The Negative and Persistent Impact of Social Housing on Employment

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June 30, 2017

Abstract

Social renters are known to have lower residential mobility rates and to experience lower supply rates of job opportunities than other tenants. This may have negative and lasting consequences on the labour market. We test whether social housing could be contribute to the dynamics of unemployment. We put forward an original model on the joint dynamics of individual home and labor market positions estimated with UK panel data. We provide evidence of significant crossed-state dependence effects (i.e., the labor market affecting home tenure and vice versa). In the medium term, about 20% of the gap in the probabilities of being employed between initially employed and unemployed household heads, both private tenants, can be explained by a transition to social housing.

JEL Codes: R23, R31, C33, C35

Keywords: Social housing, unemployment, path analysis, multivariate dynamic logit.

A Introduction

The persistence in unemployment dynamics is a well-established fact which has been analyzed by several researchers (see Heckman, 1981, or Heckman in his Nobel lecture, 2001). Individuals who are jobless in one period are more likely to be jobless in future periods. This persistence may be due to different factors. First, the observed or unobserved characteristics of the individual – low educational attainment, lack of work experience, poor health condition, etc. – might explain a higher probability of being unemployed. As some of these characteristics are persistent, they affect the duration of unemployment spells. Second, past unemployment may itself have a causal impact on future unemployment: this property is called state dependence (Biewen and Steffes, 2010). Many papers have provided evidence of state

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dependence in labor market spells (see among others Vishwanath, 1989, Arulampalam et al., 2000., Gregg, 2001, Olberholzer-Gee, 2008). For example, there are the possible disincentive effects of unemployment insurance explaining that some jobseekers might refuse offers with wages that are initially too low. A depreciation of human capital due to lack of use when unemployed might also explain the lower probability of finding a job. Some contributions have also addressed the question of stigmatization effects to explain state dependence in unemployment: jobseekers have a lower probability of finding a job because being unemployed is interpreted as a negative signal by firms.

The purpose of this paper is to extend this literature and consider another possible factor contributing to the persistence in unemployment (and inactivity) dynamics: the role of home tenure, and more precisely of social housing. Beside socio-demographic qualities, households can indeed be characterized in economic terms over their life-cycle by at least two key positions that affect their choices: their labor market position (they can be employed, unemployed, or out-of-the-labor-force) and their housing tenure (they can own their house or rent it from a private owner or from the social service of a local authority). These two positions are naturally linked to their two respective underlying assets: their human capital and their real estate assets, which have contrasting properties. If human capital is mobile because it moves with the agents and can be modified with some adjustment costs, real estate assets are characterized by their low liquidity, limited divisibility, uniqueness, and transaction costs. Each position on the labor market and the housing market affects the decision taken by the household regarding the other market so that home tenure may be a source of some rigidity in the labor market.

Although the literature has already emphasized the differences in job outcomes between private renters and homeowners, not much has been said on social renters. Yet it is likely that there will be more differences between social renters and private tenants than among private tenants. Indeed, there are different theoretical rationales in suggesting negative effects of social housing on employment. First, social tenants have a lower residential mobility rate (Dujardin and Goffette-Nagot, 2009): since rents in the social housing sector are below market rents and waiting lists for getting another dwelling in the public sector are long, unemployed social tenants are more reluctant to move. This negatively affects their probability of accepting a non-local job offer (Munch et al., 2006). Second, social tenants may experience a lower supply rate of job opportunities. Indeed, social housing is geographically concentrated. Households living in public housing have more frequently other social tenants as neighbors, than private tenants or owners (Whitehead, 2007). The concentration of unemployed or inactive people in social housing is likely to reduce the quality of information about available job offers (Granovetter, 1995). Moreover, social housing units are generally located far away from business districts which may negatively affect the job-finding rate of social tenants. Finally, stigmatization effects may also play a role: being a social tenant might be considered as a negative signal by employers.

These three factors suggest that when considering job market outcomes, social tenants should be treated separately and not merged with other renters. Moreover, the duration of occupancy of a social housing is very long on average suggesting lasting negative effects on employment. Indeed, in some countries being a social tenant may be a quasi-definitive state which consequences on the labour market will cumulate over several periods.

Despite these well-established theoretical insights, the empirical literature testing the impact of social housing on employment provides mixed empirical evidence: Flatau et al. (2003) detect no effects of public renting in Australia on unemployment once the endogeneity in home tenure is taken into account. Using a simultaneous probit model, Dujardin and Goffette-Nagot (2009) do not find any effect either in France. By contrast, Battu et al. (2008) provide evidence of longer unemployment spells for public renters in the United Kingdom with a multiple-spells identification strategy.

However, these empirical papers suffer from some limitations as they consider a static approach to home tenure. For example, Battu et al. (2008) propose a duration model for unemployment spells conditional on initial home tenure. Such a setup has two shortcomings. First, the dynamics of home tenure, and notably the duration of social housing spells, are not considered. Since we expect social housing spells to be long (this will be empirically assessed in the paper), they may have lasting consequences on the labor market, largely beyond the first unemployment spell. Social housing might explain frequent multiple spells of unemployment. When exploring the persistence in unemployment dynamics, we need to proceed with a medium run analysis: this means that we should explicitly model the dynamics of home tenure to identify their contribution to the succession of events on the labor market. Second, no dynamic reverse causation effect is treated. Most of the previously mentioned papers control for the endogeneity of tenure (unobserved factors affecting both home tenure and employment), but do not consider the causal impact of the labor market position on housing choices. Being unemployed or inactive may impact home tenure (due to the nature of the benefit system, unemployed or inactive people have higher transition rates into public housing), which may further affect the likelihood of getting a job.

We build an empirical dynamic setup at the household level for assessing the consequences of social housing on the duration of unemployment and spells out-of-the-labor-force. In order to assess the indirect contribution of social housing spells on labor market dynamics, we need a model dealing simultaneously with both positions. Indeed, our framework should first provide an estimate of the entry rate into social housing according to the labor market position and, second, the probability of finding a job (or remaining employed) of social tenants compared to private tenants, or homeowners. We introduce a statistical setup which models the joint dynamics of the two positions (labor and housing) because they are interrelated and may have cross-persistent impacts. We rely on a dynamic bivariate multinomial logit modeling scheme with unobserved heterogeneity. We address endogeneity in both statuses (through correlation between unobserved heterogeneity terms) as well as simultaneity in both decisions (explicit modeling of labor-housing odds ratios). With household level data from the British Household Panel Survey (BHPS) on the 1992-2008 sample period, we model all possible transitions across nine states (three for the labor market: employed, jobseeker and out-of-the-labor-force; and three for home tenure: owner, private renter and public renter) at an annual frequency taking into account several factors such as family composition, spouse's activity, the household head's educational attainment and health condition, the amount of housing benefit (we explicitly identify households with a full rent rebate), lagged labor and housing markets individual positions, and the lagged macroeconomic or local environment. *We choose to explicitely model the three positions for home tenure : owner, private renter and public renter instead of reducing the model to only two positions (public renter and non-publi renter). This is because home tenure dynamics are complex. For example, entry rates into the social housing stock may differ according to the previous home status (owner or private renter). Moreover, the job market consequences of an exit from the social rental stock may differ depending on the new housing status (owner, private renter). Hence we have to build a comprehensive framework encompassing a large set of effects directly or indirectly linked to social housing to provide a good measure of the impact of social housing on employment at different time horizons.* We complement this set of equations with a housing cost equation and a wage equation (changes in wages for employed people and starting salaries for previous jobseekers). We use the complete set of equations to simulate individual paths on both markets in the medium term.

Our contribution is twofold. First, our results provide significant evidence of cross-causality effects between home tenure and the labor market: as exemplified in the literature, home tenure influences transition rates on the job market (we find a lower probability of gaining employment of social tenants *ceteris paribus*) and labor market status also influences home tenure (in particular, we find a higher transition rate into social housing of inactive or unemployed household heads). Overall, we illustrate that modeling simultaneously both markets leads to significantly different probability distributions in the various labor and housing statuses to those obtained when considering separately both markets. Second, using the dynamic completeness of our setup, we can illustrate and measure impacts of particular events in the medium term in simulating individual paths on the housing and labor markets. Drawing on Kuha and Goldthorpe's (2010) path analysis, we illustrate the impact of some intermediate status on the likelihood of finding a job in the medium term. Interestingly, the gap in the probability of being employed between being initially-employed or without a job (either being a jobseeker or inactive) is indeed linked to a differential in the probability of becoming a social renter. We compare two otherwise similar profiles of household heads living in the private sector: employed or jobseeker (or inactive). We estimate their probability of being (or remaining) employed over different horizons (2 to 8 years). We compute the share of the probability differential between these two profiles that could be attributed to social housing spells. The indirect role of social housing appears quantitatively large and significant. Indeed, almost 20% of the gap in employment probability in the medium term between an initially employed head and a jobseeker can be attributed to a higher likelihood of living in the social sector by the latter. Hence, a significant share of the persistence in unemployment or out-of-the-labor-force dynamics may be linked to the joint dynamics on the housing market.

The rest of the paper is organized as follows: Section B presents the literature on home tenure and employment. The main section of the paper (Section C) presents some general facts about the UK housing and labor markets, as well as our data sample. Section D set outs the statistical methodology. Section E gives the main results: parameter estimates, sensitivity analysis and model simulations. Section F concludes.

B Literature on home tenure and employment

Some theoretical papers have already emphasized the impact of housing tenure on the labor market, but without explicitly considering the social housing sector. Oswald (1997) and Dohmen (2005) proposed frameworks comparing the labor supply of owners and renters. Due to home illiquidity, owners face restricted residential mobility and cannot freely move to another region if the local labor demand is low. Consequently, renters are less likely to be unemployed than owners. Munch et al. (2006) and Coulson and Fisher (2009) reached more contrasted conclusions using search-theoretic models.

A large empirical literature also deals with the consequences of home tenure on labor market positions. In his seminal macroeconomic contribution, Oswald (1996) provides evidence for the fact that unemployment and homeownership rates are significantly and positively correlated, suggesting in an important "moving cost" effect for homeowners. This pattern is further confirmed by Nickell and Layard (1999) or Green and Hendershott (2001), also using macro data. These findings are questioned by micro-studies on the impact of home occupation status on the durations of unemployment spells and job spells, as well as on wages. Using a Dutch individual panel dataset, van Leuvensteijn and Koning (2004) provide evidence that homeownership has no significant impact on job-to-job mobility, but lowers the risk of unemployment. Munch et al. (2006, 2008) with a Danish dataset suggest that the overall effect of homeownership on the transition rate out of unemployment is positive: the effect of a lower local reservation wage for owners compared to renters dominates the opposite one for non-local jobs. They argue that homeowners have a lower transition (job-to-job mobility) rate into non-local jobs, but are generally offered higher earnings since firms prefer to invest in firm-specific human capital, and prefer less mobile owners to renters. Overall, owners encounter longer durations in a specific job and a higher wage throughout their employment spell.[1]

To our knowledge, Flatau et al. (2003), Battu et al. (2008) and Dujardin and Goffette-Nagot (2009) provide the main empirical contributions explicitly dealing with the consequences for an individual's labor market situation due to a spell in social housing. Flatau et al. (2003) compare the probability of being unemployed for public and private tenants in a micro framework. Once having controlled for the endogeneity of home tenure, they do not detect any significant effect of social housing on unemployment. Dujardin and Goffette-Nagot (2009) estimate a simultaneous probit for unemployment and public housing. They use public housing characteristics based on both the gender composition of children and the share of public housing at the city level. Their main result is that public housing has no effect on unemployment. Battu et al. (2008) simultaneously considered the impact of home tenure on both job and unemployment durations using a UK dataset for individuals. They provide evidence of a negative effect of homeownership on the job-to-job transition rate (with a distant move), but no homeownership effect on the exit rate from unemployment to a new job. Using refinements across housing tenure types (public and private renting sectors are distinguished) and across socioeconomic classes, they find a lower probability of becoming employed for unemployed public renters. The authors detect no significant differences in the probability of getting a new job with no residential move between private and social tenants, i.e., no demand-side discrimination by employers against social renters. By contrast, they provide evidence of a significantly higher probability of obtaining a new job when private tenants move homes.

