtained earlier. In Column 1, we see that homeownership reduces the likelihood of job termination and an increase in the average residual increases the likelihood of job termination. Column 2 interacts homeownership and the average mismatch, and we see that the coefficient of the interaction is positive. These results suggest that previous estimates of the differential labor market outcomes of homeownership are both due to homeownership itself and as well as the selection into ownership highlighted by our theory. The results also indicate that the impact of home ownership on the job termination hazard can be overcome by a sufficiently bad job match. In the specification in Column 1, a 1.2 standard deviation increase in mismatch would negate the effect of ownership on the hazard of job termination. Columns 3 through 6 present the proportional hazard model results based on inclusion of estimated residuals from the other two model specifications.[17]

[17] Table 13 in the Appendix presents the regression results for the hazard model separately for negative and positive residuals. We compute the average residual in a job spell and estimate the model separately for spells with negative and positive average residuals. While higher average mismatch indicates an increased likelihood

Finally, we ask whether the results differ by the state of Danish housing cycle. Figure 7 presents an overview of the evolution of Danish house prices from 2005-2019 from Eurostat. During the period of our study, from 2008 to 2012 house prices were more or less flat in Denmark, and then from 2013-2016 there was a price boom.[18] One might be concerned that the tenure decision of Danes might have been different during these two regimes. To investigate if this is so, we split our data into two periods, a flat price period from 2008-2012, and a boom period of 2013 to 2016.

Table 11 presents the estimated linear probability models of the homeownership binary as a function of the absolute value of the mismatch residual based on data for different sub-periods. As earlier, the table presents the estimated regression coefficients for two models for each of the three residuals obtained from different model specifications. Throughout, the coefficient of the absolute residual is statistically significant, and of the expected negative sign. In addition, the coefficient for the interaction term is positive and statistically significant. Next, Table 12 presents the estimated transition regressions across two specifications for each set of residuals. Here too, the estimated coefficients imply that renters change housing tenure to homeownership when the level of mismatch decreases. Our findings are robust to data subsets collected under different housing market conditions.

4 Concluding Remarks

It is a truism that the entry and exit costs of homeownership ought to be amortized over a sufficiently long period of time. Therefore, the usual advice that one should not purchase a home until one's employment situation is stable is warranted. In this paper, we use a measure of job mismatch proposed by Groes et al. (2015) to measure the stability of employment. We find that households with a higher level of job mismatch are less likely to be homeowners, and that reductions in mismatch induce renters to buy. Since lower mismatch is also associated with

of job termination for both spells with positive and negative average residuals, the effect is more pronounced in those with positive residuals.

[18] One theory about the reason for the boom is that the Danish Kroner is pegged to the Euro. When the Euro was going through a crisis, there was a positive probability that the Danish central bank would go off the peg. Thus Euro investors saw Denmark as an attractive investment destination to hedge Euro risk.

longer employment spells, households do delay homeownership until they have the expectations of a long and stable employment situation. This selection into homeownership does not rule out a separate role for homeownership itself in increasing employment spell duration as highlighted by previous theory.

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Figure 1: Employed renter policy function

