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. Our goal is to rectify that omission. To test this hypothesis, 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.

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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)). These longer spells have substantial ramifications both for occupants and their neighborhoods. Longer spells facilitate investment in both physical and social capital, the expense of which is easier to amortize over a longer residence spell, and 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)).

The greater stability of owner-occupiers 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). Acquiring and selling a house are both more expensive, in time and money, than moving into and out of a rental unit. However, while stability in housing incentivizes investment in property, it also reduces the mobility of the residents, which may be costly if job separation occurs. 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 job 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) and Fowler et al. (2021) who study young academics, 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]

The purpose of this paper is to fill this gap in the literature. We first 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 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. We show, consistent with the cross-sectional implication of the theory, that owners have lower average levels of mismatch than renters. The dynamic implication 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.

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

The paper proceeds as follows. The next section presents an intuitive narrative, followed by corresponding empirical tests in Section 3. Finally, we discuss the implications of our work and conclude in Section 4.

2 Job Security and Home Purchases

Our description of a theoretical framework has three parts. First we discuss the idea of job match and length of the job spell. We relate this to work by Groes et al. (2015) which discusses occupation match, but which can easily be ported to job match. Second, we discuss the desirability of homeownership as it relates to expected job spell. Third, we lay out our hypotheses that relate job match to tenure choice.

Groes et al. (2015) find, using the same Danish administrative database as we do, that workers who are both underpaid and overpaid relative to others in the same occupation tend to exit their occupations at a higher rate. There would seem to be little mystery why those who are underpaid might change occupations. However, Groes et al. (2015) proffer a model that predicts that both underpaid and overpaid workers (relative to occupational norms) will change occupations. In their model, worker types are optimally matched to jobs that correspond well to their skill level. Workers know their type only imperfectly, but each period observe their productivity which is the basis on which they are paid (in one version of the model). Workers that are paid sufficiently higher or lower than the skill level at which they thought they were now rethink the occupation type at which they are best matched, and change occupations accordingly. Only those whose wages are around the average will wish to stay in the same occupation, precisely because their best information is that they are currently matched well.

At a formal level, there should be no difference between a model that describes occupational changes and job changes. One could define occupations as being firm-specific, for example, and the theoretical analysis would go through unchanged. Since our empirical work centers around job changes—which includes occupational changes within a firm, changes in firm within the same occupation, and changes in both firm and occupation—this is a more relevant context in which to consider individual labor histories. We will find that job tenure is also related to this wage differential.

We turn then to homeownership. As noted above, homeownership is largely thought of as a superior tenure choice, largely because of the larger set of property rights that accrue to owner-occupiers relative to renters (Sekkat and Szafarz, 2011). The cost of owner-occupation of property at the intensive margin is lower as well, due to the tax advantages of ownership, which center around the deductability of mortgage interest and exclusion of implicit renter income from taxable income.[2] However, the costs of homeownership at the extensive margin – the fixed costs of acquiring, and selling, a home – can be substantial. Taxes, search costs, title expenses, agency commissions and so on, are all part of the acquisition process for homebuyers. Since a worker may need to either move and/or sell her home after a job detachment, a job with a shorter expected tenure will discourage homeownership when these costs are high. This is because job detachment comes with the loss of the home (Gerardi et al., 2018) or moving location. Botsch and Morris (2020) combine these elements in a formal model of home acquisition in the face of the fixed cost of ownership, and expected job loss and income reduction.

This can be illustrated by the calcuation of the implicit cost of capital when buying a home, as a function of these up-front costs and the expected tenure. Piazzesi et al. (2020) find that the search and transaction cost of home purchase can amount to as much as 14% of home value. Now let the mortgage interest rate be 4% for a standard fully-amortizing 30 year fixed rate mortgage. Table 1 provides the effective rate of interest on the sequence of payments that begin with the initial loan less the fixed costs (expressed as a percentage of the mortgage), monthly payments based on the terms above, and a final retirement of the principle at the end of the spell.[3] This effective rate is given for a variety of fixed costs and spell lengths. When there are no fixed costs, the spell length is irrelevant; the effective rate of interest is simply the mortgage rate. As can be seen from the Table, as the fixed costs rise or the spell length decreases, the effective rate of interest rises. If the term length is 30 years, the rise in the

[2]Mortgage interest is deductable in both Denmark, the focus of our empirical exercise, and many other countries including the United States.