There is a distinct literature on the determinants of home tenure, though it does not always involve explicit modeling of the social housing sector. Henderson and Ioannides (1983), Fu (1995) and Sinai and Souleles (2005) provide theoretical contributions explicitly dealing with the conflict between housing consumption and investment motives. Some empirical contributions have assessed the role of specific factors concerning the status of home tenure, namely: neighborhood externality risk (Hillber, 2005) or house price risk (Turner and Seo, 2007). Few contributions explicitly integrate the role of individual job history. For the UK housing market, Henley (1998) investigates the impact of homeownership (and more precisely of negative housing equity) on residential moving. He finds evidence that homeowners' mobility in response to changing labor market conditions is lower than renters' mobility.

The existing literature thus focuses either on the determinants of labor market positions (and the possible role of housing tenure) or on the determinants of housing tenure choices. Few studies have jointly investigated home tenure and labor market decisions. Böheim and Taylor (2002) is probably the most significant contribution in the study of

[1] It should be noted that Barceló (2006) found contrasting results with a sample from the European Community Household Panel for five European countries.

the interaction between housing and labor markets. They propose a bivariate probit model and detect a significant positive correlation between job and residential mobility. However, in their setup, they do not differentiate transitions from and to employment, nor do they model changes in home tenure.

C UK labor and housing markets

C.1 Presentation

From 1991 to 2008, the changes in the national jobseeker's rate were naturally related to the chronology of the business cycle experienced by the UK economy over the period (see Figure 1). The unemployment rate increased during the recession of the late 1980s and early 1990s, and then experienced a long decrease from 1993 onwards, falling from 10.4% in England (according to the ONS Labor Force Survey), to 4.7% in 2005. The unemployment rate remained steady in 2006 and 2007 before increasing again in 2008, following the financial crisis. Spatial disparities for the jobseeker's rate are large: regions in the North of England (North West, North East, and Yorkshire & Humber) routinely suffer unemployment rates above the national average, whereas jobseeker's rates are especially low in the southern part of the country. Unemployment in London was very high for the whole period (with rates comparable to those of the North East region: 13.5% in 1993, 6.9% in 2005 and 7% in 2008). If all regions experienced the same decrease in unemployment rates between 1993 and 2005, dynamic unemployment patterns have been more contrasted since 2005: almost steady in North East or London between 2005 and 2007, but rising in the south.

It should also be noted that the inactivity rate is rather high in England among the working-age population (20.6% in 1993 and 21.2% in 2005, according to the ONS Labor Force Survey). This leads us to consider transitions from and to the out-of-the-labor-force status besides usual transitions between employment and jobseeker positions within the labor force. This inactivity rate experienced large movements between 1991 and 2008 in some English regions, especially in the later period.

[Insert Figure 1]

If we turn now to the UK housing market, let us first consider the evolution of home sale prices. We observe that following a short period of stability between 1992 and 1995, nominal home prices have been steadily rising since 1996 in almost all regions of England, as shown in Figure 2. The average annual growth rate of prices over this period is between 12.92% in London (the most expensive English region) and 10.28% in the North East (the least expensive one). This pattern (already documented in the literature) is linked to a rise in homeownership rates (the number of owner-occupied dwellings was 16.2 million in 1997, and around 18 million in 2008 for the whole of the United Kingdom [ONS, 2010]), and was mainly driven by innovations in the mortgage credit sector. It is also to be noted that migration rates towards the London metropolitan area or southern regions rose in the 1990s (see Hughes and McCormick, 2000).

[Insert Figure 2]

In the United Kingdom, social housing is owned by two types of registered providers: Local Authorities *(or Local Governments)* and Housing Associations (i.e., non-commercial organizations that are financially regulated and funded by the government). Social rents are historically low (see Table 1 below) and their changes are set by law. Eligibility to public housing depends on various factors: households may be eligible if their income is below a certain level, if they work in the area or if their members have local connections. Certain groups of people are given an explicit priority for public housing, including persons suffering health problems, living in unsanitary or overcrowded homes, or who are about to lose their home, etc. From 1991 to 2008, the number of dwellings rented by the social sector decreased steadily (from 5.3 million to 4.5 million). The decline in new social housing rentals is partly due to a fall in government-subsidized new construction and an increase in social housing sales to sitting tenants (a long-standing government program). The share of Local Authority housing in the social sector is decreasing compared to the new Register of Social Landlords by the Housing Associations (see Whitehead, 2007). Moreover, about 400,000 social housing sales to sitting tenants took place between 2001 and 2010 (Communities and Local Governments, 2011). By contrast, the number of privately rented dwellings started to increase in the early 2000s. In 2005, the total number of households in the UK private rental sector was about 2.4 million (ONS). Whitehead (2007) has also explained that the median rent for social renters (Housing Association as well as Local Authority) in the United Kingdom was zero, after deduction of housing benefits in 2005 according to the Family Resources Survey. Moreover, the net rent is only 4% of household income, on average for public renters (25% in the private sector). Between 20% and 30% of private renters receive allowances covering their entire housing costs (excluding charges). This explains why we distinguish between renters with 100% rent rebates (either social or private), from those with positive net housing costs in the rest of the paper.

C.2 Datasets

We use data of the BHPS from 1991 to 2008. This nationally representative survey combines both individual and household-level data from 18 annual waves. The first wave (in 1991) surveyed 5,500 households (more than 10,000 individuals) in Great Britain. Additional samples first for Wales and Scotland and second for Northern Ireland were added in 1999 and 2001. The total number of surveyed households in 2008 was about 9,000.

The BHPS contains a large amount of detailed information concerning current labor market status (employed, unemployed, out-of-the-labor-force), past positions (previous status, the date at which the current labor market spell began) and income (wage dynamics since the previous year's interview and possible benefits when unemployed or out-of-the-labor-force). Moreover, the survey also includes a wide range of information about individual and household characteristics (educational attainment, family type, health, etc.) that will be useful for the estimation. These variables will be set out in Section E. All these pieces of information (labor market, housing market, and individual/households characteristics) are recorded annually. Hence, we will build our dynamic setup with an annual frequency: home tenure, labor market positions, or socio-demographic characteristics at year t corresponding to the date of the interview of the head of household, while lagged terms are taken from the previous year's interview.[2] We use some local economic variables: the regional unemployment rate and regional home prices. The regional unemployment rate comes from the ONS. Regional home prices are from Nationwide (the mortgage lender): these are mix adjusted,[3] and seasonally adjusted house price indexes derived from the Nationwide mortgage dataset.[4]

We select our reference population and accordingly proceed with some processing of the dataset. We only consider the labor market position of the head of household: because we study the impact of housing tenure on work life history, we consider data at the household level such as information on the spouses' work-life histories as frequently less accurate. We exclude households with heads under the age of 16, or above 64 for men and 59 for women. Finally, we restrict our analysis to England: legislation regarding public renting is different in Scotland, Wales, or Northern Ireland and, as explained above, the sample period is much shorter for non-English households in the BHPS. After selection, our sample under study is composed of 39,862 yearly observations of English household statuses (corresponding to 5,737 individuals). Table 1a summarizes the main descriptive statistics of socio-demographic characteristics, labor position and the home of household heads according to tenure. When living in the private rental sector, household heads are generally young, with few children and high educational attainment compared to the public sector. As expected, total family income is much higher for homeowners than for private renters because the former are older on average. Notice that net housing costs are also the highest for homeowners though around 40% of them are outright owners. This is also due to the large amount of housing benefit received by private renters (see above). Rents in

[2] All short job, unemployment, or inactivity spells (beginning and ending between interviews) have been dropped from the sample. Such a treatment is standard in the literature using the BHPS (cf. Battu et al., 2008).

[3] With a correction for potential structure effects among four types of properties: detached, semi, terraced and flats; and 2 types of buyers: first-time buyers and others; and 3 property ages: new, modern and old.

[4] We also gathered simple averages (i.e., without any correction) of home prices at the Local Authority District Level. An alternative version of the model has been estimated with this other measure of prices, to check for the robustness of our results.

the social rental sector are very low and a large number (steadily above 30%) of public renters have zero net housing costs. Public renters are less frequently employed than private renters and homeowners. It should be noted that the inactivity rate among working-age social renters is above 40%. Also, the number of rooms per person in the household is the lowest in the social rental sector.

[Insert Table 1a]

We then provide some descriptive statistics on the duration of unemployment (or inactivity) and social housing spells. As shown in Table 1b, annual transition rates out of the social sector are low (less than 5%) and even lower when unemployed (2% approximately) or out-of-the-labor-force (around 2.5%). The probability of becoming a social tenant is substantially higher for private tenants than for owners (5.32% against only 0.16%). In both cases, transition rates into social housing increase when considering private tenants or owners without a job. Finally, transition rates into employment are substantially lower for unemployed social tenants than for unemployed private tenants or homeowners. Overall, these preliminary results suggest a two-sided relationship between social housing and labor market status: social housing has a positive incidence on unemployment or inactivity probability which further lowers the likelihood of moving to the private housing sector.

[Insert Table 1b]

D The Model

Our model is composed of two sets of equations: on the one hand, the transition probabilities between nine states obtained in crossing three labor market positions and three home tenure statuses; on the other hand, the modeling of changes in wage or the wage level for newly, hired employees as well as the housing costs. Indeed, these two variables (housing costs and wages) enter the dynamic logit equations as covariates and are affected by current home tenure and labor market position choices of each household.

