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The role of the housing market in workers' resilience to job displacement after firm bankruptcy*

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Abstract

This paper examines the importance of the housing market for workers who have become displaced. We used Dutch administrative data, which were analysed with a quasi-experimental empirical design. The estimates indicate that displaced workers experience an increase in commute and decrease in moving home, employment and wage. Furthermore, these patterns change across time – the evidence suggests that workers who have longer unemployment duration prefer lower gains in commute to higher losses in wage. Finally, the worker-specific housing state has a substantial effect on the costs of job displacement, which is comparable to the effects of various demographic and job characteristics.

Keywords: Housing, Unemployment, Wages, Commuting, Mobility, Worker Characteristics

JEL classification: J31, J63, J65, R21

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Introduction

As in many other OECD countries, the Great Recession that started in 2008 resulted in strong negative developments in the Dutch labour market and the owner-occupied housing market simultaneously (OECD, 2010).[1] The large scale at which the transaction prices and home property values fell in the Dutch housing market is very rare – it previously occurred in the period 1978-1982. The key question this paper addresses is how the housing market affects workers' resilience to a negative employment shock due to firm bankruptcy, by focusing on the use of various margins of labour adjustment and the importance of the worker-specific housing state.

So far, the literature on job displacement has focused on two key margins of labour adjustment in response to job displacement – the significant losses in employment and in wage (Hamermesh, 1987; Topel, 1990; Ruhm, 1991; Jacobson *et al.*, 1993; Stevens, 1997; Kuhn, 2002; Couch and Placzek, 2010). More recent studies focus on the importance of worker-specific characteristics for the costs of displacement, for which workers are distinguished by gender, age, skill, job tenure, industry and labour market networks (Madden, 1987; Carrington, 1993; Carrington and Zaman, 1994; Chan and Stevens, 1999, 2001; Eliason and Storrie, 2006; Hijzen *et al.*, 2010; Farber, 2015; Hellerstein *et al.*, 2016). However, the literature on job displacement has not integrated features of the housing market. In this paper, we pay explicit attention to two specific features of the housing market: the role of space in the use of alternative margins of labour adjustment, and the importance of workers' housing state as a source of worker heterogeneity in the process of adjustment.

The first aim of this paper is to examine whether the spatial structure of homes and jobs leads to additional margins of adjustment for displaced workers. Previous studies demonstrate that commuting patterns and household moves are key to employment outcomes and wage dispersion (Zax, 1991; Simpson and Van der Veen, 1992; Smith and Zenou, 1997, 2003; Brueckner *et al.*, 2002; Manning, 2003; Fernandez and Su, 2004). In the context of this paper, displaced workers can improve their labour market prospects by accepting an increase in the commuting distance or by moving to another home in a distant labour market. Therefore, we integrate commute and moving home with employment and wage as key margins of adjustment in response to job displacement.

Our second aim is to examine the importance of the displaced workers´ housing state for the costs of job displacement. The housing state can act as an incentive device on job search through search intensity and search efficiency (Morescalchi, 2016). Specifically, workers who have a relatively high search intensity and efficiency might experience relatively modest losses in employment and wage or relatively modest gains in commute or move. To assess the relative importance of the housing state as a source of worker

[1] In the Netherlands, the owner-occupied housing sector experienced a strong decline in the number of transactions. Moreover, the transaction prices declined by more than 20%. Unemployment rose from 3.4% in the third quarter of 2008 to its peak of 8.1% in the first quarter of 2014. The number of bankruptcies of firms increased from 3,589 in 2007 to 8,376 in 2013. (CBS, 2016)

heterogeneity for the costs of job displacement, we also examine the role of other sources of heterogeneity including demographic and job characteristics.

For our empirical analysis we created a monthly panel of employees based on rich administrative data sets that cover Dutch data of firms, employees and households in the period from January 2006 to December 2013. This time period is particularly suited to incorporate data on declining property values of homes and the increasing number of bankruptcies of firm entities. We used data on job displacement due to bankruptcies of firm entities (hereafter: job displacement) as an exogenous negative shock to the employment status of workers. These data set the stage for a quasi-experimental empirical design. This empirical design is important, since we examined incentive effects in which adverse selection into labour turnover should play no role. The potential of selection bias based on observables was minimised by exact matching on coarsened observables of treated (displaced) to similar control (non-displaced) workers. We applied the double-differences (DD) and triple-differences (DDD) estimator to limit the selection based on unobserved heterogeneity.

The framework of the DD estimator was applied to the coarsened exact matched sample to estimate the displacement effects by comparing pre- with post-displacement outcomes between displaced and non-displaced workers. The displacement effects are inferred from reduced-form models on four margins of adjustment that may take place after job displacement, i.e. changes in employment, hourly wage, commuting distance and moving home. The DDD estimator was applied to estimate the effects of the various housing states on the costs of job displacement. The worker-specific housing state was categorised by tenancy and home-ownership, where owners were distinguished by their mortgage loan relative to the home property value (LTV).