[3]The calculations were done using the IRR function in Excel.

effective rate is modest. Even at 14% fixed costs this rate only rises to 5.30%. Once fixed costs become part of the calculation, short spell lengths become increasingly costly. Even at a rather modest 5% fixed costs, if the spell length is only one year the effective rate is very high at 9.30%. As fixed costs rise to the higher amount suggested by Piazzesi et al. (2020), a one year term brings about an effective interest rate of 19.65%. Even a 5 year term would require the assumption of a rate of 7.52%. Clearly the expectation of a shorter job spell drives up the cost of ownership, and makes ownership less likely.

There will be a threshold level of mismatch which, given the workers history and their observation of their labor market, will induce enough job security to make homeownership desirable. Once in the homeowner state, our theory suggests that this is persistent. In particular, a decrease in match quality would not induce an own-to-rent transition– this would entail a loss of the benefits of homeownership and while the probability of job loss increases, to move out of a home because of this higher probability would entail no gain.[4]

This theory suggests two tests of the relationship between mismatch and homeownership using the Danish administrative data. The first is a direct comparison of homeowners and renters; we hypothesize that homeowners have, conditional on a set of covariates, lower mismatch than renters. The attainment of the threshold level of mismatch, and the persistence of the homeowner state will combine to create this cross-sectional correlation.

The second, and perhaps more telling, test, is a direct test of the probability of a rent-to-own transition as a function of the household level of mismatch. We employ a panel regression using only the sample of renters, and we ask, in these regressions, if a better match in year t increases the probability of ownership in year t+1, conditional on a set of householder characteristics. The panel nature of these regressions of course allows us to control for the time-invariant individual fixed effects, as well as observable characteristics.

We turn to the presentation of the data and the findings from these regressions.

[4]In what follows we do not analyze own-to-rent transitions (Turner and Smith, 2009) but our data confirm that they are much less common than rent-to-own moves.

3 Empirical findings

We turn to the Danish administrative data to test the main predictions of the theoretical framework discussed in the previous section. Our 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.

We access various registers from Denmark Statistics to test our 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 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 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 is 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.[5] 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.[6] 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.[7] 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 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:

$$\ln w_{it} = \alpha + X_{it}\beta + \epsilon_{it} \tag{1}$$

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

[6]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.

[7]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. 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 is not zero as we consider the sub-sample based on head of household status, whereas the wage residual is based on all 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.[8] 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 with correlation coefficients over 0.96. [9]

Figure 1 displays a kernel density of the residuals from our first specification, separately calculated for owners and renters.[10] Owners have more concentrated residuals than renters, implying that owners overall have less occupational mismatch.[11] Figures 2, 3, and 4 provide empirical kernel densities on gender, age, and education respectively; it can be seen that men

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

[9] As a check of our measure of mismatch, Table 12 in the Appendix presents the regression results for a linear probability model that models job change as a function of mismatch and relevant controls. The results imply that the absolute residual does indeed predict job separation. Groes et al. (2015) verify that their mismatch measure is correlated with occupational mobility, whereas we are most concerned with job mobility.

[10] 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.

[11] 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.

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. We have 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 lower mismatch will be more likely to become a homeowner. In Table 6 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 age, gender, education, family structure, occupation, municipality and year fixed effects. We also include income and number of children.[12] 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 0.45 percentage point increase in the probability of being a homeowner. As a comparison, an increase in the family size by one (increase in the number of children) is associated with a 1.20 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 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 7 presents the cross-sectional regression results across negative

[12]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.

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,

$$\Delta R\_to\_O_{i,t} = \alpha + \eta_1 |\hat{\epsilon}_{i,t}| + \eta_2 \, Z_{i,t} + \zeta_{i,t} \tag{2}$$

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 present the estimated regressions for each set of residuals in Table 8.[13] 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 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

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

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. Number of children in the household, and fixed effects for age, gender, education, family structure, municipality area and job spell at the start year are used as controls. Table 9 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. These results suggest that estimates by prior studies of the differential labor market outcomes due to homeownership (i.e. longer job durations for homeowners) are both due to search frictions arising from homeownership itself and *as well* as job mismatch. Column 2 interacts homeownership and the average mismatch, and we see that the coefficient of the interaction is positive. When interpreted with the negative coefficient of homeownership and the positive coefficient of the average residual, this suggests that the impact of homeownership 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.[14]

Finally, we ask whether the results differ by the state of Danish housing cycle. Figure 5 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.[15] One might be concerned that

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

[15]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.