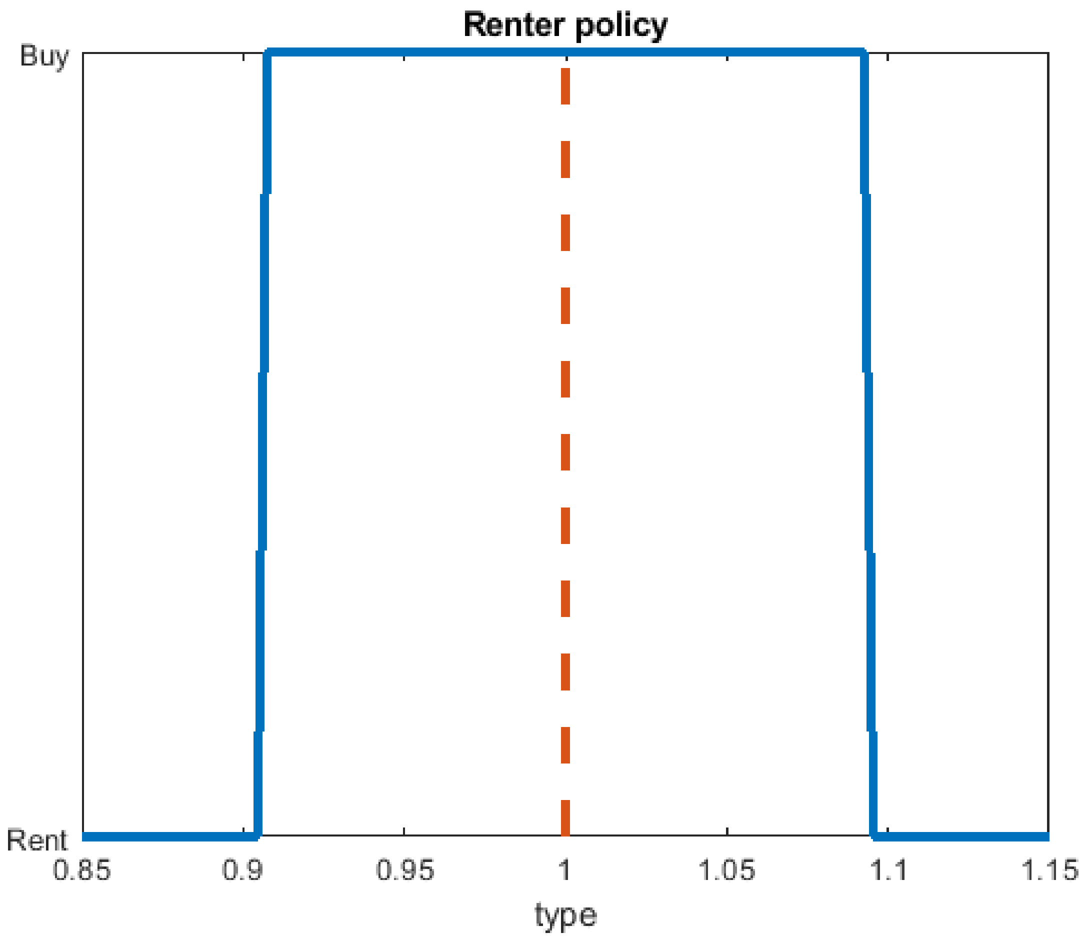

Figure 2: Comparison of value of buying vs renting for employed renters

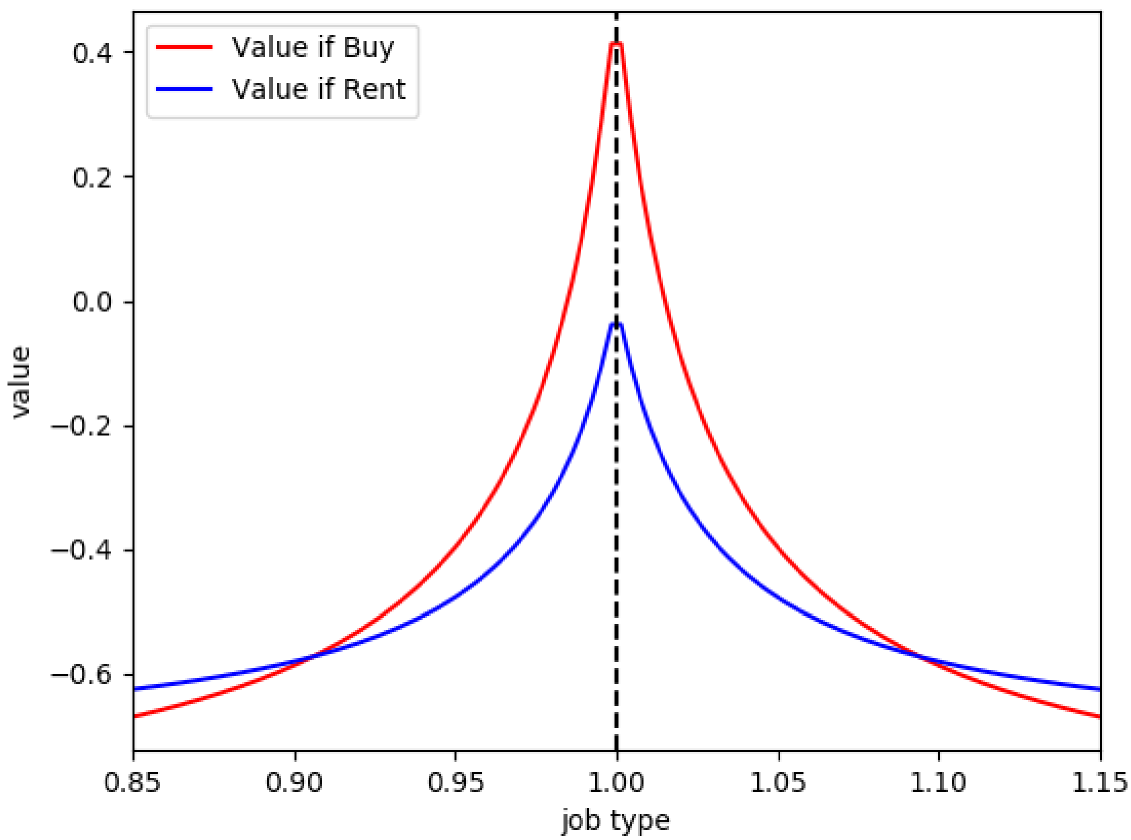

Figure 3: Kernel density of residual across housing tenure