Our analysis provides three sets of novel results and contributions. First, the estimates suggest that commuting and household moving are significant margins of labour adjustment in response to job displacement. Specifically, the average treatment effects we estimated show that displaced workers, on average, (i) are 35 percentage points less employed, (ii) experience a loss in wage of 5 per cent, (iii) experience an increase in commute of 5 kilometres and (iv) have a 0.06 percentage points lower rate of moving home. The first contribution of this paper is to show that the spatial structure reflects important margins of labour adjustment for workers in response to job displacement.

Second, the evidence suggests that workers who have a longer unemployment duration experience higher losses in hourly wage and moving home, but lower gains in commute. Moreover, we show that the role of observed worker characteristics in the costs of job displacement is relatively persistent over the post-displacement duration. The second contribution is to emphasise that the patterns in the use of margins of labour adjustment change across time after job displacement.

Third, the analysis shows that there exists strong heterogeneity in the resilience to job displacement among workers. We provide a comprehensive overview of the role of various observed worker characteristics in the costs of job displacement. We find that displaced tenants and owners who have paid off their entire mortgage (i.e. the outright owners) experience a relatively high loss in employment but a modest loss in wage. Importantly, for displaced owners an increase in the LTV leads to a lower loss in employment but a higher loss in wage. The third contribution is to demonstrate that the housing state has a substantial effect on the costs of job displacement, which is comparable to that of various demographic and job characteristics.

1. Conceptual Framework

Originally, the displacement effects on employment and wage were explained by human capital theory (Hamermesh, 1987; Topel, 1990; Jacobson *et al.*, 1993). Human capital theory predicts that workers who are displaced lose their firm-specific human capital and wage premiums, and they experience a deterioration of general human capital during the unemployment spell.

The key choice behind the length of a displaced worker's unemployment spell is whether employment is preferred to the alternative of remaining unemployed while searching for better job offers. Eq. (1) shows the exit rate into employment - represented by H – to be equal to the product of the job offer arrival rate α and the probability of accepting the job offer $1 - F(w_r)$ (Rogerson *et al.*, 2005):

$$H = \alpha[1 - F(w_r)] \tag{1}$$

where F denotes the wage-offer distribution. The optimal choice of each worker depends on the comparison:

$$w_r \geq b - g(\alpha) + \frac{\alpha}{r}\int_{w_r}^{\infty}(\mathrm{w} - \mathrm{w_r})dF(w) \tag{2}$$

where the first-order condition for an interior solution equals

$$rg'(\alpha) = \int_{w_r}^{\infty}(\mathrm{w} - \mathrm{w_r})dF(w) \tag{3}$$

Observe from (1) that the exit rate into employment H can be increased by accepting a lower reservation wage w_r. An alternative solution for the displaced worker would be to increase the arrival rate of job offers α. The arrival rate of job offers can be increased by means of an expansion of the search area, which can be achieved by accepting a higher commuting distance or moving home. Note that job displacement can have an ambiguous effect on moving home. Job displacement might increase the willingness to move home in order to become employed in a distant labour market. In contrast, the ability to move home is reduced for a displaced worker, since it is more difficult to get a new mortgage or a rent contract and to pay the transaction costs of moving. Hence, a priori it is unclear in which direction job displacement affects the probability of moving home.

Observe from (2) and (3) an ambiguous effect of an increase in the arrival rate α. On the one hand, a higher search intensity enables the unemployed worker to attract, in a given job offer period and search area, a higher number of desirable job offers α. In turn, this leads to a higher exit rate into employment. On the other, a higher α leads to a higher reservation wage w_r, which will decrease the exit rate into employment. Similarly, a higher α might lead to a lower willingness to commute and move as the costs of commuting (Glaeser *et al.*, 2008) and the costs of moving home (Van den Berg, 1992) increase with the wage. Consequently, there exists a trade-off between the costs of commuting or moving home and the wage.[2]

The intensity and pay-offs of search can be endogenous to the worker's housing state. Consider a displaced worker who is a mortgage owner. The unemployed mortgage owner faces a severe financial constraint and is obliged to amortise and to pay rent on the mortgage. The relatively high housing costs and strong payment obligations are likely to induce relatively high opportunity costs of continued unemployment and forgone wage. Hence, the unemployed mortgage owner is expected to have a relatively strong financial incentive to become employed and to have a relatively low cost on searching $g(\alpha)$, i.e. $g'_{mort}(\alpha) < g'_{other}(\alpha)$. Indeed, (Morescalchi, 2016) shows that unemployed leveraged owners search more intensively and effectively than other unemployed workers. If $g'_{mort}(\alpha) < g'_{other}(\alpha)$ holds, an unemployed mortgage owner is expected to have a relatively high search intensity and, consequently, a relatively high job offer arrival rate α. Given the log-concavity of the wage-offer distribution F (Flinn and Heckman, 1983), a relatively high search intensity can provide the opportunity to become employed more rapidly while being selective in the use of alternative margins of adjustment.

The empirical literature on housing and labour economics establishes that mortgage owners have a higher exit rate into employment than outright owners and tenants. This well-documented finding is based on differences in housing costs and payment obligations, both between owners and tenants (Coulson and Fisher, 2002, 2009; Dohmen, 2005; Munch *et al.*, 2006; Battu *et al.*, 2008; Head and Lloyd-Ellis, 2012) and within the pool of owners (Goss and Phillips, 1997; Flatau *et al.*, 2003; Baert *et al.*, 2014).