D.1 Dynamic logit equations

Let $y_{k,i,t}$ denote the categorical response variables for household's head i at calendar year t, with $i = 1, ..., n$, $t = 1992, ..., 2008$ and $k = h, l$. $y_{h,i,t}$ is the home tenure and has three categories {owner-occupier, social renter, private renter}. $y_{l,i,t}$ is the labor market position and has three categories {employed, unemployed, out-of-labour force}. $\mathbf{y}_{i,t}$

denotes the vector with elements $(y_{h,i,t}, y_{l,i,t})$ and $\mathbf{x}_{i,t}$ is the $(1 \times K)$ vector of predetermined covariates for household i at date t. This vector includes the following socioeconomic factors: gender of household head (dummy variable, one is for a woman), age (linearly specified), marital status (one for couples and zero for singles), number of children (linearly specified), spouse's previous labor market position (employed or not), log of previous year's real household income, log of previous year's real net housing costs[5,6] (when strictly positive, zero otherwise) and dummies regarding household head's educational attainment (degree or above level, teaching level, A levels, O levels/GCSEs or no diploma). The previous year's number of rooms per person is included as a proxy for possible dwelling overcrowding (which is an important criterion for social housing eligibility). We also include a dummy variable for the health condition of head: this variable equals 1, if the respondent says her health has been very good, good or fair since last interview, and 0 otherwise (i.e., poor or very poor). This vector also contains the local aggregate variables: lagged regional unemployment rate and the lagged growth rate of real regional home prices.[7] Lagged variables $\mathbf{y}_{i,t-1}$ (i.e., the last year's home tenure and labor market position) are included to capture state dependence, i.e., the direct impact of past positions on current choices. This means that our setup will focus on the transition rate from one (labor or housing) position to another within a year, and not on the probability of being in a position at a certain date. The panel structure of our data sample (we follow the same households for a long period and may have multiple spells) permits the identification of an unobserved time-constant heterogeneity term The correlation between the components of this vector allows us to control for endogeneity in housing and labor market positions. We simultaneously estimate all transition probabilities between each position on the labor and the housing markets, which is computationally costly; we keep the number of positions considered reasonably low. Consequently, we do not explicitly model job-to-job transitions (in this case, the head simply remains employed $y_{l,i,t} = y_{l,i,t-1}$), nor do we capture residential moves with no change in home tenure (for example, owners buying a new house or renters renting a new dwelling between $t-1$ and t encounter no change in their position, i.e., $y_{h,i,t} = y_{h,i,t-1}$). Moreover, we do not distinguish between outright owners and owners with a mortgage. We consider the starting condition $\mathbf{y}_{i,0}$ as given and work conditionally on this information.

Let $p(\mathbf{y}_{i,t} \mid \mathbf{x}_{i,t}, \mathbf{y}_{i,t-1}, \omega_i)$ denote the conditional distribution of the vector of endogenous variables $\mathbf{y}_{i,t}$ given the vector of predetermined covariates, lagged endogenous variables and unobserved random terms. Following Bartolucci

[5] Net housing costs mean after deduction of eventual housing allowances.

[6] The endogeneity in income and housing costs will be explicitly treated in the model with additional equations and unobserved heterogeneity terms potentially correlated with those in the transition equations.

[7] Other specifications for the tenure choice equation have been tested. In particular, we tried to add the relative housing costs among the local covariates — the ratio of house prices to rents — following Goodman (1988), but the coefficient associated with this variable was not significantly different from zero.

and Farcomeni (2008), we adopt a *local* specification for marginal logits and for log-odds ratios. More precisely, each of the four marginal logits $\eta_{k,z_k,i,t}$ is modeled as follows

$$\eta_{k,z_k,i,t} = \log \frac{p\left(y_{kit} = z_k \mid \mathbf{x}_{it}, \mathbf{y}_{it-1}, \omega_i\right)}{p\left(y_{kit} = 0 \mid \mathbf{x}_{it}, \mathbf{y}_{it-1}, \omega_i\right)} \quad z_k = 1, 2, \quad k = h, l \tag{D.1}$$

where the value taken by z_k determines the home tenure ($k = h$) or labor market position ($k = l$). In the former case, we set $z_h = 0$ to denote the "private renter" state, $z_h = 1$ the "home-owner" one, and $z_h = 2$ the "social renter" one. In the latter case, $z_l = 0$ is for out-of-labour force position, $z_l = 1$ for employment, and $z_l = 2$ for unemployment. For example, $\eta_{h,2,i,t}$ is the log of the probability of being in the social renter state compared to the private renter state for individual i at date t. Some households may be more prone to be jointly in a given position on the housing and labor markets: this is captured by the correlated pattern of the unobserved heterogeneity terms ω_i.

The four marginal log-odds ratios are specified as follows

$$\varphi_{z_h,z_l,i,t} = \log \left[\frac{p\left(y_{hit} = z_h,\ y_{lit} = z_l \mid \mathbf{x}_{it}, \mathbf{y}_{it-1}, \omega_i\right)}{p\left(y_{hit} = z_h - 1,\ y_{lit} = z_l \mid \mathbf{x}_{it}, \mathbf{y}_{it-1}, \omega_i\right)} \frac{p\left(y_{hit} = z_h - 1,\ y_{lit} = z_l - 1 \mid \mathbf{x}_{it}, \mathbf{y}_{it-1}, \omega_i\right)}{p\left(y_{hit} = z_h,\ y_{lit} = z_l - 1 \mid \mathbf{x}_{it}, \mathbf{y}_{it-1}, \omega_i\right)} \right] \quad z_h = 1, 2,\ z_l = 1, 2 \tag{D.2}$$

These log odds ratios measure the gap between each pair of conditional logits. For example, a large value for $\varphi_{1,1,i,t}$ (i.e. a log odds ratio significantly above zero) would mean that the ratio of probability of being an owner-occupier ($z_h = 1$) compared to a tenant in the private rental sector ($z_h = 0$) for household i at calendar year t is higher when employed ($z_l = 1$) rather than for being out-of-labor force ($z_l = 0$). The log odds ratios $\varphi_{z_h,z_l,i,t}$ explicitly capture the simultaneity (at an annual frequency) of households' decisions in the two markets. We propose the following simple linear setup for marginal logits and log-odds ratios

$$\begin{cases} \eta_{k,z_k,i,t} = \alpha_{k,z} + \mathbf{x}_{i,t}\beta_{k,z} + \mathbf{y}_{i,t-1}\gamma_{k,z} + \omega_{k,z,i}, \quad z_k = 1, 2, \quad k = h, l \\ \varphi_{z_h,z_l,i,t} = \overline{\alpha}_{z_h,z_l}, \quad z_h = 1, 2,\ z_l = 1, 2 \end{cases} \tag{D.3}$$

$\alpha_{k,z}$ and $\overline{\alpha}_{z_h,z_l}$ are the intercept terms for each marginal logit (resp., log-odds) equation. The unobserved heterogeneity factors $\omega_{k,z,i}$ ($k = h, l,\ z = 1, 2$) are elements of vector ω_i. As will be set out in the next subsection, ω_i also includes terms from the wage and real housing costs equations. We follow Bartolucci and Farcomeni (2008) and treat the log odds ratio as constant. This choice has been investigated, but no significant dependence on some covariates has been evidenced.[8] $\beta_{k,z}$ is the vector of parameters that evaluates the impact of covariates in marginal

[8] It should be noted that supposing some factors affecting the marginal logits do not impact the log odds ratios is consistent with an assumption that the underlying utility function of households is separable from these factors: the contribution of this variable to the current endogenous household's decision on one market (home tenure, for example) does not distort the current endogenous decision on the other market (labor in this case). A more general version of the model where $\varphi_{z_h,z_l,i,t}$ depends on some covariates $\mathbf{x}_{i,t}$ and the state dependent terms $\mathbf{y}_{i,t-1}$ have been rejected with likelihood ratios (LR) tests.

logits. $\gamma_{k,z}$ is the vector of parameters assessing the contribution of the previous year's home tenure and labor market position on current marginal logits.

Overall, the simultaneous estimation of the four marginal logits $\eta_{k,z,i,t}$ and the four log-odds ratios $\varphi_{z_h,z_l,i,t}$ deliver a complete characterization of the joint conditional distribution of $y_{l,i,t}$ and $y_{h,i,t}$. Once the eight corresponding equations have been estimated, we use the iterative procedure described by Colombi and Forcina (2001) to obtain $p\left(\mathbf{y}_{i,t} \mid \mathbf{x}_{i,t}, \mathbf{y}_{i,t-1}, \omega_i\right)$ from the vector $\left\{\eta_{i,t}, \varphi_{i,t}\right\}$. This procedure is costly because it requires solving a nonlinear system of eight equations within our likelihood maximization procedure.[9] This accentuates our need to keep the number of parameters reasonably low.

D.2 Continuous equations

We need to estimate *(i)* the starting salary per hour w_{it} of newly employed head of household i previously unemployed or out-of-labor force since this affects the family income which will further influence future home tenure or labor market decisions, as well as wage dynamics over job spells, (ii) the net housing costs c_{it} of household i changing home tenure (either from rental sector to home-ownership or conversely) at date t.

For the estimation of the initial hourly salary, we rely on a standard Mincerian equation for the heads of household. Among the set of explanatory variables $\mathbf{x}_{w,i,t}$, we include almost all those already present in vector $\mathbf{x}_{it}$ as well as additional factors usually present in this kind of model (log of hours worked per week, age squared, occupational status, industrial classification), as well as time dummies to capture the trending pattern of hourly wages over the period considered. The Mincerian equation is specified as follows

$$\log\left(w_{it}\right) = \alpha_w + \mathbf{x}_{w,i,t}\beta_w + \mathbf{y}_{i,t-1}\gamma_w + \omega_{w,i} + \varepsilon_{w,i,t} \tag{D.4}$$

We also include the $\mathbf{y}_{i,t-1}$ vector since the previous labor market position (unemployed or inactive) and home tenure (owner, social, or private renter) may influence wage outcomes. $\omega_{w,i}$ is an unobserved heterogeneity term, possibly correlated with those included in system (D.3). $\varepsilon_{w,i,t}$ is assumed to be a homoskedastic Gaussian error term, $\varepsilon_{w,i,t} \sim \mathcal{N}\left(0, \sigma_w^2\right)$. We denote $g\left(w_{it} \mid \mathbf{x}_{w,i,t}, \mathbf{y}_{i,t-1}, \omega_{w,i}\right)$ the density of initial hourly wage conditional on observed and non-observed factors.

Equation (D.4) only gives the hourly wage for newly employed heads. We need to model all other components of the family income for the simulation experiment: dynamics of wage per hour for ongoing labor spells, head of household's benefits, or pensions when unemployed or inactive, spouse's income, capital income. A separate equation

[9] We use MATLAB codes made available by Bartolucci (2007).

(independent from the rest of the model) will be estimated for each variable.

For the estimation of log of net housing costs c_{it}, we focus on the sub-sample of households that changed their home tenure between $t-1$ and t, and become homeowners. We propose a hedonic-type equation, since we include variables regarding the type of accommodation (number of rooms, detached, semi-detached, terraced, or flat), regional location dummies and time dummies among covariates. We also include the previous net housing costs of the household. We propose the following equation for net housing costs of households entering home-ownership:

$$\log(c_{it}) = \alpha_c + \mathbf{x}_{c,i,t}\beta_c + \mathbf{y}_{i,t-1}\gamma_c + \omega_{c,i} + \varepsilon_{c,i,t} \tag{D.5}$$

This specification is almost similar to equation (D.4). $\omega_{c,i}$ is the time-constant heterogeneity factor and $\varepsilon_{c,i,t}$ is a Gaussian error term with constant variance σ_c^2. All ten equations (D.3), (D.4), and (D.5) are simultaneously estimated. We denote $h(c_{it} \mid \mathbf{x}_{c,i,t}, \mathbf{y}_{i,t-1}, \omega_{c,i})$ the density of initial net housing costs for home-owners, conditional on observed and unobserved factors.

We proceed in a different manner to estimate housing costs for households becoming renters. We estimate two separate equations (one for housing costs in the social rental sector and the other in the private sector), independently from the rest of the model. Indeed, we assume that rents in the social or private sectors are independently determined and not related to housing costs for homeowners. This choice comes from the fact social rents are heavily regulated. The maximum applicable social rent (notably for Council tenancies) depends directly on observable households or dwelling characteristics. This leaves almost no room for bargaining. Hence, we suppose that social rent levels for new tenants might not be significantly affected by the endogenous home tenure decisions of the household (in particular they should not be deeply linked to its unobserved characteristics). The same reasoning applies for private rent levels, though the role of negotiation may be more important. The tenant may receive some help from local communities if he or she feels the newly bargained rent is substantially above the local market level. This may reduce the importance of bargaining between landlord and tenant and explains why we estimate the rent equations separately. We use a Tobit (type I) model for the estimation of these two equations since net housing costs can be zero in many cases (due to possible full rent rebates for both private and social renters).