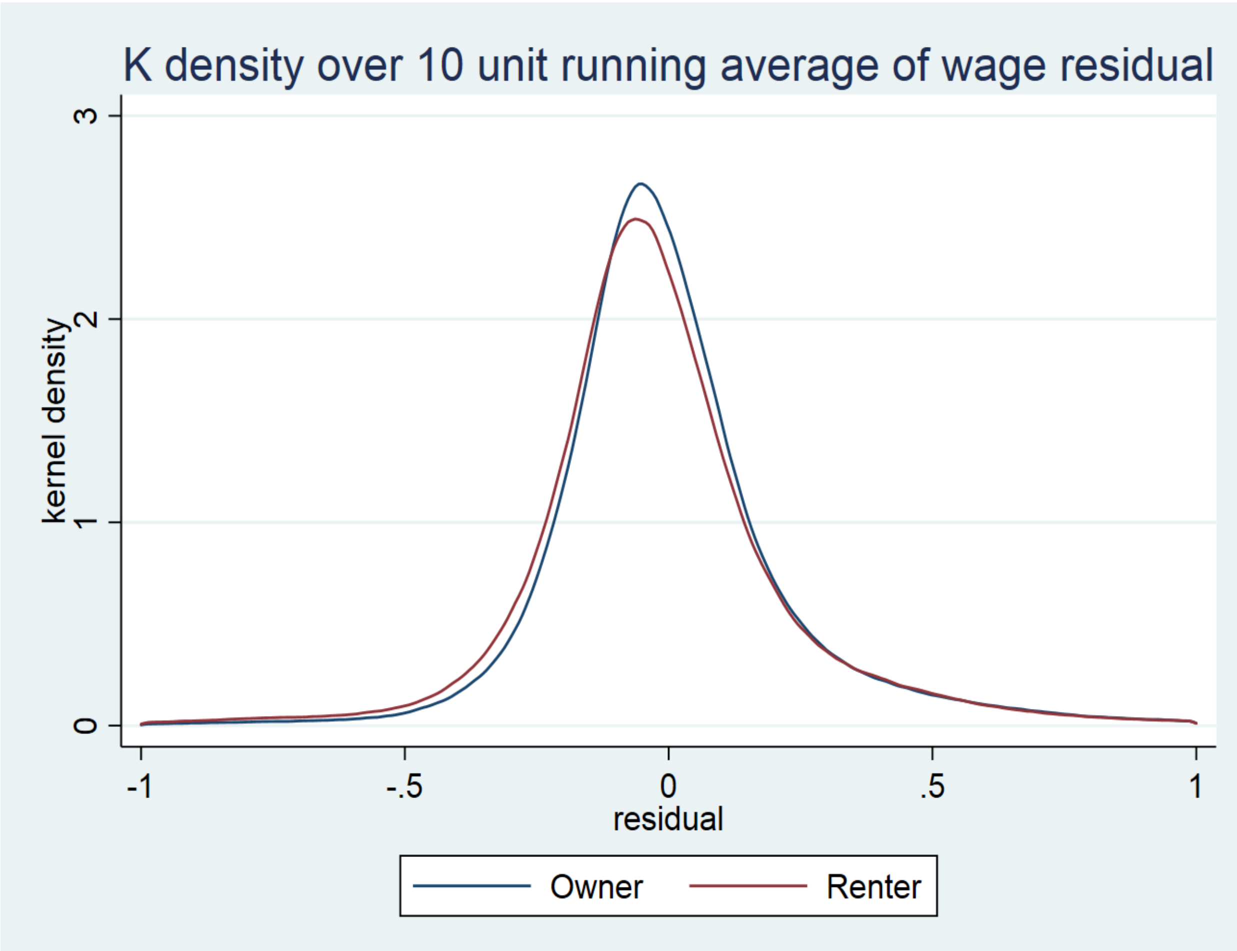

Figure 4: Kernel density of residual across gender

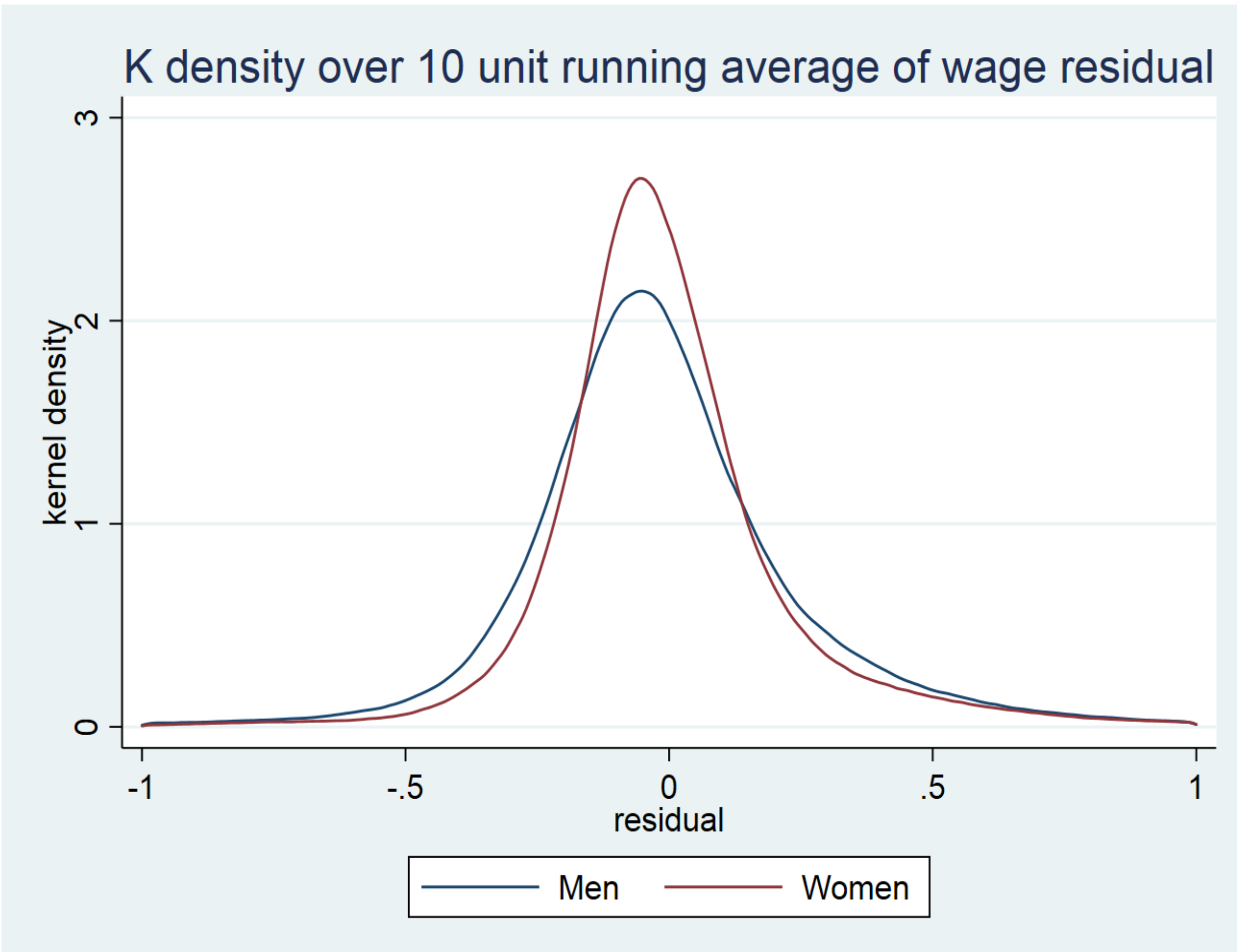

Figure 5: Kernel density of residual across age groups