2. Institutional Background and Data

In the Netherlands, a bankruptcy is declared over a single legal entity of a firm. Workers who are collectively displaced, for example through mass-layoffs, are protected by the Law Collective Redundancy Act. This Act does not hold for dismissals if the firm is declared bankrupt, as job displacement due to firm bankruptcy concerns an 'urgent' case of

[2] In this spirit, Mulalic *et al.* (2014) show that workers who experience a plant relocation prefer an increase in wage to a shorter commuting distance.

displacement. This has two implications for workers whose labour contract is terminated due to bankruptcy of the firm entity.

First, the notification requirement to displaced workers, which is specified in the Law Collective Redundancy Act, applies only at the request of the Public Employment Service. Therefore, in general, no advance notification is required from bankrupt firm entities to displaced workers. Second, if an entity goes bankrupt, no severance or transition payments are provided by the firm to the displaced worker. This is important as heterogeneity in the advance notification and severance pay can have a confounding effect on the post-displacement length of the unemployment spell and earnings (Addison and Portugal, 1987; Nord and Ting, 1991).

2.1 *Data Sets*

We took advantage of various administrative data sets, retrieved from Statistics Netherlands, to create a monthly panel that is weakly balanced. We observe each individual employee for eighteen months prior until eighteen months after the actual or potential job displacement. Note that the actual month of job displacement of a displaced worker is equivalent to the potential month of displacement of a matched non-displaced worker. The data sets we used cover monthly and annual data of individuals, households and firms over the time period 2006-2013. We selected the employees whose job was terminated due to bankruptcy between July 2007 and June 2012. In Appendix A, we provide additional information on the data construction and sample selections that were applied in order to create the appropriate sample of individual employees.

2.2 *Key Dependent Variables*

The four key dependent variables, which represent the various margins of labour adjustment, were operationalised as follows. Employment status was expressed as a zero-one indicator variable that equals one if the individual is employed. The natural logarithm of the hourly wage was constructed by the monthly gross wage relative to the monthly number of hours worked. The commuting distance was calculated by taking the absolute distance between the central business district (CBD) of the work municipality and the CBD of the neighbourhood of the home. [3] Moving home was expressed as an indicator variable and equals one if the household has relocated.

[3] Note that the hourly wage and commuting distance of workers are observed conditional on employment. Moreover, for some workers the commuting distance is not observed. The number of observations that are missing for the model in which commuting distance is the dependent variable can be observed by the comparison with the model on hourly wage. See Appendix A for additional information on the data and see Table E1 in Appendix E for the results using a sample where all individuals have complete information on commuting distance. The results are robust. See Table D1 in Appendix D for the within change in the hourly wage and commuting distance for displaced and non-displaced workers.

2.3 *Key Independent Variables and Covariates*

The set of key independent variables consists of variables that represent the treatment status, post-displacement status, housing state, demographic characteristics and job characteristics. All of these variables were expressed as zero-one indicator variables. The treatment status equals one for workers who experience job displacement.

The post-displacement status equals one if the month under observation is after the month of job displacement. To allow for flexibility in the effect over the duration after job displacement, the post-displacement indicator variable was in some of the models replaced by thirty-seven indicator variables that range from minus eighteen to plus eighteen months. Each of the thirty-seven indicator variables equals one if the period since job displacement corresponds to the specific time gap. Thereby, we were able to assess the time dimension of the displacement effects.

The worker-specific housing state reflects the worker's financial incentive to work and it was represented by six indicators. We distinguished between tenants and homeowners, where owners were separated based on the loan-to-value (LTV) on the home.[4] The LTV, which is expressed as a percentage, was constructed by the observed mortgage debt relative to the property value of the home. The first two indicators equal one if the worker is a tenant (base category) or an outright owner (i.e. an owner who has an LTV of 0% as the entire mortgage is paid off), respectively. The four remaining indicators equal one if the worker has an LTV between 0% and 133.33%, in increments of 33.33%, respectively.[5]

The set of demographic characteristics consists of indicators for female, Dutch nationality, and age (4 categories). The set of job characteristics represents the worker's time-invariant job characteristics in the month of job displacement. The set of job characteristics consists of indicators for job tenure (4 categories), industry (manufacturing and services sector), and year of job displacement. In addition, the set of covariates includes indicators for children aged 18 or lower, spouse and the number of household members (4 categories).

[4] Although we were not able to distinguish between tenants who rent social or private housing, we emphasise that most tenants in our sample rent social housing. In 2012, there were in total 7,141,000 Dutch households. Of these households, 4,236,000 (59.32%) were owner-occupied and 2,905,000 (40.68%) were rented. Of the 2,905,000 households that rent, 2,570,000 (88.47%) rent social housing and 335,000 (11.53%) rent private housing. (CBS, 2016)

[5] In a robustness check that is discussed in Appendix C, we show that the empirical evidence is robust to the use of the loan-to-income (LTI) ratio as an additional approximation of the financial incentive to work. We prefer the LTV to the LTI ratio as our main approximation of the housing state, because the LTV allows for within change caused by changes in the property value and the mortgage debt.