Among the two sets of explanatory variables $x_{w,i,t}$ (in the wage equation) and $x_{c,i,t}$ (in the housing costs equation), we include region dummies (see Tables 2b and 2c for a definition). These variables help to control for the impact of spatial factors and city size on wages and housing costs. Typically, we expect higher wages and rents in Inner London or Outer London than in the rest of the country. Nevertheless, these region dummies do not control for all spatial mechanisms such as distance to job opportunities. Unfortunately, we do not have information about *the household location within city (city center or suburbs) which may of course have important consequences on employment. We know that the social housing stock is farther away from job centers than the private housing stock and this disconnection affect employment prospects. Hence, it means that the interpretation of the results mus encompass all aspects of social housing : its physical amenities and costs, but also its location and the amount of social interactions it provides. We are not able to dinstinguish between these different factors*[10].

D.3 Unobserved heterogeneity

The joint distribution of the ten (four marginal logits, four log odds ratios, two continuous equations) heterogeneity terms of vector ω_i is assumed to be normal[11] $\omega_i \sim \mathcal{N}(0, \Omega)$. Ω is supposed to be time homogenous. We have to estimate ten variance terms (included in vector $\boldsymbol{\sigma}_\omega^2$) and 45 linear correlation terms (vector ρ_ω).

D.4 Likelihood inference

Let $\mathcal{L}_{i,t}(\omega_i)$ be the likelihood expression for household i at date t conditional on all predetermined covariates (omitted from the argument of likelihood to keep notations simple), on past labor market position and home tenure of the household (also omitted) and on heterogeneity terms ω_i. The expression for log-likelihood is

$$\mathcal{L}_{i,t}(\omega_i) = \{p(\mathbf{y}_{i,t} \mid \mathbf{x}_{i,t}, \mathbf{y}_{i,t-1}, \omega_i) [g(w_{it} \mid \mathbf{x}_{w,i,t}, \mathbf{y}_{i,t-1}, \omega_{w,i})]^{e_{w,i,t}} [h(c_{it} \mid \mathbf{x}_{c,i,t}, \mathbf{y}_{i,t-1}, \omega_{c,i})]^{e_{c,i,t}}\} \tag{D.6}$$

with $e_{w,i,t} = 1$ if household i leaves unemployment or inactivity at t and zero otherwise. $e_{c,i,t} = 1$ if household i leaves the rental sector (either social or private) at t and zero otherwise and

$$p(\mathbf{y}_{i,t} \mid \mathbf{x}_{i,t}, \mathbf{y}_{i,t-1}, \omega_i) = \prod_z p(y_{i,t} = z \mid \mathbf{x}_{i,t}, \mathbf{y}_{i,t-1}, \omega_i)^{1_{y_{i,t}=z}}$$

where z is a pair composed of a labor market position and housing tenure and $\{p(y_{i,t} = z \mid \mathbf{x}_{i,t}, \mathbf{y}_{i,t-1}, \omega_i)\}_z$ is derived from the set of equations (D.3). We deduce the overall expression of the joint conditional log-likelihood

$$\mathcal{L} = \sum_i \log \left[\int \prod_t \mathcal{L}_{i,t}(\omega_i) \, dF(\omega_i \mid \mathbf{y}_{i,0}; \mathbf{x}_{i,0}) \right] \tag{D.7}$$

[10] Another version of the model has been estimated where region dummies were replaced by LAD (Local Authority District) dummies. This is a much more detailed spatial variable (there are 278 LADs in the UK). It permits to differentiate between city center and suburbs in some importants cities. However, due to the large number of parameters, we had to estimate the wage and housing costs equation separately (i.e., assuming no correlation between ω_c or ω_w and ω). The results (not reproduced here) are very close to those of our benchmark.

[11] The alternative modeling procedure proposed by Heckman and Singer (1984) and extended by Mroz and Guilkey (1996), where ω is a discrete random vector with finite support is not convenient in our large sample, multivariate case.

where $F(.|\ y_{i,0}; \mathbf{x}_{i,0})$ is the cumulative normal distribution function with variance-covariance matrix Ω. *The precise functional form of* $F(.|\ \mathbf{y}_{i,0}; \mathbf{x}_{i,0})$ *will be discussed in the identification subsection.* The complete model of transitions on housing and labor market, wages, and housing costs is estimated with simulated maximum likelihood techniques. After the estimation, the model is used to simulate individual paths in the medium term.

D.5 Identification

Our setup involves several individual decisions that are not observed (e.g., applying for social housing or a job) and outcomes that may be randomly delayed, depending on resource availability and rules implemented by local authorities. As we only observe transitions (and not application decisions), we use a reduced form that models only two elements of a dynamic choice model, namely the transition probabilities and the pay-off functions. We resort to a standard parametric functional specification for each of them,[12] and allow unobserved permanent heterogeneity terms ω_i to capture (i) agents' endowment of better information than the econometrician, (ii) heterogeneity in individual propensities (to apply for social housing, for example), the impact of which varies with the current statuses. Type I extreme values and normal distributions are chosen to complete the specification. Working with a reduced form in which the choice equations are left implicit limits the number of primitives that can be identified (Heckman and Navarro, 2007).[13] We restrict our interest to the identification of dynamic links between statuses and transitions in a stationary set-up. To allow for the interpretation of the results, we assume that agents cannot perfectly anticipate the transition date (Abbring and Van den Berg, 2003), but its distribution depends on the heterogeneity term ω_i.

Timing is relevant for identification: we assume that differences in $(t+1)$ positions of two individuals differing in only one dimension in t (i.e., different labor market statuses or different home tenure), but otherwise perfectly similar (same ω_i term) may be directly attributed to this initial difference, and not to multiple intra-year transitions. For example, if a social tenant and a private tenant (otherwise perfectly similar) have different probabilities to moving into employment in $t+1$, it is the direct consequence of their initial home tenure difference and does not result from a possible intra-year (between t and $t+1$) and non-modelled change in home tenure – i.e., a short homeowner spell – further changing labor market position in $t+1$. The direct effect of being either private or social tenant in t on the probability of becoming homeowner in $t+1$ is separately identified (with a distinct logit equation). The likelihood of more than one home tenure transition in a year is supposed to be negligible. Conversely, we assume that differences in

[12] There are several negative results on the nonparametric or semiparametric identification in dynamic discrete structural models (see *inter alios* Rust, 1994; Magnac and Thesmar, 2002; or Abbring, 2010, for a survey).

[13] We cannot, for instance, make the distinction between preferences and private evaluations and the outcomes or allow agents to learn about their environment (Cunha and Heckman, 2008).

home tenure annual transitions between two households with different labor market statuses cannot be attributed to non-modeled intra-year labor market spells, though short unemployment spells might happen. This timing-dependent identification assumption strongly relies on the average duration of spells of our variables of interest. Home tenure and job position are rather persistent variables (see Table 1b), and therefore multiple, intra-year transition spells are rare.

Moreover, our setup encompasses state dependence and unobserved heterogeneity. As usually done, we distinguish between them by simply including the lagged response $y_{i,t-1}$ *as an additional covariate in a model with a random intercept term* ω_i*. This identification technique raises problems as the corresponding maximum likelihood estimators may be inconsistent due to the initial condition problem. As explianed by Skrondal and Rabe–Hesketh (2014), "the initial response at the start of the observation period is affected by the random intercept and presample responses, andingnoring this endogeneity leads to inconsistent estimates". To tackle this issue we use a conditional maximum likelihood approach in the spirit of Wooldridge (2005) with an auxiliary model for the conditional random-intercept distribution : we specify a density for* ω_i *given* $x_{i,0}$ *and the initial value* $y_{i,0}$*. More precisely, our auxiliary model is expressed as follows*

$$\omega_i \approx \mathbf{y}'_{i,0}\delta_y + \mathbf{z}'_i\delta_z + u_i \tag{D.8}$$

where z'_i *are the time invariant covariates in vector* $x_{i,0}$*.* $u_i \sim N\left(0, \sigma_u^2\right)$ *is independent of* $y_{i,0}$ *and* z_i*. This is a constrained version of Wooldridge solution since we assume that the random intercpt does not depend initial or futures values of the time-varying covariates. This choice has been made to keep the estimation numerically tractable. Wooldridge (2005) showed that the conditional ML estimates are consistent.*[14] *if the auxiliary model is correct.*

E Results

This section is divided into two parts. In the first subsection, we interpret parameter estimates of the complete model (i.e., equations D.3, D.4, and D.5). In the second subsection, we simulate the model and compute the average transition rates in home tenure and labor market position for each household. We then compare transition probabilities of different subgroups and simulate the medium term interrelations between home tenure and labor market positions.

[14] As explained by Wooldridge (2005), conditioning on $y_{i,0}$ instead of explicitly modelling the density of $y_{i,0}$ conditional on $\mathbf{x}_i$ only leads to an efficiency loss.

E.1 Model estimates

Table 2 summarizes the results of model estimation. Table 2a presents parameter estimates for the system of transition equations (D.3), Table 2b for the wage equation (D.4), and Table 2c for the net housing costs equation (D.5). Each column in Table 2a corresponds to a marginal conditional logit ratio (except last line which reports the estimated value of the log of odds ratio). $\eta_{h,1,i,t}$ (respectively, $\eta_{h,2,i,t}$) is the log of ratio of conditional probabilities of being owner (resp., social renter) compared to private renter. $\eta_{l,1,i,t}$ (respectively, $\eta_{l,2,i,t}$) is the log of ratio of conditional probabilities of being employed (respectively of being a job seeker) compared to being out of the labor force. As stated previously, we adopt a simple constant specification for the log of odds ratios.

[Insert Tables 2a,b,c,d]

The main results concerning the role of socio-demographic characteristics are in line with the current literature. Women (heads of household) more frequently move to the social housing sector and are more likely to quit the labor force than men. Elderly household heads (age is linearly specified) have a higher probability of leaving the private rental sector and of becoming economically inactive. Married heads have a higher probability of becoming a homeowner (especially when the spouse is employed) and a lower one of being economically active (unless the spouse has a job). The higher the number of children (linearly specified), the higher the probability of exiting to homeownership. We detect no significant contribution of this variable on marginal logits regarding labor market outcomes. The educational attainment has a significant impact on both home tenure and labor market positions. Household heads with at least a degree are more likely to become homeowners (and less likely to move to the social housing sector) and find a job more quickly than heads with no diploma (no diploma is the reference in Table 2a). Heads with a teaching level diploma, A levels or O levels/GCSEs also experience more frequent transitions to employment than those with no diploma. As expected, household heads in good health are less likely to move to the social housing sector and to become economically inactive.

The number of rooms per person has a significant impact on home tenure decisions. Families living in an overcrowded dwelling (i.e., low number of rooms per person) have a higher probability of being eligible for the social housing sector and of moving less frequently to homeownership. They also have a higher probability of becoming unemployed.

Households with a high total real income (including head and spouse labor earnings as well as possible allowances, benefits, pensions, capital income) exit more frequently to homeownership and employment. They also encounter a restricted access to the social housing sector (income is one of the criteria for Local Authority Housing eligibility).