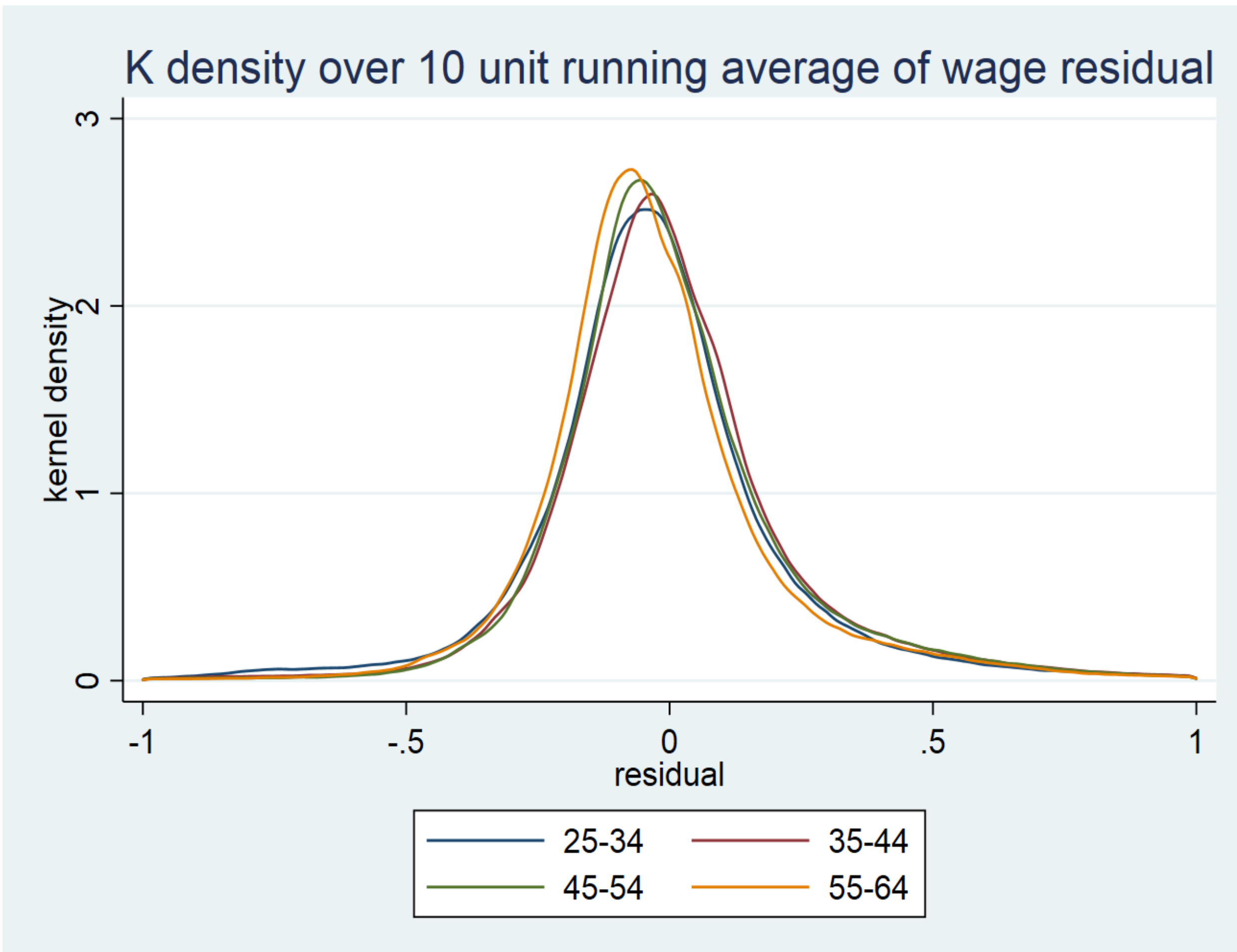

Figure 6: Kernel density of residual across education groups

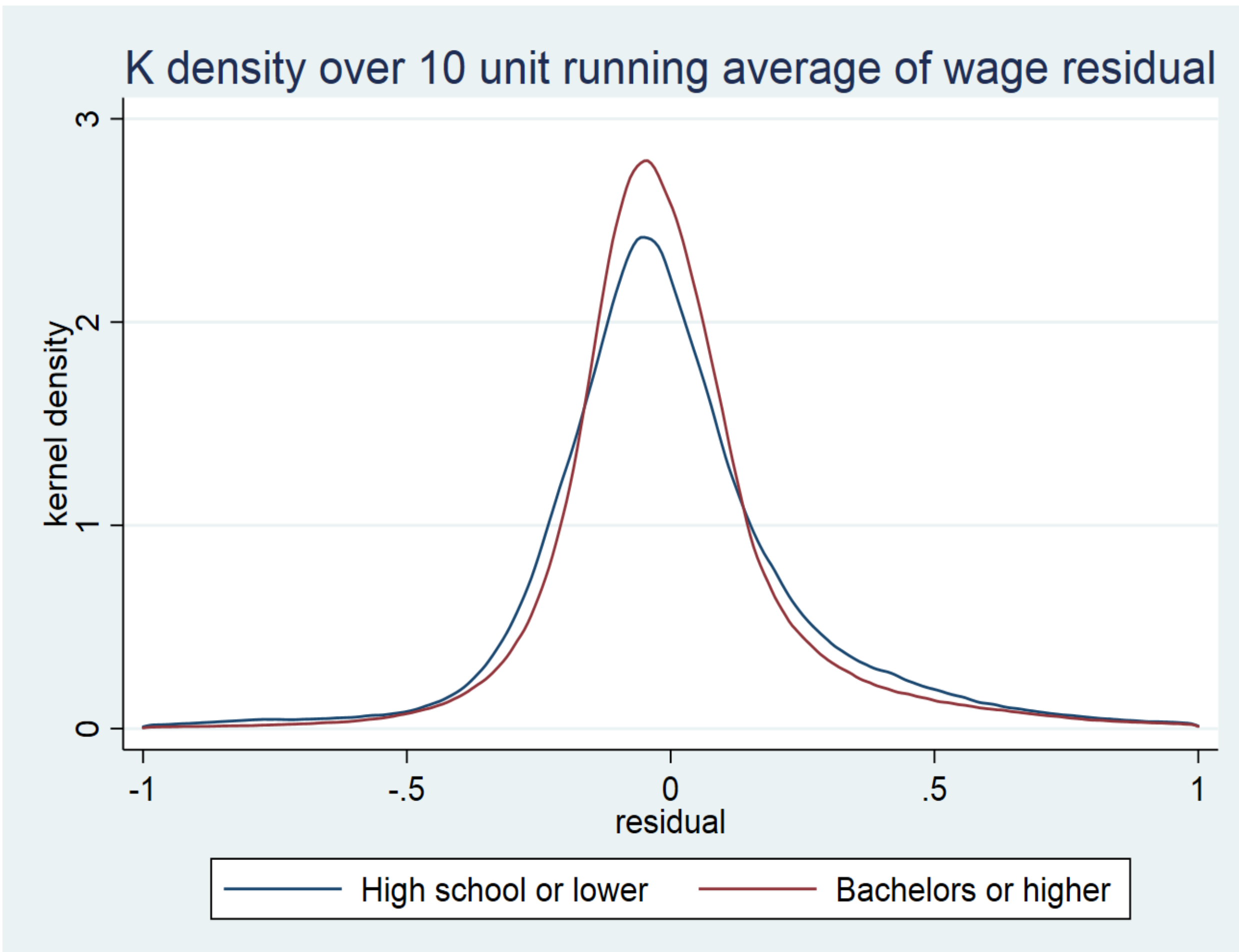

Figure 7: Eurostat Danish House Price Index (Quarterly)