3. Identification Strategy

3.1 *Identification Challenges*

For our paper, two endogeneity issues required particular attention. The first issue concerns the potential of selection into labour turnover. Selection effects into labour turnover are likely as various worker characteristics, e.g. age and gender (Kuhn, 2002), job tenure (Farber, 1999), industry and education (Farber *et al.*, 1993), and housing state (Flatau *et al.*, 2003; Van Leuvensteijn and Koning, 2004; Munch *et al.*, 2008), affect the probability or cause of exit into unemployment. In turn, the selection effect could be problematic as the cause of unemployment affects, through signalling, the magnitude of displacement costs in post-unemployment labour market outcomes (Gibbons and Katz, 1991; Stevens, 1997; Kuhn, 2002; Hu and Taber, 2011; Frederiksen *et al.*, 2013).

The second issue of endogeneity concerns the potential of selection into the housing state. For example, it is likely that there exists a sorting mechanism – e.g. based on human capital – that simultaneously directs workers into a housing state and influences labour market outcomes. In this spirit, multiple papers argue that the choice of home ownership and the likelihood of having a stable job are likely to be correlated (Coulson and Fisher, 2002; Van Leuvensteijn and Koning, 2004; Moriizumi and Naoi, 2011).

We controlled for the two aforementioned empirical issues in a number of ways. First, data were used on workers who experience unforeseen job displacement due to bankruptcy of the firm entity. Thereby, job displacement acts as an exogenous negative employment shock, which sets the stage for a quasi-experimental empirical design. Moreover, by using these displacement data, the potential of selection into labour turnover is limited as workers have an identical signalling value on post-unemployment labour market outcomes. Also, the use of job displacement due to firm bankruptcies limits the potential of selection effects based on advance notification and severance pay (Addison and Portugal, 1987; Nord and Ting, 1991).

Second, we applied "Coarsened Exact Matching" (CEM) on observables to make displaced and non-displaced workers balanced in covariates. CEM is a member of the class of "Monotonic Imbalance Bounding" (MIB) matching methods, and dominates the propensity score methods (Iacus *et al.*, 2011). By balancing workers in covariates, the selection bias into displacement based on observables, which can arise from lack of common support, was greatly reduced (Heckman *et al.*, 1997, 1998; Heckman and Smith, 1999). See Appendix B for additional information on CEM.

Third, the double-differences (DD) and triple-differences (DDD) estimators were applied to remove bias based on unobserved heterogeneity. DD was used to compare the pre- and post-displacement outcomes of matched displaced workers and non-displaced workers. DDD was applied to assess the differences in the displacement effects among heterogeneous workers. The key identification restriction of the DD and DDD model requires that, conditional on observables, the outcomes of the displaced workers and non-displaced workers would have followed parallel paths if job displacement of the displaced workers had not occurred (see Section 4 for further discussion).

Fourth, workers with a job tenure of at least three years were selected for the pool of displaced and non-displaced workers. This sample selection ensured that the potential of selection into the housing state, based on the belief of having a stable job, was limited. Thereby, all workers had, prior to job displacement, a stable employment pattern.

Finally, we controlled for many factors that have an effect on the exit rate into unemployment, likelihood of home ownership and the LTV on the home. For example, we controlled for changes in age and the presence of children aged 18 or lower. Moreover, indicator variables for calendar month (95) and NUTS 3 area (39) were included to capture business cycle effects and area fixed effects, respectively. Individual fixed effects were incorporated to eliminate bias from any time-invariant unobserved variables, e.g. constant skill that might simultaneously direct workers into a housing state and affect labour market outcomes. To correct for unobserved heterogeneity driven by human capital, we controlled for education level, and changes in wealth position and in duration of home occupancy, respectively, in two robustness checks that are shown in Appendix C.

3.2 *Margins of Adjustment*

For each of the margins of adjustment a generic empirical model is specified. In what follows, Y represents one of the four possible margins of adjustment - employment, hourly wage, commuting distance and moving home. The static empirical model is given as

$$Y_{it} = \delta(DISPLACED_i \times POST_{it}) + \rho POST_{it} + \beta_{X_j} X_{it,j} + \alpha_i + N_n + D_t + \varepsilon_{it} \qquad (4)$$

$i \in \{ 1, 2, \ldots, N\}; t \in \{1, \ldots, 96\}$

where subscripts i, t, j and n denote the worker, month, covariate and NUTS 3 area, respectively. The indicator variable $DISPLACED$ equals one for workers who experienced job displacement.[6] The indicator variable $POST$ equals one for the post-displacement period of eighteen months after job displacement.[7] The base and omitted categories of the variables $DISPLACED$ and $POST$ are the controls and the pre-displacement period, respectively. The systematic differences in the outcome variables are captured by the coefficient δ of the two-way (double) interaction term between the indicator variables $DISPLACED$ and $POST$. All individual-specific time-varying covariates are represented by vector X. Individual-specific fixed effects are referred to by α. N represents indicators for

[6] We consider workers' job displacement between July, 2007 and June, 2012. Consequently, there is variation over time in the variable that reflects treatment of workers. This greatly reduces the potential of standard errors that understate the standard deviation of the estimator (Bertrand *et al.*, 2004).