Households in the private sector with fully covered housing costs (i.e., 100% rent rebate) exit more frequently to the social housing sector. This result was expected because some of the private renters receiving housing benefits are on waiting lists for social housing. Moreover, they have a higher probability of becoming inactive than other households.

We then turn to the dynamic (i.e., state-dependent) relationships between the two types of statuses (home tenure and labor market positions). Our results suggest that home tenure conditions future labor market outcomes, as already exemplified in the literature. Importantly, we observe that households living in the social rental sector in $t-1$ have a lower probability of getting a job in t, and a higher probability of becoming unemployed in t than those living in the private rental sector. This is consistent with the results of Battu et al. (2008). We also confirm that homeowners experience shorter unemployment spells than renters (and especially those in the social sector) with similar socio-demographic profiles (Battu et al., 2008, Munch et al., 2006). This contrasts with Oswald's (1996) seminal results. Simultaneously, we also show that the past position on the labor market has a significant impact on decisions regarding home tenure. Unemployed or inactive heads experience a higher probability of exiting to the social housing sector than those with a job. Moreover, our results provide quantitative evidence that home tenure and labor market position are mutually, dynamically linked and consequently that one should not limit the setup to the sole "one-sided" impact of home tenure on the labor market, for medium term analysis. Some of the individual dynamics in one market depend on the position in the other market. For example, the probability of becoming a homeowner for a renter is influenced by the current job position and recent labor income. In the simulation subsection, we set out the role of such cross state dependencies on the relationship between aggregates such as unemployment and homeownership rates.

Let us now comment on the contribution of local aggregate variables (the log of regional unemployment rate, and the growth rate of real regional home prices). As expected, the higher the previous year's local unemployment rate, the lower the current probability of getting a job: both transition rates to unemployment and inactivity increase. Our results suggest that the local unemployment rate does not significantly influence transition rates of households on the housing market. Hence, an unexpected local increase in jobseeker's rate would only have a limited impact on home tenure, at the one year horizon. However, it could have an impact over a longer horizon, due to state dependence (lagged labor market position) on home tenure transitions $\eta_{h,1,i,t}$ and $\eta_{h,2,i,t}$.

Finally, the higher the previous year's growth rate of local home prices, the higher the probability of becoming a homeowner. This result is somewhat surprising because, following a surge in home prices, the home-buying capacity of renters is mechanically reduced, but it could be linked to the persistence in home prices. After a rise in home price growth rates, households expect this trend to last for several periods. Hence, some of them may choose to become owners sooner than they would have with constant prices (see Banks et al., 2010). Conversely, following a drop in home price levels, some would-be buyers currently living in the rental sector may decide to postpone their home purchase because they expect prices to decline further. It should be noted that changes in growth rates of regional house prices do not appear to affect significantly transition rates on the labor market.

None of the log of odds ratio is significantly different to zero, except $\varphi_{2,2,i,t}$ which is positive. $\varphi_{2,2,i,t}$ is the log of the ratio of probability of being in the social sector, rather than being a homeowner when unemployed over the same ratio when employed. The significant positivity of this log-odds ratio suggests a simultaneity effect; it means that the conditional probability of becoming unemployed compared to becoming employed is larger when simultaneously moving to the social sector, instead of becoming homeowner. Such an effect could not have been captured with separate logit models (one for the housing market and another for the labor market). It illustrates that labor status and home tenure decisions are particularly linked for unemployed people living in the social sector.

Results concerning wages and net housing cost equations (Tables 2b and 2c, respectively) are quite usual compared to standard mincerian and hedonic price models respectively. The unobserved heterogeneity variance-covariance estimated matrix $\widehat{\Omega}$ is given in Table 2d. We find significant volatility for the terms of ω_i corresponding to $\eta_{h,1,i,t}$, $\eta_{l,1,i,t}$ and the wage and housing costs continuous equations. The heterogeneity term corresponding to $\eta_{h,1,i,t}$ (respectively $\eta_{l,1,i,t}$) is positively correlated with the term corresponding to the housing costs (respectively wage) equation. This endogeneity effect means that some heads with specific unobserved characteristics may be more likely to find a new job (respectively a home to buy) with a higher wage per hour (respectively higher net costs per room).

E.2 Robustness analysis

E.2.1 On the interrelationship of labour and housing markets

At this stage, we propose a complementary analysis to study the adequacy of our original setup. We compare the properties of our benchmark model summarized by equations (D.3), (D.4), and (D.5) with those of two split models, i.e., two split standard logit models similar to those presented in equation (D.1) but with no correlated unobserved heterogeneity and no cross-state dependence effects,[15] each one being estimated with its corresponding continuous equation: the home tenure logit equation is estimated simultaneously with equation (D.5) and the labor market position logit with equation (D.4). The gap between the two specifications, the simultaneous (benchmark) and the split ones, may come either from the role of the dynamic terms $\mathbf{y}_{i,t-1}$ (*directed causality*), from the log-odds ratios

[15] For example, the logit equation for housing tenure will only include the lagged home tenure term among covariates, not the lagged labor market position.

$\eta_{k,z_k,i,t}$ (*simultaneous causality*), or from the correlated hidden heterogeneity terms (*structural simultaneity*).

Once estimated, both models are simulated and the distributions of home tenure and labor market positions are compared for some well-chosen socio-demographic profiles. We choose a four year horizon: i.e., we estimate the probability of being in each of the three home tenure or labor positions in $t+4$ of households that were inactive and living in the rental sector at date t. We select inactive heads because this choice delivers larger gaps between the benchmark and the separate models. For the sake of illustration, we choose two cases: a young single household (head's age between 30 and 40 years) with no child and an elderly household (head's age between 45 and 55 years) of two adults and at least one child. For each profile, we impute the corresponding average family income, net housing costs and number of rooms per person. We assume the head is a man in good health. The comparison of the two conditional distributions is given in Table 3, standard errors are in parentheses.[16]

[Insert Table 3]

We detect big discrepancies between the two probabilities, either in the labor market or in the housing market. This result is not surprising for the labor market position, because the literature has already evidenced that home tenure does indeed impact on household's job decisions. The omission of this factor in the split model is responsible for substantial differences in the probability of being unemployed. We also provide evidence that the omission of lagged labor market position terms $y_{l,i,t-1}$ in the separate models lead to important biases in the probability of becoming a homeowner, over a four-year horizon. For example, if we consider the case of an elderly couple with children, the split model substantially overestimates the probability of becoming a homeowner whatever the initial home tenure (i.e., social or private renter). These results support our benchmark specification.

E.2.2 Misspecifications

In our model, we made no explicit distinction between outright owners and those with a mortgage. This is a non-standard assumption compared to the literature, in particular Henley (1998) who evidenced a "negative home equity" effect on residential mobility. However, this choice is motivated by two facts: i) had we considered four categories for the response variable $y_{h,i,t}$, i.e., {outright owner-occupier, owner-occupier with a mortgage, social renter, private renter}, the total number of positions on the labor and housing market would have been 12, which is much too costly

[16] Standard errors are obtained by drawing a huge number (100,000) of individual labor and home tenure position paths for each of the four socio-economic profiles retained in Table 2e. We bootstrap among continuous equation residuals, simulate individual time-constant unobserved heterogeneity terms, and simulate within the distribution of parameter estimates.

from a computational point of view;[17] *ii) in another version of the model, we have added the value of home equity among the covariates and get no significant estimates associated with this variable, even with a specific dummy for households with negative home equity. Results by Henley (1998) were obtained in the early 1990s, when prices were still decreasing in some English regions. We work with a longer sample period with rapidly increasing prices, the number of households in a negative home equity positions is very low, and we do not get significant estimates. Notice also that the distinction between mortgage free and other homeowners can be made through there housing costs variable (zero for outright owners and strictly positive for other owners).*

E.3 Simulations

The dynamic completeness of our setup allows us to simulate individual paths on the both markets (nine possible positions) at an annual frequency. We can then illustrate the durable consequences of the onset of a spell in one market (becoming a social renter, for example) on the other (the probability of being employed a few years later).

Our main point is to assess the indirect contribution of social housing to the dynamics of highly persistent unemployment or inactivity. In order to provide a quantitative answer to this question, we start our analysis with three preliminary simulations: i) the comparison of the probability of finding a job of persons initially not employed (either jobseekers or inactive) homeowners and private renters, ii) the same comparison for private and public renters initially not employed, and iii) the comparison of the probability of becoming a homeowner of private and public renters who are initially not employed. All three questions are examined both in the short (two-year horizon) or medium term (4-, 6- or 8-year horizons). In each case, we compare two heads with a different initial status $\mathbf{y}_{i,t-1}$, but with otherwise perfectly similar profiles: individual simulations with each initial status considered are run on the full sample of heads socioeconomic profiles and averaged over all initial years (up to eight years before 2008). Hence, the sole initial position (e.g., private vs. social renter) is responsible for differences in ownership or employment probability. Socioeconomic differences are averaged out.

Drawing on Kuha and Goldthorpe (2010) path analysis, we then decompose the gap in homeownership or job probabilities of two household heads with different initial positions into the contribution of the impact of an indirect variable (e.g., E^I for the indirect effect) and a remainder associated to the direct effect (e.g., E^D). The additivity

[17] We estimated another model with the same nine endogenous positions as in our benchmark, but distinguishing outright and mortgage owners among the dynamic terms $\mathbf{y}_{i,t-1}$. We detect no qualitative difference in estimated coefficients between this model and our benchmark. Moreover, this enlarged model could not be used for the simulation experiment: it would have required an additional equation for the estimation of the probability of being an outright/mortgage owner.

property of this methodology ensures that the total gap in homeownership or job probability (e.g., E^T) is the sum of the direct and indirect effect. $E^T = E^D + E^I$. For example, it may be of interest to quantify the role of a possible intermediate spell in the social housing sector (E^I_{social}) in explaining the gap in the employment probability of owners and private renters (case a, see E^I_{social}/E^T in Tables 4a and 4b). According to parameter estimates in Table 2a, we expect owners and private renters to have different transition rates into social housing, and we further know that social renters have lower transition rates into employment. Hence, social housing spells may explain some of the labor market outcomes differences between owners and private tenants. This methodology is presented in the Appendix.

[Insert Tables 4a,b, 5a,b, 6a,b]

As explained in the introduction, question i) has been much studied in the literature. However, our setup offers a new dynamic view of this question: we consider two non-employed heads at initial date t, one is an owner and the other is a private tenant, and we compare their probability of being employed in $t+h$, for different horizons h. Table 4a (resp., 4b) gives the result if the household heads are initially unemployed (respectively inactive). As suggested in Table 2a, and in line with the rest of the literature, we find that owner-occupiers have shorter unemployment (or inactivity) spells than renters. The probability of being employed on a two-year horizon for an unemployed owner is 0.70, while only 0.52 for unemployed private renters. The lower regional mobility of homeowners (mostly due to the intrinsically low liquidity of physical real estate) is more than compensated by their strong incentives to seek jobs with low commuting times and their attractive profile for local employers. Interestingly, this differential is very persistent and still significant at an eight-year horizon: home tenure spells are very long and then have persistent consequences on the labor market position. Actually, we claim that the duration of home tenure spells may explain a substantial share of the well-documented persistence on unemployment or on the population out of the labor-force (Heckman, 2001). This appears clearly when measuring the indirect effect of social housing (i.e., having been a social tenant between $t+1$ and $t+h$). The indirect effect is low in the short term (around 9% at a 2-year horizon), but close to 35% at an 8-year horizon. Being initially non-employed increases the probability of becoming eligible for the social housing sector, but the transition rate is higher for private tenants (most of the households on the social housing waiting lists live in the private rental sector). This increased likelihood of being a social tenant further increases the probability of remaining out of the labor force or unemployed, through lower incentives to look for a job and/or stigmatizing effects (Battu et al., 2008). Moreover, since social housing spells are long, their labor market impact is higher in the medium run.