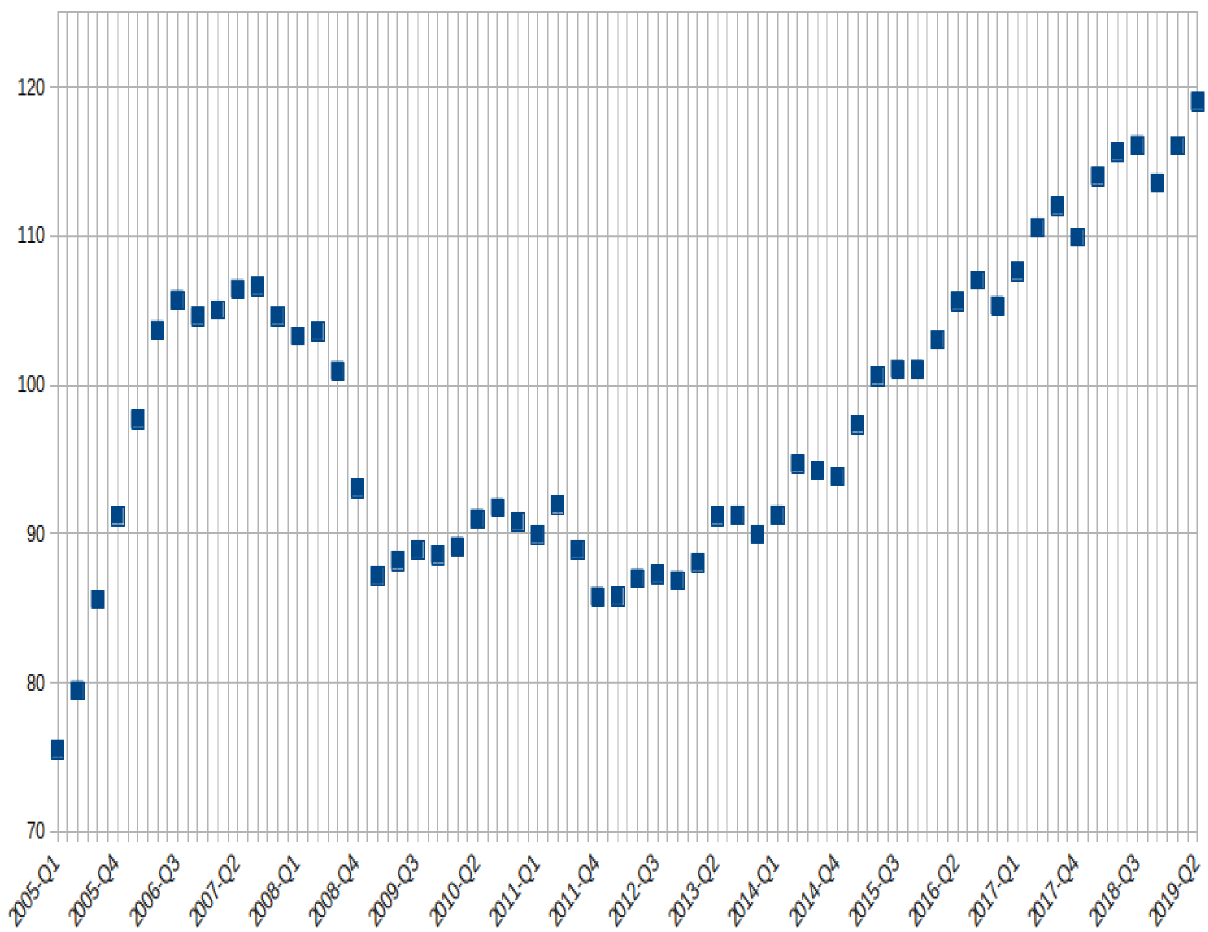

Table 1: Model Calibration

Parameter	Notation	Value
Discount Factor	β	0.97
Owning Value	M	1.09
Job Find Prob	λ	0.55
Unemp Replacement	B	0.85
Buying Cost	F	0.9
House Loss Prob	δ	0.06

Table 2: Summary Statistics

	N	Mean	Std. Dev.
Household Income	7,653,826	50,852.630	49,445.605
Wage	7,653,826	198.622	142.922
Age	7,653,826	45.033	10.049
# Children	7,653,826	0.894	1.060
Job Duration	7,653,826	1,431.775	875.504

This table presents some summary statistics of the data obtained from the Danish Registry. Hourly Wage and Monthly Household Income are specified in Danish Kroner. Job duration is days at a job.

Table 3: Frequency Distribution

Variable	Percent
Female	83.41
Couples	66.06
Registered partnership	0.16
Single	33.78
High School or less	19.19
Trade School/Apprenticeship	38.68
Shorter tertiary and Bachelor	31.91
Long tertiary	10.21
Homeowner	68.67
R to O	5.24
O to R	1.33
Occupation Change	35.25
Firm Change	29.80
Observations	7,653,826
Same Firm & Same Occ	76.07
Same Firm & Diff Occ	13.10
Diff Firm & Same Occ	6.18
Diff Firm & Diff Occ	4.65
Observations	6,022,449

This table presents the frequency distribution across variables obtained from the Danish Registry. R to O indicates the percentage transitioning from renting to homeownership. O to R indicates the percentage transitioning from homeownership to renting. Occupation Change depicts the percentage that change occupations (even within the same firm). Firm Change depicts the percentage transitioning across firms. Same Firm & Same Occ depicts the percentage that do not change either firms or occupations. Same Firm & Diff Occ depicts the percentage that changes occupations. Diff Firm & Same Occ depicts the percentage that changes firms. Diff Firm & Diff Occ depicts the percentage that changes both firms and occupations.

Table 4: Summary Statistics on the Wage Residuals

	N	Mean	Std. Dev.	Skewness	Kurtosis
Wage Residual Model 1					
Residual	7,653,826	-0.003	0.286	0.906	22.363
Absolute Residual	7,653,826	0.178	0.224	4.616	40.230
Wage Residual Model 2					
Residual	7,653,826	-0.004	0.277	0.946	22.596
Absolute Residual	7,653,826	0.171	0.218	4.613	40.466
Wage Residual Model 3					
Residual	7,653,826	-0.005	0.277	0.937	22.526
Absolute Residual	7,653,826	0.172	0.218	4.606	40.382

This table presents summary statistics on the residual estimated from three wage regressions.

Table 5: Correlation between residuals based on 3 different wage models

	Model 1	Model 2	Model 3
Model 1	1		
Model 2	0.967^{***}	1	
Model 3	0.965^{***}	0.999^{***}	1

This table presents the correlation coefficients of the absolute residuals estimated from three wage regressions. *, ** and *** denote statistical significance at the 5, 1 and 0.1 % level respectively.

Table 6: Relating Mismatch and Job separation.

	(1)	(2)	(3)
Absolute Residual	0.123***	0.125***	0.124***
	(0.001)	(0.001)	(0.001)
Age	-0.008***	-0.009***	-0.009***
	(0.000)	(0.000)	(0.000)
Age Squared	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Δ Income	-0.009***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)
Δ Children	-0.019***	-0.019***	-0.019***
	(0.000)	(0.000)	(0.000)
Change in Location	0.122***	0.122***	0.122***
	(0.001)	(0.001)	(0.001)
Constant	0.392***	0.409***	0.409***
	(0.011)	(0.011)	(0.011)
Education	Yes	Yes	Yes
Family Type	Yes	Yes	Yes
Occupation	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Year	Yes	Yes	Yes
R-Squared	0.042	0.042	0.042
N	6,022,449	6,022,449	6,022,449

This table presents the estimated regression coefficients for the regression that models job change as a function of mismatch and other controls. Robust standard errors are in parentheses. *, ** and *** denote statistical significance at the 5, 1 and 0.1 % level respectively.

Table 7: Regression relating homeownership to residuals, i.e. measures of mismatch.

	(1)	(2)	(3)	(4)	(5)	(6)
Absolute Residual	-0.019***	-0.075***	-0.019***	-0.060***	-0.019***	-0.054***
	(0.001)	(0.007)	(0.001)	(0.007)	(0.001)	(0.007)
Log Income	0.082***	0.082***	0.082***	0.082***	0.082***	0.082***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age Squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# Children	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Absolute Residual × # Occupations		0.000***		0.000***		0.000***
		(0.000)		(0.000)		(0.000)
Constant	-0.553***	-0.555***	-0.556***	-0.558***	-0.556***	-0.557***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Gender	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Family Type	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.356	0.356	0.356	0.356	0.356	0.356
N	7,653,826	7,653,826	7,653,826	7,653,826	7,653,826	7,653,826

This table presents the estimated regression coefficients for linear probability models of the homeownership dummy on the absolute value of the mismatch residual. Absolute Residual is obtained from three wage regressions. # Occupations is the number of occupations in the municipality. Robust standard errors are noted in parentheses. *, ** and *** denote statistical significance at the 5, 1 and 0.1 % level respectively.