[7] By having a relatively short post-displacement period, we distance ourselves from the effect of human capital deterioration (Schultz, 1961; Addison and Portugal, 1989; Acemoglu, 1995) and stigmatisation of long-term unemployed by employers (Eriksson and Rooth, 2014) on post-unemployment labour market outcomes.

the home location at the NUTS 3 level. Calendar month indicators are denoted by D. ε refers to the idiosyncratic error term.

The second empirical model, shown in (5), is specified to assess whether the treatment effect is persistent over the duration after job displacement. Moreover, this model allows us to investigate whether the effects suffer from selection into employment. Specifically, selection into employment can be important as the hourly wage and commuting distance are observed only for workers who are employed. The dynamic empirical model is given as

$$Y_{it} = \sum_{\tau=-18}^{18} [\delta^{\tau}(DISPLACED_i \times G_{it}^{\tau}) + \rho^{\tau} G_{it}^{\tau}] + \beta_{X_j} X_{it,j} + \alpha_i + N_n + D_t + \varepsilon_{it} \tag{5}$$

We constructed the parameter τ to incorporate the time gap of the period since job displacement, which ranges from minus eighteen to plus eighteen in increments of one month. Parameter τ equals zero in the actual and potential month of displacement for the displaced and non-displaced, respectively. The indicator variables G^{τ} refer to the time gap between the month of job displacement and the month under observation. For example, indicator variable $G^{\tau=-12}$, which represents the base category, equals one if the period prior to job displacement is equal to twelve months. We used the twelfth month prior to job displacement as the base category, because workers might experience changes in outcomes in anticipation of displacement. The time-dependent differences are captured using interaction terms among the indicator variables $DISPLACED$ and G^{τ}. The main parameters of interest are referred to by coefficient δ^{τ}, where τ allows for flexibility in the effect of job displacement over the period since job displacement.

3.3 *Observed Worker Characteristics*

We added various interaction terms to assess how the displacement costs differ among different types of workers. Workers are distinguished by their housing state, demographic characteristics and job characteristics. The empirical model in (6) complements the model in (4), by adding multiple three-way (triple) interaction terms among a vector of worker characteristics X, $DISPLACED$ and $POST$. The vector X includes time-varying variables (the workers' housing state and age) as well as time-invariant variables (gender, nationality and characteristics of the terminated job). The static empirical model is given as

$$\begin{aligned} Y_{it} = \kappa_{X_j}(X_{it,j} \times DISPLACED_i \times POST_{it}) + \gamma_{X_j}(X_{it,j} \times DISPLACED_i) \\ + \eta_{X_j}(X_{it,j} \times POST_{it}) + \delta(DISPLACED_i \times POST_{it}) + \rho POST_{it} \\ + \beta_{X_j} X_{it,j} + \alpha_i + N_n + D_t + \varepsilon_{it} \end{aligned} \tag{6}$$

The main parameters of interest are denoted by coefficients κ_{X_j}.

The empirical model in (7) complements that of (5). The model in (7) allows us to assess the time dimension of the role of worker characteristics in the costs of job displacement. The time-dependent differences are captured by the multiple three-way interaction terms among the indicator variables X, $DISPLACED$ and G^{τ}. The dynamic empirical model is given as

$$
\begin{aligned}
Y_{it} = \sum_{\tau=-18}^{18} \Big[& \kappa_{X_j}^{\tau}\left(X_{it,j} \times DISPLACED_i \times G_{it}^{\tau}\right) + \eta_{X_j}^{\tau}\left(X_{it,j} \times G_{it}^{\tau}\right) \\
& + \delta^{\tau}\left(DISPLACED_i \times G_{it}^{\tau}\right) + \rho^{\tau} G_{it}^{\tau} \Big] + \gamma_{X_j}\left(X_{it,j} \times DISPLACED_i\right) \\
& + \beta_{X_j} X_{it,j} + \alpha_i + N_n + D_t + \varepsilon_{it}
\end{aligned}
\tag{7}
$$

The coefficients $\kappa_{X_j}^{\tau}$ are the main parameters of interest.

4. Empirical Results

4.1 *Margins of Labour Adjustment*

Table 1 displays the estimates of the displacement effects on the four margins of labour adjustment (Eq. (4)). Columns (1), (2), (3) and (4) show the displacement effects on employment, hourly wage, commuting distance and moving home, respectively. For the variables displacement status (DISPLACED) and post-displacement period (POST*)*, the omitted categories are the non-displaced workers and the pre-displacement period, respectively.

Table 1
Static displacement effects on the four margins of labour adjustment (Eq. (4))

	Employment (=1)	Hourly wage (log)	Commuting distance (km)	Moving home (=1)
	(1)	(2)	(3)	(4)
Two-way interaction term				
DISPLACED × POST	-0.3477***	-0.0493***	4.9620***	-0.0006***
	(0.0023)	(0.0014)	(0.2251)	(0.0002)
Number of parameters	149	149	149	149
Number of individuals	76,852	76,852	76,852	76,852
Number of observations	2,843,524	2,634,998	2,606,816	2,843,524

Notes: Each column gives the dependent variable. Clustered (by individual) standard errors are in parentheses. ∗∗∗,∗∗,∗ , correspond to the significance level of 1%, 5%, 10%, respectively. The reference categories of DISPLACED and POST consist of the non-displaced workers and pre-displacement period, respectively. The regression analyses include indicator variables for POST, housing state (5), age (3), children aged 18 or lower, spouse, the number of household members (3), the NUTS 3 location of the household (39) and calendar month (95). The period under observation is from January 2006 to December 2013, in which displaced and non-displaced workers are observed for 18 months prior until 18 months after the actual and potential month of job displacement, respectively. The parameter estimates of the covariates are not reported.