We now turn to the probability of finding a job in $t+h$ for initially non-employed private and public tenants (case ii). Table 5a (respectively 5b) gives the result if household heads are initially unemployed (respectively inactive). In line with Battu et al. (2008), social tenants have lower transition rates into employment (43% against 53% for private tenants over a 2-year horizon), and this pattern is very persistent (62% against 70% over an 8-year horizon). Most of this gap appears to be linked to another indirect variable. Homeownership spells between t and $t+h$. Households in the social sector experience very weak transition rates to ownership compared to private tenants (see Tables 6a and 6b). Intuitively, this result is at odds with some of the existing literature: when the eligibility income-based conditions are not stringent, we would expect that social renters (with low net housing costs) might have a higher savings capacity, and so accumulate wealth for a loan down-payment (see Goffette-Nagot and Sidibé, 2010, for the French case). However, this effect may be quantitatively dominated by the restricted mortgage loan eligibility of social renters, as well as their reduced interest in leaving their current social dwelling with large housing benefits (mortgage payments may also be partly covered, but in a restricted manner compared to social or even private rents). Consequently, social tenants are less likely to become owners and this impacts their probability of getting a job in the medium term: the indirect "homeownership" effect accounts for an important share — more than 60% over an 8-year horizon — of the mean differential to be employed between social and private tenants. Echoing with the results of question i), our simulations clearly show that the impact in the medium term on the labor market position of home tenure dynamics is substantial.

We also compare the probability of becoming a homeowner in $t+h$ of initially non-employed private and public tenants (question iii)). Results are summarized in Tables 6a and 6b. As detailed above, we find significant gaps in transition rates to ownership, both in the short and medium terms. The indirect role of becoming employed between t and $t+h$ is significant, though quantitatively limited (between 5 and 10% depending on the time horizon). These results combined with those shown in Tables 5a and 5b suggest that the lower job transition rate of social tenants is mostly a consequence of lower homeownership access, and not the reverse.

[Insert Tables 7a,b, 8a,b]

Building on these previous results and interpretations, we compare the employment probability of two household head profiles initially living in the private rental sector: the first one is already employed and the second one is either unemployed (Table 7a) or inactive (Table 7b). The same simulations are reproduced but with heads initially being homeowners (Tables 8a and 8b). The employment probability differential is then an illustration of the persistence of jobseeker and inactivity spells. Still drawing on Kuha and Goldthorpe (2010) method, we compute the indirect incidence of social housing on the duration of non-employment spells. In the medium term (the 8-year horizon), we find that the probability of remaining employed for a head initially employed and living in the private sector is 76%, while only 71% for a head initially unemployed. This substantial gap illustrates the long lasting properties of unemployment. Interestingly, our decomposition shows that almost 20% of this gap can be attributed to differences in the occurrence of social housing spells between these two profiles in the medium term. As evidenced in Table 2a, the likelihood of the onset of a social tenant spell is higher when unemployed (or inactive) because of the benefit system. As shown in the previous simulations, this higher probability of being in the public housing sector for an unemployed household head further decreases the probability of finding a job, either through disincentives effects (Tables 5a and 5b), or through a lower probability of becoming a homeowner (i.e., the restricted access to a mortgage as illustrated in Tables 6a and 6b), which itself negatively impacts the probability of gaining a job (Tables 4a and 4b). Due to the low entry rate into social housing (Table 1b) at an annual frequency, this indirect effect is quite limited over small horizons (i.e., only 0.99% over a 2-year horizon), but becomes more loaded for longer horizons (9.05% and 18.57% over the 6- and 8-year horizons respectively), because of the high duration of social housing spells. The indirect effect is also important when considering an inactive household head (instead of an unemployed head) as an alternative profile (8.95% over an 8-year horizon, see Table 7b). Indirect social housing effects are much lower when considering owners instead of private tenants (Tables 8a and 8b), because of the very low entry rate into social housing for homeowners compared to private tenants.

F Conclusion

The persistence in unemployment dynamics is a well-established fact and a number of explanations have been proposed. This study assesses the contribution of social housing in an original empirical model of the joint dynamics of individual home tenure and labor market dynamics, with UK panel data. Compared to the literature, the dynamics of home tenure are modeled and their long term consequences on individual job paths are addressed. Moreover, reverse causation of employment on home tenure is also explicitly taken into account. According to our estimates, in the medium term, about 20% of the gap in the probabilities of being employed between initially employed and unemployed household heads (both private tenants), can be explained by a transition to social housing: being unemployed and moving into social housing reinforce each other. Our setup needs to be further extended to account for duration dependence effects (we only consider state dependence effects here) and focus on intra-year labor spells.

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Table 1a

Variable	Homeowner	Private Renter	Social Renter
Age of head (mean)	44.84	37.17	42.13
Nb children (mean)	0.67	0.51	1.03
Head with degree (%)	18.40	20.46	3.13
Head: good health (%)	94.43	92.62	82.48
Monthly family income (mean £)	$2,800$	$1,814$	$1,324$
Net monthly housing costs (mean £)	$285,95$	$262,18$	$128,04$
Head employed (%)	87.73	75.33	47.99
Head unemployed (%)	1.72	5.60	9.14
Head out-of-labor force (%)	10.55	19.07	42.87
Nb of rooms per person (mean)	2.47	2.39	1.89

Descriptive Statistics by home tenure from the BHPS. Period: 1991-2008. $N = 39,862$

Table 1b: Annual transitions rates for labour market and home tenure

Position in $t-1$	Position in t	Probability
Social Tenant	Social Tenant	95.06%
Private Tenant	Social Tenant	5.32%
Owner	Social Tenant	0.16%
Social Tenant	Employed	49.30%
Private Tenant	Employed	78.36%
Owner	Employed	86.47%
ST & Unemployed	Social Tenant	97.02%
ST & Inactive	Social Tenant	97.57%
PT & Unemployed	Social Tenant	6.80%
PT & Inactive	Social Tenant	9.04%
Owner & Unemployed	Social Tenant	0.98%
Owner & Inactive	Social Tenant	0.60%
ST & Unemployed	Employed	26.80%
ST & Inactive	Employed	8.99%
PT & Unemployed	Employed	39.32%
PT & Inactive	Employed	22.53%
Owner & Unemployed	Employed	48.62%
Owner & Inactive	Employed	14.26%

Table 2a: Transition equations for home tenure and labour market

Variables	$\eta_{h,1,i,t}$	$\eta_{h,2,i,t}$	$\eta_{l,1,i,t}$	$\eta_{l,2,i,t}$
Intercept	1.4038^{**}	-1.6407^{**}	4.1316^{**}	0.4540
	(0.5619)	(0.7120)	(0.3415)	(0.5089)
Gender: Woman	0.0255	0.4719^{**}	-0.4025^{**}	-0.6933^{**}
	(0.0937)	(0.1150)	(0.0600)	(0.0922)
Age	0.0139^{**}	0.0256^{**}	-0.0397^{**}	-0.0411^{**}
	(0.0038)	(0.0052)	(0.0026)	(0.0037)
Dummy: Married	1.1250^{**}	0.0879	-0.2959^{**}	-0.3612^{**}
	(0.1382)	(0.1745)	(0.0749)	(0.1125)
Number of children	0.1644^{**}	0.0741	0.0136	0.0217
	(0.0455)	(0.0613)	(0.0325)	(0.0466)
Spouse works in $(t-1)$	0.3850^{**}	-0.3015^{**}	0.8910^{**}	0.2644^{**}
	(0.1162)	(0.1418)	(0.0622)	(0.0917)
Dummy: Degree	0.4100^{**}	-0.9974^{**}	0.5612^{**}	0.0628
	(0.1207)	(0.2055)	(0.0826)	(0.1824)
Dummy: Teaching	0.0825	-0.6633^{**}	0.1713	-0.0748
	(0.1658)	(0.2457)	(0.1257)	(0.1826)
Dummy: Alevel	0.1041	-0.7557^{**}	0.2036^{**}	-0.0175
	(0.1488)	(0.1537)	(0.0698)	(0.0923)
Dummy: Olevel	0.0422	-0.2984^{**}	0.2617^{**}	0.0258
	(0.1547)	(0.1108)	(0.0544)	(0.0951)
Dummy: Good health	0.1918	-0.2770^{**}	1.3481^{**}	0.9873^{**}
	(0.1466)	(0.1313)	(0.0716)	(0.1194)
Rooms per person in $(t-1)$	0.3011^{**}	-0.4655^{**}	0.0220	-0.088^{**}
	(0.0379)	(0.0564)	(0.0251)	(0.0395)
$\log\left(\text{Income}_{t-1}\right)$	0.1851^{**}	-0.1621^{*}	0.3085^{**}	0.0570
	(0.0706)	(0.0899)	(0.0431)	(0.0623)
$\log\left(\text{Net housing costs}_{t-1}\right)$	0.094	-0.2006^{**}	0.2741^{**}	0.1054^{**}
	(0.0595)	(0.0709)	(0.0336)	(0.0450)
Dummy : No housing costs_{t-1}	0.0201	-0.9685^{**}	0.7741^{**}	0.1745
	(0.3620)	(0.3441)	(0.1722)	(0.3003)

Table 2a (continued): Transition equations for home tenure and labour market

Variables	$\eta_{h,1,i,t}$	$\eta_{h,2,i,t}$	$\eta_{l,1,i,t}$	$\eta_{l,2,i,t}$
Dummy : Unemployed in $(t-1)$	-0.7251^{**}	0.3713^{*}	-2.5524^{**}	0.8182^{**}
	(0.2104)	(0.1926)	(0.0890)	(0.1054)
Dummy : Out-of-labor force in $(t-1)$	-0.5627^{**}	0.5525^{**}	-4.5984^{**}	-1.7363^{**}
	(0.1145)	(0.1270)	(0.0522)	(0.0945)
Dummy : Social renter in $(t-1)$	-4.4833^{**}	5.3470^{**}	-0.8282^{**}	0.2256^{**}
	(0.1374)	(0.1816)	(0.0626)	(0.0941)
Dummy : Private renter in $(t-1)$	-6.9027^{**}	-1.1125^{**}	-0.3613^{**}	0.4284^{**}
	(0.0870)	(0.1618)	(0.0777)	(0.1094)
Local unemployment rate in $(t-1)$	-0.0138	0.1684	-0.4841^{**}	0.2841^{**}
	(0.1260)	(0.1772)	(0.0655)	(0.1116)
Local growth rate of home prices in $(t-1)$	1.3984^{**}	-0.0281	0.4168	-0.1299
	(0.5611)	(0.8246)	(0.3684)	(0.5584)
Log odds ratios	$\varphi_{1,1,i,t}$	$\varphi_{1,2,i,t}$	$\varphi_{2,1,i,t}$	$\varphi_{2,2,i,t}$
	-0.0715	-0.2084	-0.3517	0.9484^{**}
	(0.2684)	(0.2086)	(0.3429)	(0.2952)

$N = 39,862$. Robust standard errors in (), ** = signif at 5% level, * = signif at 10% level

$\eta_{h,1}$ is the log of P(owner)/P(private tenant), $\eta_{h,2}$ is the log of P(social tenant) /P(private tenant)

$\eta_{h,1}$ is the log of P(employed) /P(inactive), $\eta_{h,2}$ is the log of P(unemployed) /P(inactive)

$\varphi_{1,1}$ is the log of $\frac{\frac{\mathrm{P(emp.\&owner)}}{\mathrm{P(emp.\&private)}}}{\frac{\mathrm{P(olf.\&owner)}}{\mathrm{P(olf.\&private)}}}$. $\varphi_{1,2}$ is the log of $\frac{\frac{\mathrm{P(unemp.\&owner)}}{\mathrm{P(unemp.\&private)}}}{\frac{\mathrm{P(emp.\&owner)}}{\mathrm{P(emp.\&private)}}}$.