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 10 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 11 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 a better match induces renters to buy. Since lower mismatch is also associated with 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: Kernel density of residual across housing tenure

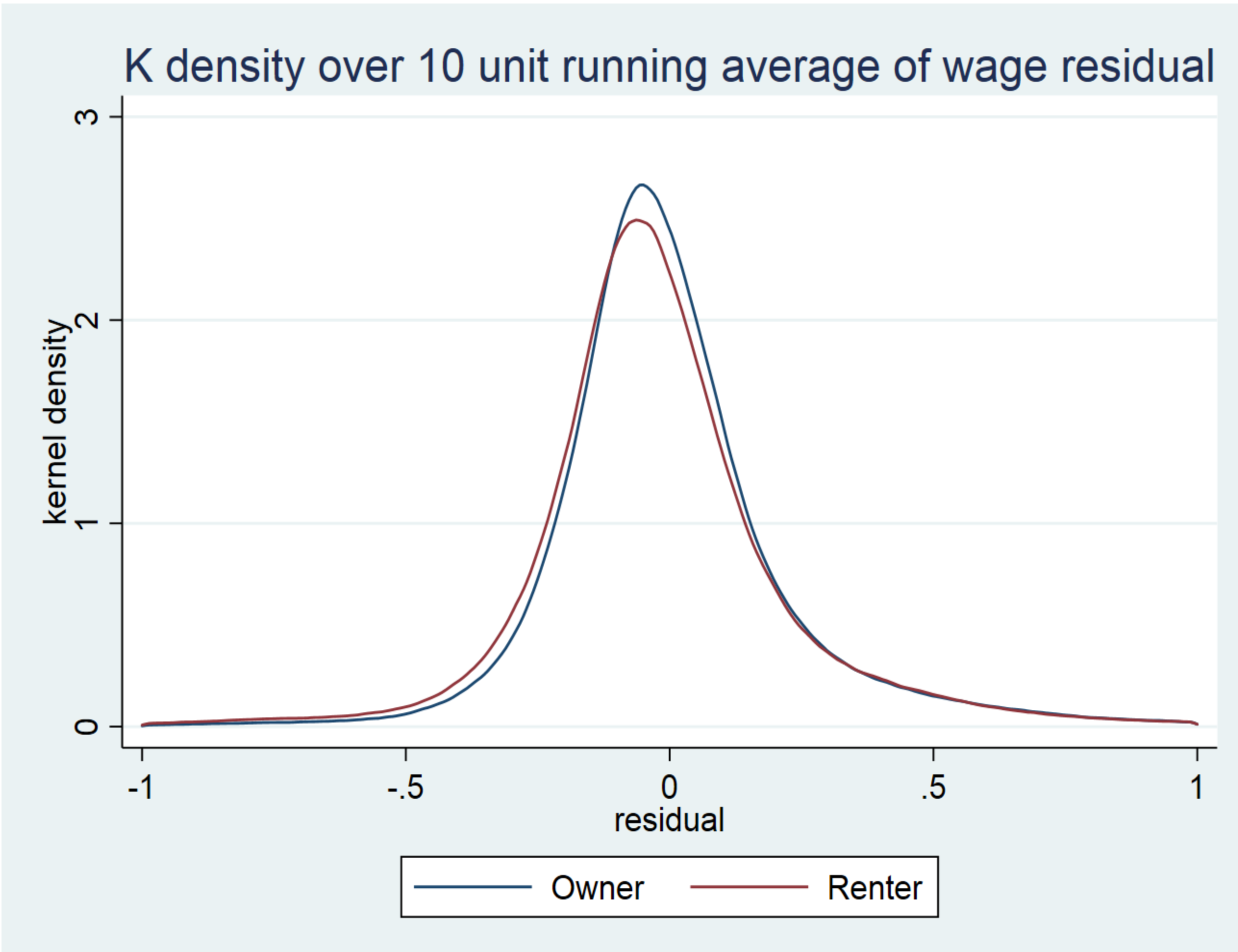

Figure 2: Kernel density of residual across gender

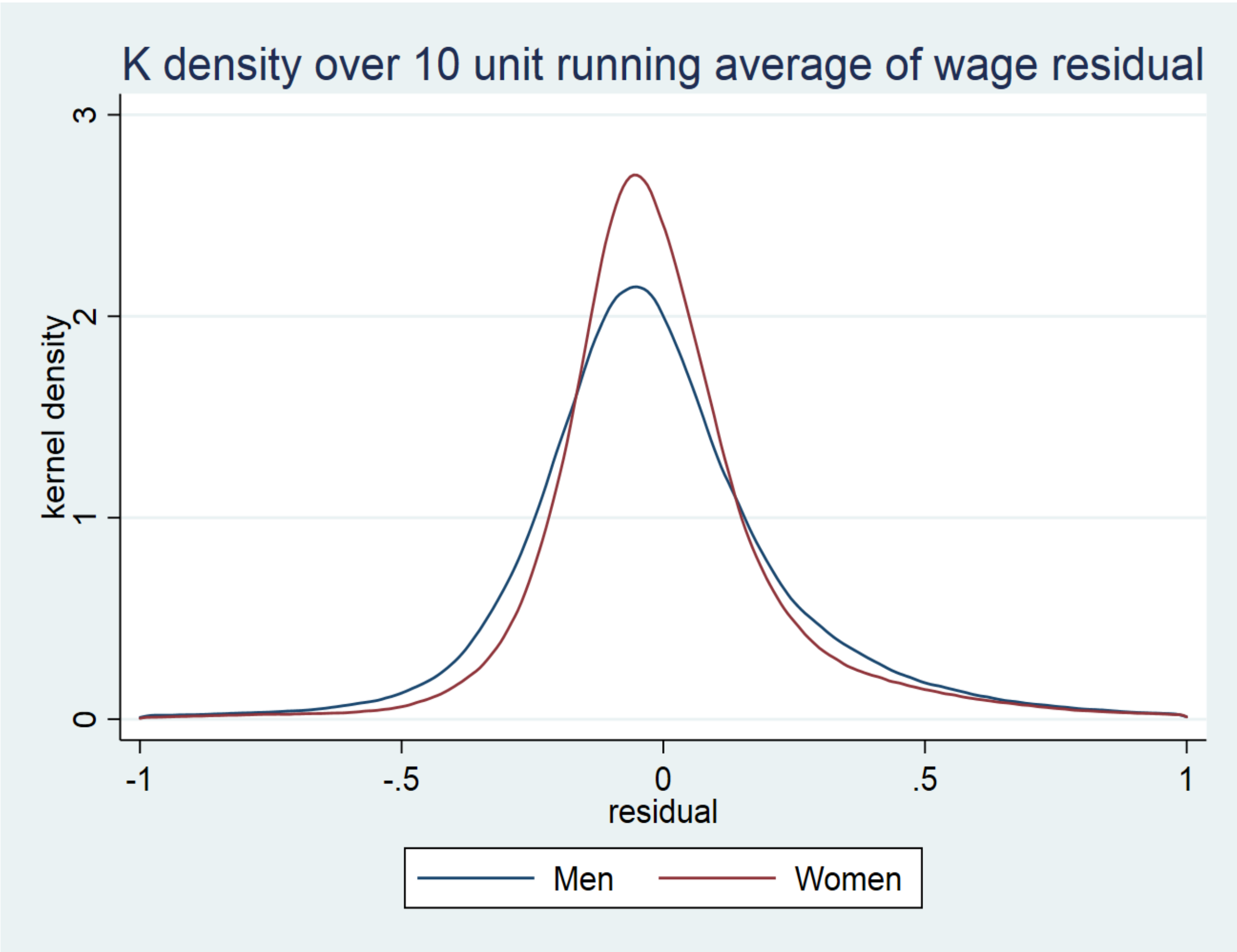

Figure 3: Kernel density of residual across age groups