Table 1 shows that displaced workers are 35 percentage points less employed than non-displaced workers over the post-displacement period of eighteen months. Moreover, displaced workers, compared with non-displaced workers, experience a loss of 5 per cent in hourly wage and a gain of 5 kilometres in the commuting distance. Finally, we observe a small negative displacement effect on the probability of moving home. As far as we know, the significant displacement effects on commute and moving home is a novel finding.

Figure 1 shows the context of changes in the outcome variables of matched displaced and non-displaced workers over the entire pre- and post-displacement period (see Eq. (5)). The fixed-effects coefficients in Figures 1A and 1D are provided on the y-axis in percentage points (pp). The coefficients in Figures 1B and 1C are provided on the y-axis in percentages (%) and kilometres (km), respectively. The x-axis registers the time gap between the month of observation and the month of job displacement. For the displaced and non-displaced, the time gap equals zero in the month of actual and potential job displacement, respectively. Figure 1 shows parallel paths in the outcome variables prior to displacement for the displaced and non-displaced workers. This observation satisfies the aforementioned identification restriction.

In Figure 1A, the vertical line between months zero and one reveals the exit rate out of employment by the displaced worker. Between twelve and eighteen months after job displacement, the loss in employment is between 27 and 23 percentage points, respectively. This finding is consistent with those reported in the job displacement literature. For example, Schwerdt (2011) finds an effect of 23 percentage points over a post-displacement period of five years. Ichino *et al.* (2016) find a loss of 27 percentage points over the period between twelve and twenty-four months after job displacement.

Except for the first month after job displacement, the negative effect of displacement on wage ranges between 4 and 6 per cent and increases over the period since job displacement (see Figure 1B). The estimates are in line with studies on the displacement effect on wage for Europe. Schwerdt (2011) finds a wage loss due to job displacement, conditional on re-employment, of 6 per cent. Huttunen *et al.* (2011) find a loss of 3 per cent in wage after 7 years. Studies that use U.S. data find higher wage losses due to the more centralised wage system (Couch and Placzek, 2010).

Figure 1C shows that, except for the first month after job displacement, the increase in commute declines over the post-displacement spell. This finding indicates that job movers commute more and that it takes time to lower the gain in commute through changes in the home or work location. Importantly, Figures 1B and 1C show composition effects that are caused by workers who exit unemployment, workers who experience job-to-job transitions and workers who move home. Interestingly, the composition effects are almost entirely driven by workers who exit unemployment and take up their first job since displacement.[8] Hence, the estimates shown in Figures 1B and 1C reveal a novel pattern, i.e. displaced workers who have longer unemployment duration prefer lower gains in commute to higher

[8] We show that this observation holds in Figure E1 in Appendix E, where we present estimates based on a sample in which we select displaced workers who are in their first job since displacement.

losses in wage. So far, this pattern has not been demonstrated in the literature on job displacement.

We find a small but statistically significant negative effect of job displacement on the probability of moving home after five months since job displacement (see Figure 1D). This finding reflects the delay in the impact of job displacement on the ability to move. Specifically, household moves are characterised by a time gap between the month of arranging and the month of the actual move. In contrast to our findings, Huttunen *et al.* (2015) show that job displacement significantly increases geographical mobility based on non-economic factors such as family ties. An appealing explanation for the difference in their findings and Figure 1D is explained by the post-displacement period we use of eighteen months. This period could be too short to observe the positive effect of job displacement on household mobility, as the inability to move is most severe relatively soon after the month of displacement. However, Huttunen *et al.* (2015) find that the increase in mobility takes place in the first two years after job displacement.