Table 8: Regression relating homeownership to residuals, i.e. measures of mismatch (across negative and positive residuals separately).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Absolute Residual	-0.034***	-0.054***	-0.020***	-0.089***	-0.030***	-0.027**	-0.019***	-0.074***	-0.031***	-0.024**	-0.019***	-0.070***
	(0.001)	(0.011)	(0.001)	(0.009)	(0.001)	(0.011)	(0.001)	(0.010)	(0.001)	(0.011)	(0.001)	(0.010)
Log Income	0.074***	0.074***	0.073***	0.073***	0.075***	0.075***	0.073***	0.073***	0.076***	0.076***	0.074***	0.074***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.005***	0.005***	0.009***	0.009***	0.006***	0.006***	0.009***	0.009***	0.006***	0.006***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age Squared	0.000***	0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Children	0.015***	0.015***	0.017***	0.017***	0.014***	0.014***	0.017***	0.017***	0.013***	0.013***	0.017***	0.017***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Absolute Residual × Occupations		0.000*		0.000***		-0.000		0.000***		-0.000		0.000***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	-0.445***	-0.445***	-0.463***	-0.465***	-0.472***	-0.472***	-0.512***	-0.513***	-0.508***	-0.508***	-0.487***	-0.488***
	(0.012)	(0.012)	(0.014)	(0.015)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)
# Children	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.370	0.370	0.340	0.340	0.368	0.368	0.341	0.341	0.367	0.367	0.343	0.343
N	4,356,454	4,356,454	3,297,372	3,297,372	4,363,716	4,363,716	3,290,110	3,290,110	4,350,856	4,350,856	3,302,970	3,302,970

This table presents the estimated regression coefficients for linear probability models of the homeownership dummy on the absolute value of the mismatch residual. Absolute Residual is obtained from three wage regressions. # Occupations is the number of occupations in the municipality. Columns (1) and (2) present the regression results for the residuals (only negative residuals) obtained from the first wage regression specification. Columns (3) and (4) present the regression results for the residuals (only positive residuals) obtained from the first wage regression specification. Similarly Columns (5) to (12) present the regression results based on the second and third wage specifications. Robust standard errors are noted in parentheses. *, ** and *** denote statistical significance at the 5, 1 and 0.1 % level respectively.

Table 9: Transitions from Renting to Homeownership.

	(1)	(2)	(3)
Absolute Residual	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
Age	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)
Age Squared	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Δ Income	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)
Δ Children	0.020***	0.020***	0.020***
	(0.001)	(0.001)	(0.001)
Same Firm & Diff Occ	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)
Diff Firm & Same Occ	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)
Diff Firm & Diff Occ	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)
Change in Location	0.321***	0.321***	0.321***
	(0.002)	(0.002)	(0.002)
Constant	0.176***	0.175***	0.175***
	(0.013)	(0.013)	(0.013)
Gender	Yes	Yes	Yes
Education	Yes	Yes	Yes
Family Type	Yes	Yes	Yes
Occupation	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Year	Yes	Yes	Yes
R-Squared	0.156	0.156	0.156
N	1,790,918	1,790,918	1,790,918

This table presents the estimated regression coefficients of the following regression: $\Delta R\_to\_O_{i,t} = \alpha + \eta_1 |\hat{\epsilon}_{i,t}| + \eta_2 \, Z_{i,t} + \zeta_{i,t}$. $\Delta R\_to\_O_{i,t}$ is an indicator characterizing transitions to homeownership and $|\hat{\epsilon}_{i,t}|$ is the absolute residual in year t. Absolute Residual is obtained from the three wage regressions. Same Firm & Diff Occ is a binary variable that indicates a change in occupations. Diff Firm & Same Occ is a binary variable that indicates a change in firms. Diff Firm & Diff Occ is a binary variable that indicates a change in both firms and occupations. Change in Location is a binary variable indicating a change in municipality of the worker. Robust standard errors are in parentheses. *, ** and *** denote statistical significance at the 5, 1 and 0.1 % level respectively.

Table 10: Hazard model of job terminations.

	(1)	(2)	(3)	(4)	(5)	(6)
Owner during Spell	-0.190***	-0.245***	-0.190***	-0.241***	-0.189***	-0.242***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Average Absolute Residual	0.700***	0.554***	0.721***	0.578***	0.719***	0.575***
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)
Age	-0.173***	-0.174***	-0.175***	-0.175***	-0.175***	-0.175***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age Squared	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# Children	-0.004***	-0.004***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Average Absolute Residual × Owner during Spell		0.269***		0.261***		0.264***
		(0.005)		(0.005)		(0.005)
Gender	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Family Type	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Job Spell Start Year	Yes	Yes	Yes	Yes	Yes	Yes
N	5,622,218	5,622,218	5,622,218	5,622,218	5,622,218	5,622,218

This table presents a hazard model of job terminations as a function of mismatch, tenure and other controls. Owner during job spell indicates if at any time during the job spell the household becomes a homeowner. Average Absolute Residual is the average mismatch over the spell. Standard errors are in parentheses. *, ** and *** denote statistical significance at the 5, 1 and 0.1 % level respectively.

Table 11: Regression relating homeownership to residuals, i.e. measures of mismatch.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2008 to 2012						
Absolute Residual	-0.017***	-0.058***	-0.016***	-0.042***	-0.017***	-0.036***
	(0.001)	(0.008)	(0.001)	(0.009)	(0.001)	(0.009)
Log Income	0.081***	0.081***	0.081***	0.081***	0.081***	0.081***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age Squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# Children	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Absolute Residual × # Occupations		0.000***		0.000***		0.000**
		(0.000)		(0.000)		(0.000)
Constant	-0.527***	-0.528***	-0.530***	-0.531***	-0.530***	-0.530***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Gender	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Family Type	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.349	0.349	0.349	0.349	0.349	0.349
N	4,861,400	4,861,400	4,861,400	4,861,400	4,861,400	4,861,400
Panel B: 2013 to 2016						
Absolute Residual	-0.027***	-0.102***	-0.026***	-0.087***	-0.027***	-0.081***
	(0.001)	(0.012)	(0.001)	(0.013)	(0.001)	(0.013)
Log Income	0.082***	0.082***	0.082***	0.082***	0.082***	0.082***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age Squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# Children	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Absolute Residual × # Occupations		0.000***		0.000***		0.000***
		(0.000)		(0.000)		(0.000)
Constant	-0.575***	-0.578***	-0.581***	-0.583***	-0.581***	-0.583***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Gender	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Family Type	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.364	0.364	0.364	0.364	0.364	0.364
N	2,792,426	2,792,426	2,792,426	2,792,426	2,792,426	2,792,426

This table presents the estimated regression coefficients for linear probability models of the homeownership dummy on the absolute value of the mismatch residual. Absolute Residual is obtained from three wage regressions. # Occupations is the number of occupations in the municipality. Regression models are estimated using data over different time periods and presented across Panels A and B. Robust standard errors are noted in parentheses. *, ** and *** denote statistical significance at the 5, 1 and 0.1 % level respectively.

Table 12: Transitions from Renting to Homeownership.