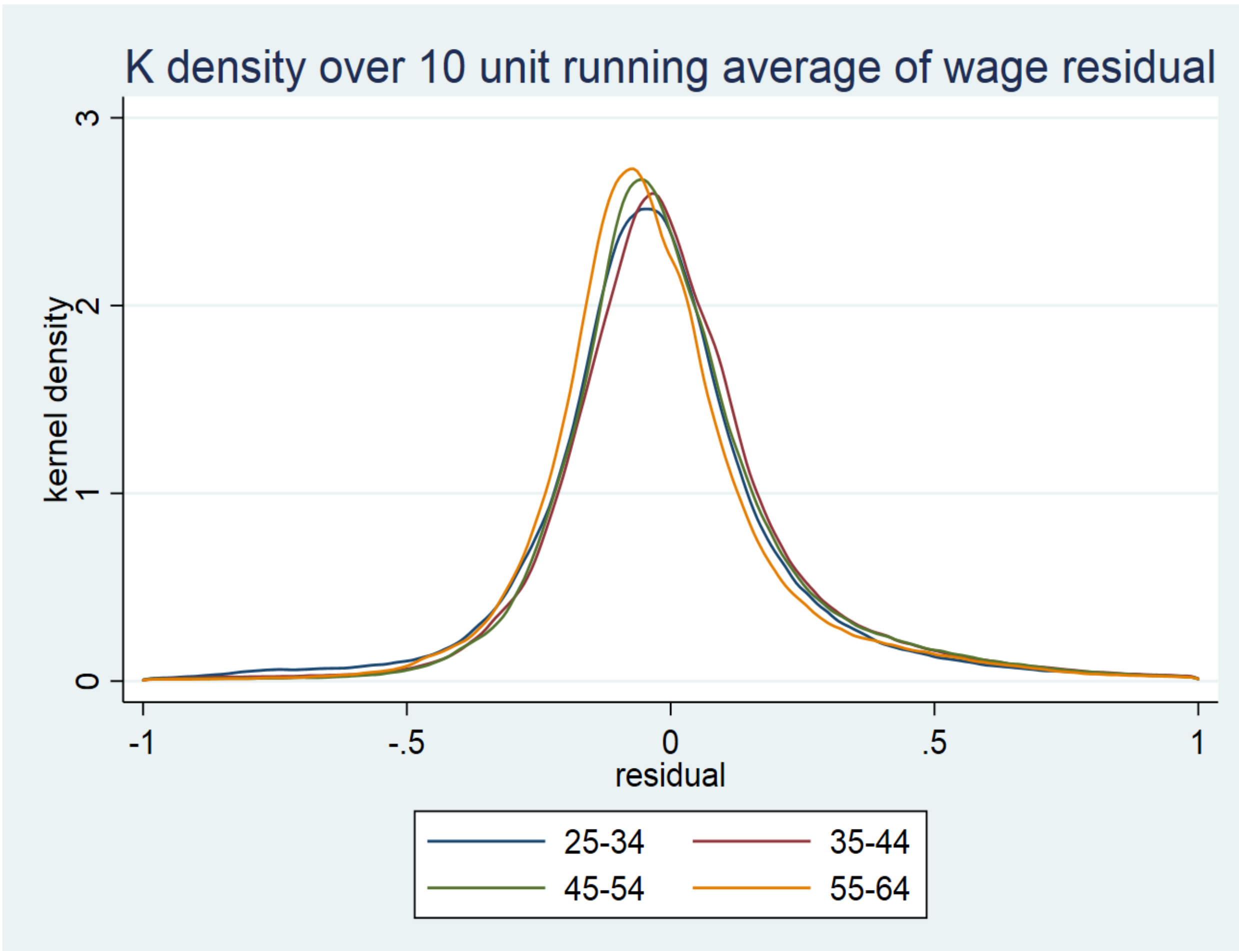

Figure 4: Kernel density of residual across education groups

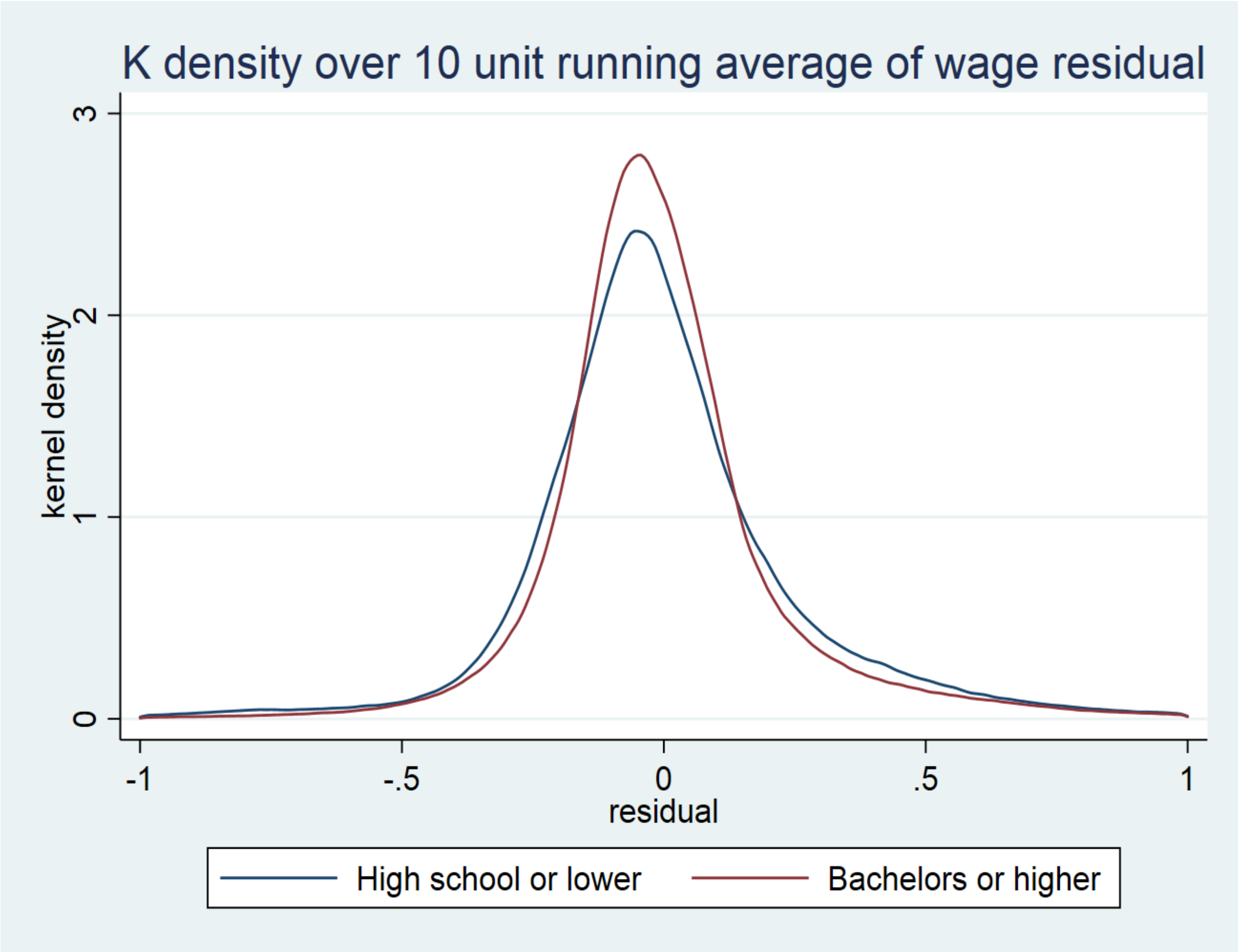

Figure 5: Eurostat Danish House Price Index (Quarterly)