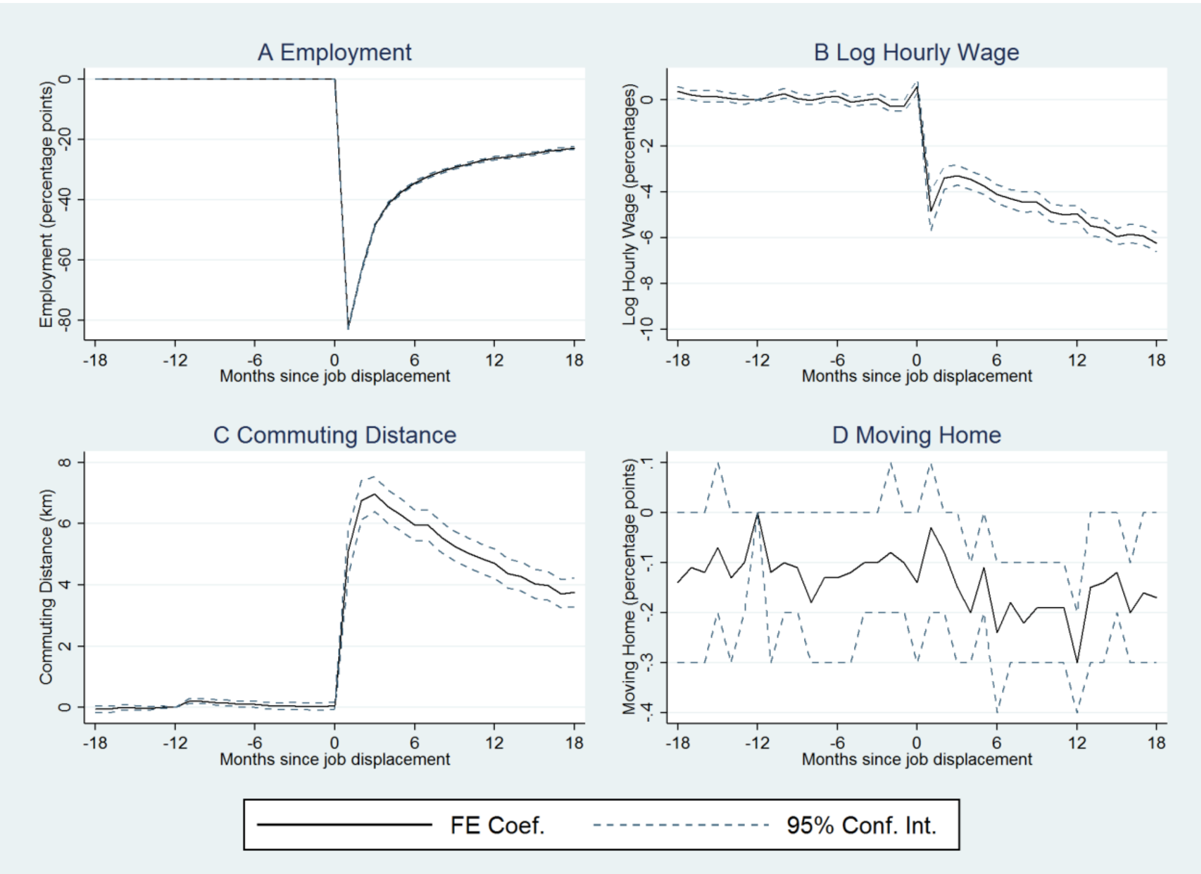

Figure 1: Displacement effects on employment (*A*), log hourly wage (*B*), commuting distance (*C*) and moving home (*D*) (Eq. (5)). The 95% confidence intervals are computed using clustered standard errors by individual. All four fixed effects regression models include 218 parameters of which there are 36 two-way interaction terms (base month is the twelfth month prior to job displacement). See Table 1 for additional notes and statistics.

4.2 *Observed Worker Characteristics*

The estimation results of the displacement effects for various worker characteristics are displayed in Table 2 (see Eq. (6)). To provide a complete picture of the role of observed worker characteristics in the costs of job displacement, differences in the displacement effects are examined for workers categorised by housing state, demographic characteristics and job characteristics. The housing state is represented by the LTV indicators, and the reference category consists of workers who are tenants. The set of demographic characteristics contains FEMALE, AGE and $\mathrm{DUTCH\ NATIONALITY}$, and the reference categories consist of workers who are male, aged 21 to 29 years and non-Dutch, respectively. The set of job characteristics contains TENURE, $\mathrm{MANUFACTURING}$ and $\mathrm{DISPLACEMENT\ YEAR}$, and the reference categories consist of workers who are 3 to 6 years in the job, active in the service sector and displaced in 2007, respectively.

The estimates shown in Column (1) underscore the importance of the worker's characteristics for the displacement effect on employment. Compared with displaced workers who are tenants, displaced workers with an LTV over 100% are 7 percentage points more employed. Tenants incur a loss in employment similar to displaced workers who have an LTV of 0%. Interestingly, our findings are at odds with the literature on house lock and unemployment duration. For example, Valletta (2013) finds no effect of negative net home equity on unemployment duration. The difference in results can be explained by our quasi-experimental empirical design that limits the potential of selection into the housing state and labour turnover. Finally, the estimates in Column (1) show that displaced workers who are female, older, non-Dutch, high-tenured and displaced during an economic downturn experience a relatively high loss in employment.

Table 2
The role of observed worker characteristics in the costs of job displacement (Eq. (6))

	Employment (=1)	Hourly wage (log)	Commuting distance (km)	Moving home (=1)
	(1)	(2)	(3)	(4)
Housing state:				
$\mathrm{DISPLACED} \times \mathrm{POST} \times$				
LTV 0%	0.0169	-0.0065	1.8472	-0.0008
	(0.0130)	(0.0081)	(1.2396)	(0.0011)
LTV 0-33%	0.0366***	-0.0036	-0.8347	0.0010*
	(0.0080)	(0.0050)	(0.7635)	(0.0006)
LTV 33-66%	0.0284***	-0.0125***	-0.1454	0.0007
	(0.0069)	(0.0045)	(0.6821)	(0.0005)
LTV 66-100%	0.0293***	-0.0185***	0.4540	0.0003
	(0.0068)	(0.0043)	(0.6795)	(0.0006)
LTV 100-133%	0.0669***	-0.0172***	-1.0155	0.0007
	(0.0080)	(0.0050)	(0.8048)	(0.0008)
F-Value joint significance of three-way interaction terms on LTV	14.85***	4.96***	1.63	1.31