	(1)	(2)	(3)
Panel A: 2008 to 2012			
Absolute Residual	-0.003***	-0.002***	-0.003***
	(0.001)	(0.001)	(0.001)
Age	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)
Age Squared	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Δ Income	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)
Δ Children	0.022***	0.022***	0.022***
	(0.001)	(0.001)	(0.001)
Same Firm & Diff Occ	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)
Diff Firm & Same Occ	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)
Diff Firm & Diff Occ	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)
Change in Location	0.297***	0.297***	0.297***
	(0.002)	(0.002)	(0.002)
Constant	0.186***	0.186***	0.186***
	(0.014)	(0.014)	(0.014)
Gender	Yes	Yes	Yes
Education	Yes	Yes	Yes
Family Type	Yes	Yes	Yes
Occupation	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Year	Yes	Yes	Yes
R-Squared	0.168	0.168	0.168
N	1,086,587	1,086,587	1,086,587
Panel B: 2013 to 2016			
Absolute Residual	-0.004***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)
Age	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)
Age Squared	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Δ Income	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
Δ Children	0.015***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)
Same Firm & Diff Occ	-0.002*	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)
Diff Firm & Same Occ	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)
Diff Firm & Diff Occ	-0.009***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)
Change in Location	0.369***	0.369***	0.369***
	(0.003)	(0.003)	(0.003)
Constant	0.156***	0.155***	0.155***
	(0.027)	(0.027)	(0.027)
Gender	Yes	Yes	Yes
Education	Yes	Yes	Yes
Family Type	Yes	Yes	Yes
Occupation	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Year	Yes	Yes	Yes
R-Squared	0.152	0.152	0.152
N	704,331	704,331	704,331

This table presents the estimated regression coefficients of the following regression: $\Delta R\_to\_O_{i,t} = \alpha + \eta_1 |\hat{\epsilon}_{i,t}| + \eta_2 \, Z_{i,t} + \zeta_{i,t}$. $\Delta R\_to\_O_{i,t}$ is an indicator characterizing transitions to homeownership and $|\hat{\epsilon}_{i,t}|$ is the absolute residual in year t. Absolute Residual is obtained from the three wage regressions. Same Firm & Diff Occ is a binary variable that indicates a change in occupations. Diff Firm & Same Occ is a binary variable that indicates a change in firms. Diff Firm & Diff Occ is a binary variable that indicates a change in both firms and occupations. Regression models are estimated using data over different time periods and presented across Panels A and B. Robust standard errors are in parentheses. *, ** and *** denote statistical significance at the 5, 1 and 0.1 % level respectively.

Appendix

5 Proof of proposition 1

Lemma 1 *$V_E^a(j,H) - V_E^a(j,R) >= V_E^a(j',H) - V_E^a(j',R)$ if the policy is buying at j and continuing to rent at j'.*

Proof of lemma: If the policy is buying, then $V_E^a(j,H) - V_E^a(j,R) = u(Ma) - u(a-F)$, since the continuation value will be the same. If the policy is continuing to rent, then $V_E^a(j,H) - V_E^a(j,R) = NB + u(Ma) - u(a-F)$, where NB is the net benefit of buying a home. This equation says that the only difference between NB and $V_E^a(j,H) - V_E^a(j,R)$ is that the period payoff for those that already own a home is $u(Ma)$, while those buying a home have period payoff $u(a-F)$. If the policy is to continue renting, then $NB <= 0$, which establishes the lemma.

Proposition 1 *If*

1. $u(BMa) - u(Ba) - (u(Ma) - u(a)) <= 0$
2. $(1 - \beta(1-\delta))\,(u(Ma) - u(a-F)) > (u(Ma) - u(a))$,

then the relative benefit of buying a home is increasing in the stability of the match.

Proof: Consider a renter of ability a employed at a firm of type j. Her relative benefit of buying a home compared with remaining a renter is:

$$\begin{aligned} NB = {} & u(a-F) + \beta\left[s(j,a)V_U^a(H) + (1-s(j,a))V_E^a(j,H)\right] \\ & - u(a) - \beta\left[s(j,a)V_U^a(R) + (1-s(j,a))V_E^a(j,R)\right] \end{aligned} \tag{7}$$

This expression involves the value of remaining a renter $V_E^a(j,R)$. Since this value depends on the policy of buying or not, it is convenient to split the proof into two cases. The first is such that $NB > 0$, so that the renter will buy. The second is when $NB <= 0$ so that the renter will continue to rent.

Case 1: $NB > 0$: In this case, the only difference between $V_E^a(j,H)$ and $V_E^a(j,R)$ is that period payoff $u(a-F)$ when a renter, and $u(Ma)$ when a home owner – agents always end up a homeowner in the next period. We can rewrite (7):

$$NB = u(a-F) - u(a) + \beta s(j,a)\left(V_U^a(H) - V_U^a(R)\right) + \beta(1-s(j,a))\left(u(Ma) - u(a-F)\right)$$

Taking the derivative with respect to job type:

$$\frac{\partial NB}{\partial j} = \frac{\partial s}{\partial j}\beta\left(\left(V_U^a(H) - V_U^a(R)\right) - \left(u(Ma) - u(a-F)\right)\right) \tag{8}$$

Expanding the term $V_U^a(H) - V_U^a(R)$:

$$\begin{aligned}
V_U^a(H) - V_U^a(R) &= u(BMa) - u(Ba) + \beta(1-\delta)(1-\lambda)\left(V_U^a(H) - V_U^a(R)\right) + \beta(1-\delta)\lambda\left(EV_E^a(j,H) - EV_E^a(j,R)\right) \\
&<= u(BMa) - u(Ba) + \beta(1-\delta)(1-\lambda)\left(V_U^a(H) - V_U^a(R)\right) + \beta(1-\delta)\lambda\left(u(Ma) - u(a-F)\right) \\
&<= \frac{1}{1-\beta(1-\delta)(1-\lambda)}\left(u(BMa) - u(Ba)\right) + \frac{\beta(1-\delta)\lambda}{1-\beta(1-\delta)(1-\lambda)}\left(u(Ma) - u(a-F)\right)
\end{aligned}$$

The first inequality is from Lemma 1, and the last line is just continuing the expansion. Plugging back into (8):

$$\frac{\frac{\partial NB}{\partial j}}{\frac{\partial s}{\partial j}} <= \frac{\beta}{1-\beta(1-\delta)(1-\lambda)}\left(u(BMa) - u(Ba) - (1-\beta(1-\delta))\left(u(Ma) - u(a-F)\right)\right) < 0 \tag{9}$$

That this expression is less than zero is implied by the two conditions in the proposition. That the right-hand side of Inequality (9) is less than zero means that the net benefit of buying moves in the opposite direction as the separation probability, which is what we want to show.