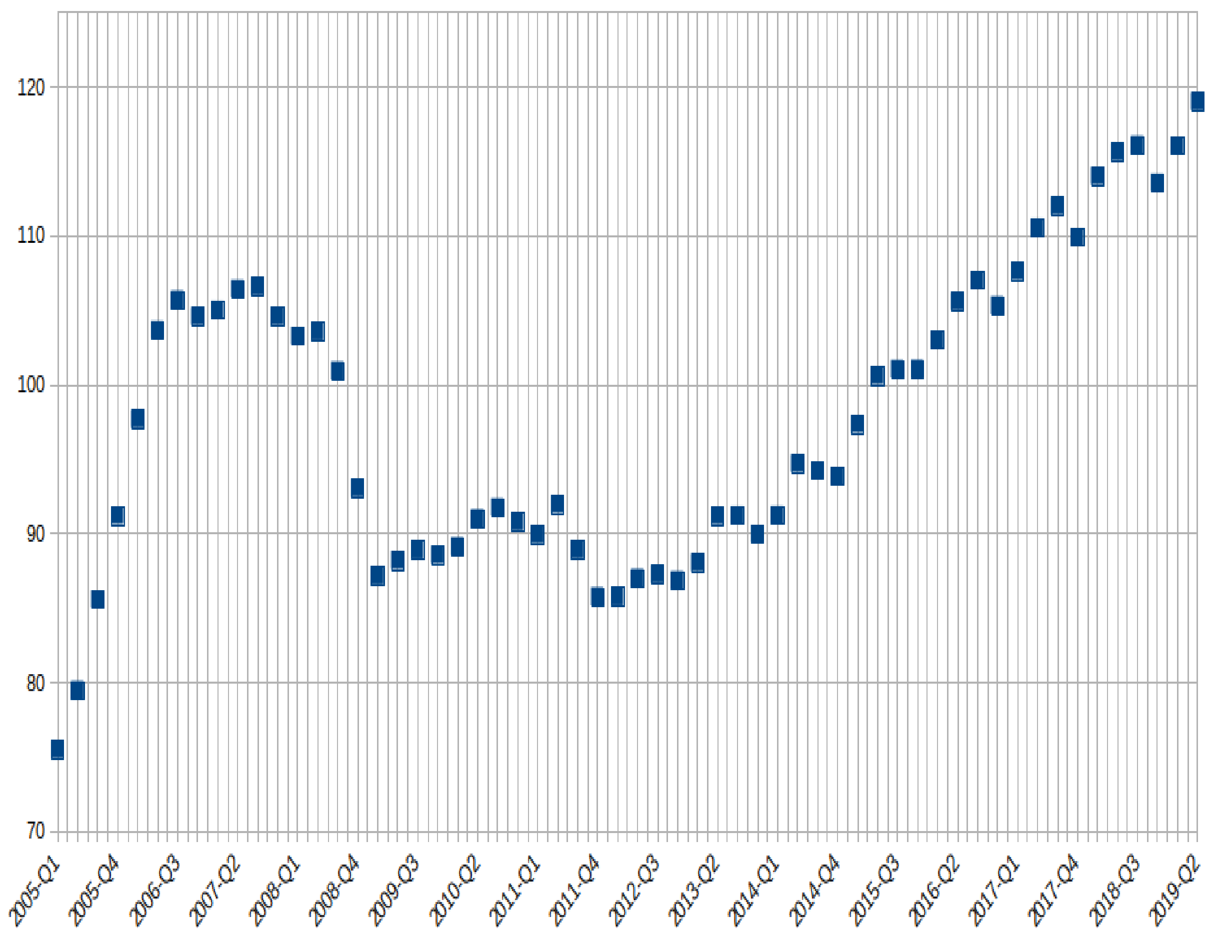

Table 1: Effective interest rate on 30 year mortgage with fixed costs

	Fixed costs (% of mortgage)			
House spell length	0	0.05	0.1	0.14
1	4.00	9.3	14.91	19.65
5	4.00	5.19	6.45	7.52
10	4.00	4.69	5.42	6.04
30	4.00	4.43	4.90	5.30

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

	(1)	(2)	(3)	(4)	(5)	(6)
Absolute Residual	-0.020***	-0.078***	-0.019***	-0.061***	-0.019***	-0.055***
	(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)
# Children	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Absolute Residual × Occupations		0.006***		0.004***		0.004***
		(0.001)		(0.001)		(0.001)
Constant	-0.427***	-0.429***	-0.430***	-0.431***	-0.429***	-0.431***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Age	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
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 7: 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	-0.033***	-0.059***	-0.020***	-0.089***	-0.030***	-0.028**	-0.019***	-0.075***	-0.031***	-0.025**	-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***	0.074***	0.074***	0.076***	0.076***	0.074***	0.074***	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)
# Children	0.014***	0.014***	0.016***	0.016***	0.012***	0.012***	0.015***	0.015***	0.011***	0.011***	0.015***	0.015***
	(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		0.003**		0.007***		-0.000		0.005***		-0.001		0.005***
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
Constant	-0.352***	-0.353***	-0.314***	-0.316***	-0.353***	-0.353***	-0.347***	-0.348***	-0.385***	-0.385***	-0.327***	-0.328***
	(0.012)	(0.012)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.012)	(0.012)
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gender	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	0.342	0.342	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 8: Transitions from Renting to Homeownership.