$\varphi_{2,1}$ is the log of $\frac{\frac{\mathrm{P(emp.\&social)}}{\mathrm{P(emp.\&owner)}}}{\frac{\mathrm{P(olf.\&social)}}{\mathrm{P(olf.\&owner)}}}$. $\varphi_{2,2}$ is the log of $\frac{\frac{\mathrm{P(unemp.\&social)}}{\mathrm{P(unemp.\&owner)}}}{\frac{\mathrm{P(emp.\&social)}}{\mathrm{P(emp.\&owner)}}}$.

Table 2b: Wage equation (D.4) : log of nominal wage per hour

Variable	Estimates	Standard Error
Intercept	3.33928	0.03656
log(hours)	-0.0012	0.0003
Dummy : unemployed in $(t-1)$	-0.22473	0.0391
Age	0.00462	0.0003168
Age^2	-0.00000324	$1.65 * 10^{-7}$
Time spent without job	0.000215	0.000471
SOC 2	-0.0518	0.00988
SOC 3	-0.1593	0.00941
SOC 4	-0.4463	0.00968
SOC 5	-0.2998	0.00954
SOC 6	-0.4261	0.01121
SOC 7	-0.4473	0.01303
SOC 8	-0.3554	0.00999
SOC 9	-0.44691	0.01244
SIC 1	0.3136	0.02872
SIC 2	0.3097	0.02644
SIC 3	0.2840	0.02592
SIC 4	0.2676	0.02624
SIC 5	0.0806	0.02620
SIC 6	0.1669	0.02563
SIC 7	0.2955	0.02568
SIC 8	0.2358	0.02582
SIC 9	0.1594	0.02556
Dummy: Degree	0.4149	0.00943
Dummy: Teaching	0.3431	0.01101
Dummy: Alevel	0.2475	0.00797
Dummy: Olevel	0.1473	0.00734
Dummy : Year 1993	-0.0322	0.01575
Dummy : Year 1994	-0.00496	0.01587

Table 2b (continued)

Variable	Estimates	Standard Error
Dummy : Year 1995	0.0256	0.0158
Dummy : Year 1996	0.0427	0.0157
Dummy : Year 1997	0.0767	0.0158
Dummy : Year 1998	0.1046	0.0152
Dummy : Year 1999	0.1434	0.0154
Dummy : Year 2000	0.1761	0.0155
Dummy : Year 2001	0.2127	0.0158
Dummy : Year 2002	0.2546	0.0162
Dummy : Year 2003	0.3081	0.0163
Dummy : Year 2004	0.3274	0.0164
Dummy : Year 2005	0.3741	0.0164
Dummy : Year 2006	0.3717	0.0166
Dummy : Year 2007	0.3960	0.0166
Dummy : Year 2008	0.4193	0.067
Local income per head (log in $t-1$)	0.4948	0.1981

Table 2b (continued)

Variable	Estimates	Standard Error
Dummy location: Outer London	0.0456	0.0166
Dummy location: R. of South East	−0.0478	0.0146
Dummy location: South West	−0.1395	0.0157
Dummy location: East Anglia	−0.1719	0.0180
Dummy location: East Midlands	−0.1898	0.0158
Dummy location: West Midlands Conurb	−0.1938	0.0193
Dummy location: R. of West Midlands	−0.1625	0.0168
Dummy location: Greater Manchester	−0.1308	0.0178
Dummy location: Merseyside	−0.1188	0.0215
Dummy location: R. of North West	−0.1669	0.0174
Dummy location: South Yorkshire	−0.2186	0.0196
Dummy location: West Yorkshire	−0.1900	0.0189
Dummy location: Yorkshire & Humber	−0.1585	0.0189
Dummy location: Tyne & Wear	−0.1704	0.0208
Dummy location: R. of North	−0.1783	0.0179

Parameter Estimates for equation (D.4). Standard errors are robust. The reference is a head out of the labor force in $t-1$, with Occupational Status SOC 1(managers and administrators or personnel and protective service occupations), with Industry Classification SIC 0 (agricultural activities), with no diploma in 1992. The variance estimation of ω_w is given in Table 2d. The meaning of SOC and SIC classification is given in BHPS user guide.

Table 2c: log of nominal net housing costs per room (for new owners)

Variable	Estimates	Standard Error
Intercept	4.2755	0.09760
Log of housing costs per room in $(t-1)$	0.1785	0.0034
Dummy: Gender woman	-0.1084	0.01874
Dummy: Married	-0.4139	0.02105
Age	-0.0222	0.00080
Number of Children	-0.1154	0.00877
Dummy: Spouse works	0.06155	0.01919
Log of real income in $(t-1)$	0.13564	0.01125
Dummy : Unemployed in $(t-1)$	-0.73622	0.0414
Dummy : Out-of-labor force in $(t-1)$	-0.7923	0.0233
Dummy : Social renter in $(t-1)$	0.2235	0.0258
Dummy: Detached house	-0.04757	0.0217
Dummy: Semi detached house	-0.06626	0.01690
Dummy: Terraced house	0.08015	0.0921
Dummy : Year 1993	0.00094	0.03457
Dummy : Year 1994	0.02106	0.03266
Dummy : Year 1995	0.05066	0.0353
Dummy : Year 1996	0.09495	0.0360
Dummy : Year 1997	0.08574	0.0360
Dummy : Year 1998	0.1136	0.0361
Dummy : Year 1999	0.1484	0.0365
Dummy : Year 2000	0.1407	0.0362
Dummy : Year 2001	0.1703	0.0363
Dummy : Year 2002	0.1820	0.0367
Dummy : Year 2003	0.1878	0.0388
Dummy : Year 2004	0.1801	0.0387
Dummy : Year 2005	0.2529	0.0386
Dummy : Year 2006	0.2716	0.0386
Dummy : Year 2007	0.3210	0.0388

Table 2c (continued)

Variable	Estimates	Standard Error
Dummy : Year 2008	0.3495	0.0389
Dummy location: Outer London	−0.2623	0.0405
Dummy location: R. of South East	−0.1211	0.0406
Dummy location: South West	−0.2899	0.0422
Dummy location: East Anglia	−0.3103	0.0500
Dummy location: East Midlands	−0.4056	0.0498
Dummy location: West Midlands Conurb	−0.2428	0.0521
Dummy location: R. of West Midlands	−0.3430	0.0522
Dummy location: Greater Manchester	−0.2090	0.0587
Dummy location: Merseyside	−0.3358	0.0511
Dummy location: R. of North West	−0.3678	0.0525
Dummy location: South Yorkshire	−0.4244	0.0592
Dummy location: West Yorkshire	−0.2163	0.0533
Dummy location: Yorkshire & Humber	−0.3637	0.0534
Dummy location: Tyne & Wear	−0.2736	0.0575
Dummy location: R. of North	−0.3987	0.0545
Local deviation of home prices in $(t-1)$	0.0854	0.0428

Parameter Estimates for equation (D.5). Standard errors are robust. The reference is a man, non-married, employed in $(t-1)$, living in a flat (private rental sector) located in Inner London in 1992. The variance estimation of ω_c is given in Table 2d.

Table 2d

$\widehat{\Omega}$	$\widehat{\sigma}^2$	$\widehat{\rho}_{\cdot,\omega_{h,2}}$	$\widehat{\rho}_{\cdot,\omega_{l,1}}$	$\widehat{\rho}_{\cdot,\omega_{l,2}}$	$\widehat{\rho}_{\cdot,\omega_w}$	$\widehat{\rho}_{\cdot,\omega_c}$
$\omega_{h,1}$	0.2497^{**}	-0.0251	0.0034	-0.0013	-0.0042	0.1311^{**}
$\omega_{h,2}$	0.3625	$-$	-0.0005	0.0120	-0.0066	-0.0075
$\omega_{l,1}$	0.1108^{**}	$-$	$-$	-0.0007	0.1082^{**}	0.0116
$\omega_{l,2}$	0.2713	$-$	$-$	$-$	-0.0005	-0.0008
ω_w	0.5609^{**}	$-$	$-$	$-$	$-$	0.0439
ω_c	0.4305^{**}	$-$	$-$	$-$	$-$	$-$

Estimates of variance $\widehat{\sigma}^2$ and correlation $\widehat{\rho}_{\cdot,\omega}$ of ω. Robust standard errors.

** = signif at 5% level, * = signif at 10% level

Table 3

head profile in t	Model used	Position in $t+4$											
		P(emp)		P(unemp)		P(olf)		P(owner)		P(social)		P(private)	
30-40 y, single,	separate	64.35%	(4.72)	8.75%	(1.13)	26.50%	(2.16)	16.85%	(2.21)	7.66%	(0.66)	75.09%	(3.30)
inactive, private	benchmark	58.26%	(4.57)	6.66%	(0.79)	34.55%	(2.27)	10.18%	(1.80)	9.04%	(0.77)	81.03%	(3.33)
30-40 y, single,	Separate	52.62%	(4.35)	10.88%	(1.29)	36.37%	(2.55)	0.07%	(0.04)	75.21%	(2.40)	18.25%	(1.20)
inactive, social	benchmark	39.88%	(3.85)	19.07%	(1.43)	41.22%	(2.57)	0.04%	(0.03)	78.49%	(2.44)	18.41%	(1.22)
45-55 y, children	Separate	40.11%	(3.35)	5.76%	(0.62)	54.10%	(3.09)	38.88%	(4.08)	20.20%	(2.27)	41.07%	(2.12)
inactive, private	benchmark	42.80%	(4.00)	6.55%	(0.66)	50.85%	(3.06)	28.15%	(3.63)	22.91%	(2.28)	49.30%	(2.21)
45-55 y, children	Separate	32.41%	(2.55)	5.91%	(0.64)	61.75%	(3.68)	10.06%	(2.13)	84.42%	(2.47)	5.42%	(0.57)
inactive, social	benchmark	29.78%	(2.50)	12.08%	(0.90)	58.45%	(3.67)	6.25%	(1.85)	87.58%	(2.45)	6.35%	(0.59)

Comparison of conditional distributions at four years horizon: "benchmark" vs "separate" models. Log-odds ratios (D.2) and correlative pattern of ω are not modelled in the "separate" model.

Table 4a

Position $t = 0$	$h = 2$		$h = 4$		$h = 6$		$h = 8$	
	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$
Owner, Unemp.	0.70		0.79		0.83		0.84	
		10.37%		19.02%		27.84%		37.56%
Private Tenant, Unemp.	0.52		0.62		0.68		0.71	

Simulation and Path Analysis. Comparison of the probability of being employed in $(t + h)$ of two profiles in t: unemployed owner and unemployed private tenant. Profiles are otherwise similar (same socioeconomic characteristics). Standard errors for each probability are given in (). E^I_{social} is the indirect effect due to the event "being a social renter between $t + 1$ and $t + h$", i.e., the share (%) of the gap in probability of finding a job between the two profiles that could be attributed to a possible social tenant intermediate position.