Case 2: $NB < 0$. In this case, the difference between $V_E^a(j,H)$ and $V_E^a(j,R)$ is $NB + u(Ma) - u(a-F)$. We can rewrite (7):

$$NB = u(a-F) - u(a) + \beta\left(s(j,a)\left(V_U^a(H) - V_U^a(R)\right)\right) + \beta\left((1-s(j,a))\left(NB + u(Ma) - u(a-F)\right)\right)$$

Taking the derivative with respect to job type in this case:

$$\begin{aligned}
\frac{\partial NB}{\partial j} &= \frac{\partial s}{\partial j}\beta\left(V_U^a(H) - V_U^a(R)\right) - \left(NB + u(Ma) - u(a-F)\right) + \beta(1-s)\frac{\partial NB}{\partial j} \\
\frac{\frac{\partial NB}{\partial j}}{\frac{\partial s}{\partial j}} &= \frac{\beta}{1-\beta(1-s)}\left(V_U^a(H) - V_U^a(R) - \left(V_E^a(j,H) - V_E^a(j,R)\right)\right)
\end{aligned}$$

We expand $V_E^a(j,H) - V_E^a(j,R)$:

$$\begin{aligned}
V_E^a(j,H) - V_E^a(j,R) &= u(Ma) - u(a) + \beta s\left(V_U^a(H) - V_U^a(R)\right) + \beta(1-s)\left(V_E^a(j,H) - V_E^a(j,R)\right) \\
&= \frac{\beta s}{1-\beta(1-s)}\left(V_U^a(H) - V_U^a(R)\right) + \frac{1}{1-\beta(1-s)}\left(u(Ma) - u(a)\right)
\end{aligned}$$

Letting D be the right hand side of (9) divided by β, we can write $V_U^a(H) - V_U^a(R) <= D + u(Ma) - u(a-F)$. Plugging in:

$$\begin{aligned}
\frac{\frac{\partial NB}{\partial j}}{\frac{\partial s}{\partial j}} &= \frac{\beta}{(1-\beta(1-s))^2}\left((1-\beta)\left(V_U^a(H) - V_U^a(R)\right) - \left(u(Ma) - u(a)\right)\right) \\
&<= \frac{\beta}{(1-\beta(1-s))^2}\left((1-\beta)D + (1-\beta)\left(u(Ma) - u(a-F)\right) - \left(u(Ma) - u(a)\right)\right) \\
&< \frac{\beta}{(1-\beta(1-s))^2}\Big((1-\beta)D + (1-\beta)\left(u(Ma) - u(a-F)\right) - (1-\beta(1-\delta))\left(u(Ma) - u(a-F)\right)\Big)
\end{aligned}$$

The last inequality is from condition (2) of the proposition. The last line is less than zero. This concludes the proof.

6 Proof of Corollary 1

Conditional on job stability, if utility is log the relative benefit of buying a home is increasing in ability a.

Proof: We condition on job stability s, so we treat it as a parameter and drop its arguments. Consider a renter of ability a employed at a firm of type j. Her relative benefit of buying a home compared with remaining a renter is:

$$\begin{aligned} NB &= \ln(a-F) + \beta\left(sV_U^a(H) + (1-s)V_E^a(j,H)\right) \\ &\quad - \ln(a) - \beta\left(sV_U^a(R) + (1-s)V_E^a(j,R)\right) \\ &= \ln(a-F) - \ln(a) + \beta s\left(V_U^a(H) - V_U^a(R)\right) \qquad (10) \\ &\quad + \beta(1-s)\left(V_E^a(j,H) - V_E^a(j,R)\right) \qquad (11) \end{aligned}$$

The general insight in this proof is that with log utility, there are only two possible derivatives of period utility with respect to a. If period utility is $\ln(a-F)$, then the derivative is $\frac{1}{a-F}$. If the period utility is $\ln(Ca)$ for any constant, then the derivative is $\frac{1}{a}$. Moreover, this difference in period utilities can only be maintained for a single period, because the act of buying moves a renter to the homeowner value function. Thus the minimum possible value of $\frac{\partial V_E^a(j,H)}{\partial a} - \frac{\partial V_E^a(j,R)}{\partial a} = \frac{1}{a} - \frac{1}{a-F}$. The difference between the value of being unemployed is more complicated, because it involves an expectation. The same argument goes through, however, since state by state the minimum difference between period utility is $\frac{1}{a} - \frac{1}{a-F}$. Thus, again the minimum difference $\frac{\partial V_U^a(H)}{\partial a} - \frac{\partial V_U^a(R)}{\partial a} = \frac{1}{a} - \frac{1}{a-F}$. We want to show that $\frac{\partial NB}{\partial a} > 0$.

Taking the derivative of NB with respect to ability:

$$\begin{aligned} \frac{\partial NB}{\partial a} &= \frac{1}{a-F} - \frac{1}{a} + \beta s\left(\frac{\partial V_U^a(H)}{\partial a} - \frac{\partial V_U^a(R)}{\partial a}\right) \\ &\quad + \beta(1-s)\left(\frac{\partial V_E^a(j,H)}{\partial a} - \frac{\partial V_E^a(j,R)}{\partial a}\right) \end{aligned}$$

From our argument above:

$$\begin{aligned} \frac{\partial NB}{\partial a} &>= \frac{1}{a-F} - \frac{1}{a} + \beta\left(s\left(\frac{1}{a} - \frac{1}{a-F}\right)\right) \\ &\quad + \beta\left((1-s)\left(\frac{1}{a} - \frac{1}{a-F}\right)\right) \\ &\quad = (1-\beta)\left(\frac{1}{a-F} - \frac{1}{a}\right) > 0 \end{aligned}$$

This concludes the proof.

Table 13: Hazard Model of job terminations (across negative and positive residuals separately).

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Negative residuals						
Owner during Spell	-0.171***	-0.249***	-0.165***	-0.237***	-0.166***	-0.239***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Average Absolute Residual	0.721***	0.512***	0.767***	0.563***	0.769***	0.564***
	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
Age	-0.165***	-0.165***	-0.176***	-0.176***	-0.175***	-0.175***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age Squared	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Absolute Residual × Owner during Spell		0.445***		0.425***		0.430***
		(0.006)		(0.007)		(0.007)
# Children	Yes	Yes	Yes	Yes	Yes	Yes
Gender	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Family Type	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Job Spell Start Year	Yes	Yes	Yes	Yes	Yes	Yes
N	3,155,492	3,155,492	3,168,297	3,168,297	3,171,132	3,171,132
Panel B: Positive residuals						
Owner during Spell	-0.196***	-0.221***	-0.204***	-0.231***	-0.203***	-0.229***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Average Absolute Residual	0.778***	0.707***	0.791***	0.713***	0.780***	0.704***
	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
Age	-0.181***	-0.181***	-0.176***	-0.177***	-0.177***	-0.178***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age Squared	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Absolute Residual × Owner during Spell		0.118***		0.132***		0.130***
		(0.006)		(0.007)		(0.007)
# Children	Yes	Yes	Yes	Yes	Yes	Yes
Gender	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Family Type	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Job Spell Start Year	Yes	Yes	Yes	Yes	Yes	Yes
N	2,466,726	2,466,726	2,453,921	2,453,921	2,451,086	2,451,086

This table presents a hazard model of job terminations as a function of mismatch, tenure and other controls. Owner during job spell indicates if at any time during the job spell the household becomes a homeowner. Average Absolute Residual is the average mismatch over the spell. The average residual in a job spell is computed and the model is estimated separately for spells with negative and positive average residuals. Standard errors are in parentheses. *, ** and *** denote statistical significance at the 5, 1 and 0.1% level respectively.