	(1)	(2)	(3)
Absolute Residual	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
Δ Log 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)
Constant	0.100***	0.100***	0.100***
	(0.013)	(0.013)	(0.013)
Age	Yes	Yes	Yes
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	0.090	0.090	0.090
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. Robust standard errors are in parentheses. *, ** and *** denote statistical significance at the 5, 1 and 0.1 % level respectively.

Table 9: Hazard model of job terminations.

	(1)	(2)	(3)	(4)	(5)	(6)
Owner during Spell	-0.192***	-0.246***	-0.192***	-0.243***	-0.191***	-0.244***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Average Absolute Residual	0.696***	0.551***	0.717***	0.574***	0.715***	0.571***
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)
# Children	-0.034***	-0.034***	-0.033***	-0.033***	-0.033***	-0.033***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Average Absolute Residual × Owner during Spell		0.267***		0.260***		0.263***
		(0.005)		(0.005)		(0.005)
Age	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
R-Squared						
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 10: 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***	-0.061***	-0.016***	-0.042***	-0.017***	-0.037***
	(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)
# 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		0.004***		0.003***		0.002**
		(0.001)		(0.001)		(0.001)
Constant	-0.408***	-0.410***	-0.410***	-0.411***	-0.410***	-0.411***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Age	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
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***	-0.105***	-0.026***	-0.088***	-0.027***	-0.081***
	(0.001)	(0.012)	(0.001)	(0.013)	(0.001)	(0.013)
Log Income	0.083***	0.083***	0.083***	0.083***	0.083***	0.083***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# Children	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Absolute Residual × Occupations		0.008***		0.006***		0.005***
		(0.001)		(0.001)		(0.001)
Constant	-0.467***	-0.470***	-0.471***	-0.474***	-0.471***	-0.473***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Age	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
Occupation	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.365	0.365	0.365	0.365	0.365	0.365
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 11: Transitions from Renting to Homeownership.

	(1)	(2)	(3)
Panel A: 2008 to 2012			
Absolute Residual	-0.002**	-0.002**	-0.002***
	(0.001)	(0.001)	(0.001)
Δ Log Income	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)
Δ # Children	0.023***	0.023***	0.023***
	(0.001)	(0.001)	(0.001)
Constant	0.107***	0.107***	0.107***
	(0.014)	(0.014)	(0.014)
Age	Yes	Yes	Yes
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	0.114	0.114	0.114
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)
Δ Log 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)
Constant	0.073**	0.072**	0.072**
	(0.032)	(0.032)	(0.032)
Age	Yes	Yes	Yes
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	0.057	0.057	0.057
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

Table 12: Relating Mismatch and Job separation.

	(1)	(2)	(3)
Absolute Residual	0.123***	0.125***	0.124***
	(0.001)	(0.001)	(0.001)
Δ Log Income	-0.009***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)
Δ # Children	-0.017***	-0.017***	-0.017***
	(0.000)	(0.000)	(0.000)
Constant	0.262***	0.273***	0.273***
	(0.010)	(0.010)	(0.010)
Age	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	0.040	0.040	0.040
N	6,022,449	6,022,449	6,022,449

This table presents the estimated regression coefficients for the linear probability model 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 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	-0.172***	-0.250***	-0.166***	-0.239***	-0.167***	-0.241***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Average Absolute Residual	0.716***	0.507***	0.761***	0.556***	0.763***	0.556***
	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
# Children	-0.046***	-0.047***	-0.036***	-0.037***	-0.039***	-0.040***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Average Absolute Residual × Owner during Spell		0.446***		0.428***		0.433***
		(0.006)		(0.007)		(0.007)
Age	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	-0.199***	-0.223***	-0.207***	-0.233***	-0.206***	-0.231***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Average Absolute Residual	0.775***	0.708***	0.791***	0.716***	0.780***	0.707***
	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
# Children	-0.024***	-0.024***	-0.028***	-0.027***	-0.025***	-0.024***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Average Absolute Residual × Owner during Spell		0.113***		0.127***		0.124***
		(0.007)		(0.007)		(0.007)
Age	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.