Table 4b

Position $t = 0$	$h = 2$		$h = 4$		$h = 6$		$h = 8$	
	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$
Owner, Inactive	0.44		0.66		0.77		0.81	
		8.65%		17.77%		26.10%		35.01%
Private Tenant, Inactive	0.34		0.51		0.61		0.66	

Simulation and Path Analysis. Comparison of the probability of being employed in $(t + h)$ of two profiles in t: inactive owner and inactive private tenant. Profiles are otherwise similar (same socioeconomic characteristics). Standard errors for each probability are given in (). E^I_{social} is the indirect effect due to the event "being a social renter between $t + 1$ and $t + h$", i.e., the share (%) of the gap in probability of finding a job between the two profiles that could be attributed to a possible social tenant intermediate position.

Table 5a

Position $t=0$	$h=2$		$h=4$		$h=6$		$h=8$	
	P(job)	$\frac{E^I_{own}}{E^T}$	P(job)	$\frac{E^I_{own}}{E^T}$	P(job)	$\frac{E^I_{own}}{E^T}$	P(job)	$\frac{E^I_{own}}{E^T}$
Private Tenant, Unemp	0.53		0.62		0.66		0.70	
		35.25%		47.12%		54.80%		62.76%
Social Tenant, Unemp	0.43		0.54		0.59		0.62	

Simulation and Path Analysis. Comparison of the probability of being employed in $(t+h)$ of two profiles in t: unemployed private tenant and unemployed social tenant. Profiles are otherwise similar (same socioeconomic characteristics). Standard errors for each probability are given in (). E^I_{own} is the indirect effect due to the event "being a homeowner between $t+1$ and $t+h$", i.e., the share (%) of the gap in probability of finding a job between the two profiles that could be attributed to a possible transition to homeownership.

Table 5b

Position $t=0$	$h=2$		$h=4$		$h=6$		$h=8$	
	P(job)	$\frac{E^I_{own}}{E^T}$	P(job)	$\frac{E^I_{own}}{E^T}$	P(job)	$\frac{E^I_{own}}{E^T}$	P(job)	$\frac{E^I_{own}}{E^T}$
Private Tenant, Inactive	0.32		0.50		0.60		0.66	
		33.13%		44.88%		52.74%		60.30%
Social Tenant, Inactive	0.23		0.40		0.50		0.55	

Simulation and Path Analysis. Comparison of the probability of being employed in $(t+h)$ of two profiles in t: inactive private tenant and inactive social tenant. Profiles are otherwise similar (same socioeconomic characteristics). Standard errors for each probability are given in (). E^I_{own} is the indirect effect due to the event "being a homeowner between $t+1$ and $t+h$", i.e., the share (%) of the gap in probability of finding a job between the two profiles that could be attributed to a possible transition to homeownership.

Table 6a

Position $t = 0$	$h = 2$		$h = 4$		$h = 6$		$h = 8$	
	P(own)	$\frac{E^I_{job}}{E^T}$	P(own)	$\frac{E^I_{job}}{E^T}$	P(own)	$\frac{E^I_{job}}{E^T}$	P(own)	$\frac{E^I_{job}}{E^T}$
Private Tenant, Unemp	0.15		0.30		0.41		0.50	
		7.27%		5.71%		5.11%		4.66%
Social Tenant, Unemp	0.04		0.12		0.20		0.28	

Simulation and Path Analysis. Comparison of the probability of being homeowner in $(t + h)$ of two profiles in t: unemployed private tenant and unemployed social tenant. Profiles are otherwise similar (same socioeconomic characteristics). Standard errors for each probability are given in (). E^I_{job} is the indirect effect due to the event "finding a job between $t + 1$ and $t + h$", i.e., the share (%) of the gap in probability of being homeowner between the two profiles that could be attributed to a possible transition into employment.

Table 6b

Position $t = 0$	$h = 2$		$h = 4$		$h = 6$		$h = 8$	
	P(own)	$\frac{E^I_{job}}{E^T}$	P(own)	$\frac{E^I_{job}}{E^T}$	P(own)	$\frac{E^I_{job}}{E^T}$	P(own)	$\frac{E^I_{job}}{E^T}$
Private Tenant, Inactive	0.12		0.25		0.37		0.46	
		7.73%		6.44%		6.27%		6.06%
Social Tenant, Inactive	0.04		0.10		0.17		0.21	

Simulation and Path Analysis. Comparison of the probability of being homeowner in $(t + h)$ of two profiles in t: inactive private tenant and inactive social tenant. Profiles are otherwise similar (same socioeconomic characteristics). Standard errors for each probability are given in (). E^I_{job} is the indirect effect due to the event "finding a job between $t + 1$ and $t + h$", i.e., the share (%) of the gap in probability of being homeowner between the two profiles that could be attributed to a possible transition into employment.

Table 7a

Position $t=0$	$h=2$		$h=4$		$h=6$		$h=8$	
	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$
Private Tenant, Job.	0.85		0.80		0.76		0.76	
		0.99%		3.47%		9.05%		18.57%
Private Tenant, Unemp.	0.52		0.62		0.68		0.71	

Simulation and Path Analysis. Comparison of the probability of being employed in $(t+h)$ of two profiles in t: employed private tenant and unemployed private tenant. Profiles are otherwise similar (same socioeconomic characteristics). Standard errors for each probability are given in (). E^I_{social} is the indirect effect due to the event "being a social renter between $t+1$ and $t+h$", i.e., the share (%) of the gap in probability of finding a job between the two profiles that could be attributed to a possible social tenant intermediate position.

Table 7b

Position $t=0$	$h=2$		$h=4$		$h=6$		$h=8$	
	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$
Private Tenant, Job	0.85		0.80		0.76		0.76	
		0.17%		1.03%		3.89%		8.95%
Private Tenant, Inactive	0.34		0.51		0.61		0.66	

Simulation and Path Analysis. Comparison of the probability of being employed in $(t+h)$ of two profiles in t: employed private tenant and inactive private tenant. Profiles are otherwise similar (same socioeconomic characteristics). Standard errors for each probability are given in (). E^I_{social} is the indirect effect due to the event "being a social renter between $t+1$ and $t+h$", i.e., the share (%) of the gap in probability of finding a job between the two profiles that could be attributed to a possible social tenant intermediate position.

Table 8a

Position $t=0$	$h=2$		$h=4$		$h=6$		$h=8$	
	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$
Owner, Job.	0.92		0.90		0.89		0.87	
		0.34%		1.09%		2.86%		7.22%
Owner, Unemp.	0.70		0.79		0.83		0.84	

Simulation and Path Analysis. Comparison of the probability of being employed in $(t+h)$ of two profiles in t: employed owner and unemployed owner. Profiles are otherwise similar (same socioeconomic characteristics). Standard errors for each probability are given in (). E^I_{social} is the indirect effect due to the event "being a social renter between $t+1$ and $t+h$", i.e., the share (%) of the gap in probability of finding a job between the two profiles that could be attributed to a possible social tenant intermediate position.

Table 8b

Position $t=0$	$h=2$		$h=4$		$h=6$		$h=8$	
	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$	P(job)	$\frac{E^I_{social}}{E^T}$
Owner, Job	0.92		0.90		0.89		0.87	
		0.23%		0.95%		2.70%		5.24%
Owner, Inactive	0.44		0.66		0.77		0.81	

Simulation and Path Analysis. Comparison of the probability of being employed in $(t+h)$ of two profiles in t: employed owner and inactive owner. Profiles are otherwise similar (same socioeconomic characteristics). Standard errors for each probability are given in (). E^I_{social} is the indirect effect due to the event "being a social renter between $t+1$ and $t+h$", i.e., the share (%) of the gap in probability of finding a job between the two profiles that could be attributed to a possible social tenant intermediate position.

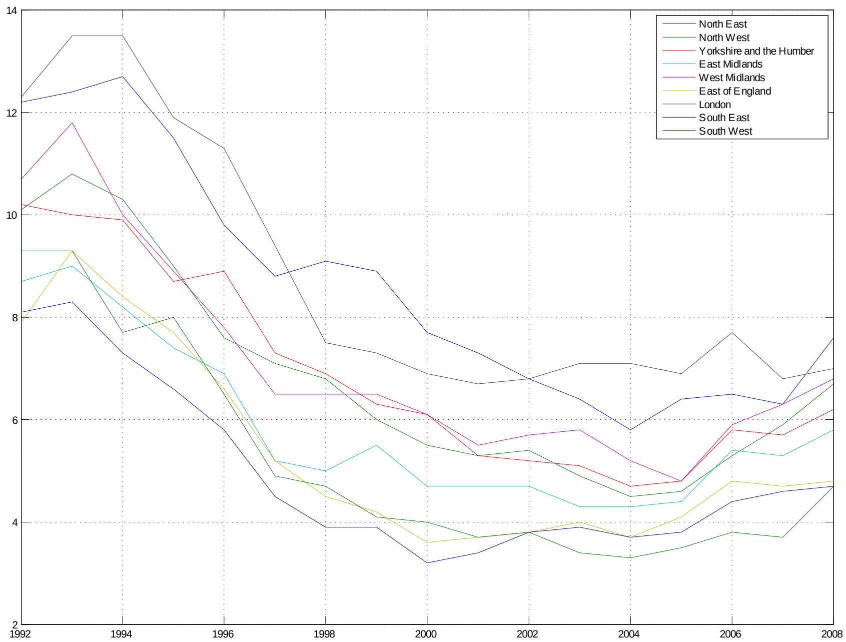

Figure 1: Evolution of regional unemployment rates (source: ONS, Labour Force Survey)

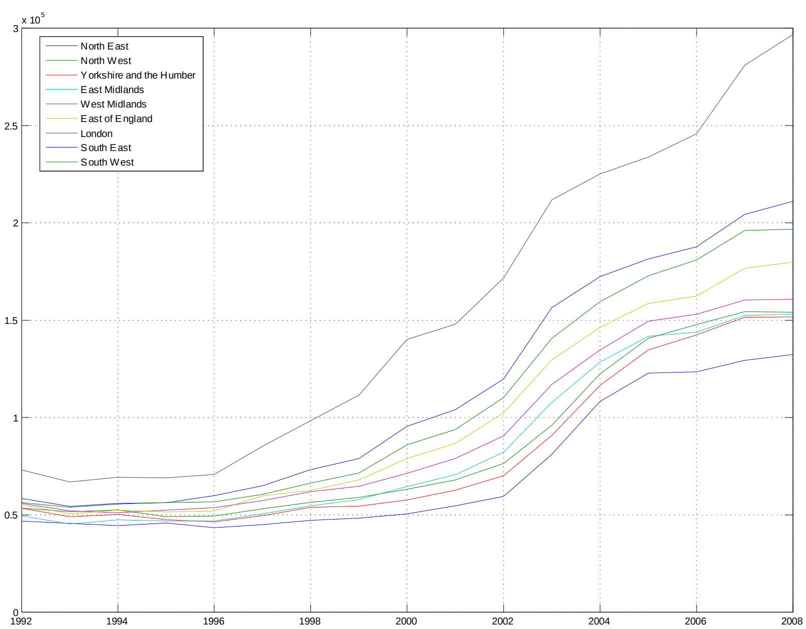

Figure 2: Evolution of housing prices (£) by Region (source: Nationwide, all properties)