Demographic characteristics:				
DISPLACED × POST ×				
FEMALE	-0.0755***	-0.0014	-4.5064***	-0.0005
	(0.0060)	(0.0039)	(0.6316)	(0.0004)
AGE 30-39 years	-0.0368***	-0.0245***	-0.5997	0.0007
	(0.0085)	(0.0056)	(0.8907)	(0.0011)
AGE 40-49 years	-0.0760***	-0.0410***	0.6853	0.0014
	(0.0088)	(0.0057)	(0.8951)	(0.0011)
AGE 50-59 years	-0.1992***	-0.0448***	0.4518	0.0007
	(0.0094)	(0.0062)	(0.9580)	(0.0011)
DUTCH NATIONALITY	0.1025***	-0.0107	-0.3848	-0.0010
	(0.0114)	(0.0074)	(0.9221)	(0.0008)
F-Value joint significance of three-way interaction terms on AGE	210.30***	21.77***	1.45	1.81
Job characteristics:				
DISPLACED × POST ×				
TENURE 6-12 years	-0.0205***	-0.0061	2.3545***	-0.0007
	(0.0059)	(0.0037)	(0.6020)	(0.0005)
TENURE 12-18 years	-0.0345***	-0.0096**	2.0458***	0
	(0.0065)	(0.0041)	(0.6567)	(0.0004)
TENURE 18+ years	-0.0834***	-0.0358***	3.0455***	-0.0002
	(0.0071)	(0.0046)	(0.7307)	(0.0004)
MANUFACTURING	-0.0018	-0.0220***	1.6141***	0
	(0.0048)	(0.0031)	(0.4919)	(0.0003)
DISPLACEMENT YEAR 2008	-0.0914***	-0.0007	-1.3652	0.0013
	(0.0111)	(0.0073)	(1.0827)	(0.0009)
DISPLACEMENT YEAR 2009	-0.1360***	0.0040	-2.2968**	0.0012
	(0.0104)	(0.0068)	(1.0311)	(0.0008)
DISPLACEMENT YEAR 2010	-0.1390***	-0.0037	-0.9998	0.0015*
	(0.0105)	(0.0068)	(1.0600)	(0.0009)
DISPLACEMENT YEAR 2011	-0.1494***	-0.0097	-0.8124	0.0019**
	(0.0106)	(0.0071)	(1.0285)	(0.0009)
DISPLACEMENT YEAR 2012	-0.1895***	-0.0163**	-0.7734	0.0018**
	(0.0116)	(0.0075)	(1.0933)	(0.0009)
F-Value joint significance of three-way interaction terms on tenure	47.71***	21.70***	7.62***	1.31
F-Value joint significance of three-way interaction terms on displacement year	61.80***	3.15***	2.29**	1.26
Number of parameters	210	210	210	210
Number of individuals	76,852	76,852	76,852	76,852
Number of observations	2,843,524	2,634,998	2,606,816	2,843,524

Notes: Parameter estimates of the three-way interaction terms are reported. Loan-to-value (LTV) represents five indicator variables for homeowners' LTV expressed as a percentage. The reference category of each LTV indicator consists of workers who are tenants. The reference categories of FEMALE, AGE and DUTCH NATIONALITY consist of workers who are male, aged 21 to 29 years and non-Dutch, respectively. The reference categories of TENURE, MANUFACTURING and DISPLACEMENT YEAR consist of workers who are 3 to 6 years in the job, active in the service sector and displaced in 2007, respectively. The parameter estimates of the main effects and two-way interaction effects of the aforementioned independent variables are not reported. The regressions include zero-one indicator variables for children aged 18 or lower, spouse, the number of household members (3), the NUTS 3 location of the household (39) and calendar month (95). The main, two-way interaction and three-way interaction effects of children aged 18 or lower, spouse and the number of household members are not reported. The main effects of the NUTS 3 location and calendar month are not reported.

The parameter estimates in Column (2) highlight the role of worker characteristics in the displacement effect on hourly wage. Compared with displaced tenants and owners who have an LTV below 33%, displaced owners with an LTV over 33% experience a 1 to 2 percentage points higher loss in hourly wage. This finding suggests that owners who have a mortgage loan larger than the home property value are less selective in wage when choosing jobs after job displacement. Moreover, the estimates show that the loss in hourly wage increases with age and tenure in the displaced job, and is higher for displaced workers who are active in the manufacturing sector compared with workers who are active in the service sector. To the best of our knowledge, this paper is the first to demonstrate the importance of the worker-specific housing state for the losses in employment and hourly wage after job displacement.

Column (3) shows that various worker characteristics lead to a difference in the displacement effect on the commuting distance. Specifically, the parameter estimates indicate that displaced workers who are male, high-tenured and active in the manufacturing sectors experience a relatively high gain in commute.

The parameter estimates in Column (4) show that, in response to job displacement, moving home does not vary with worker characteristics. Importantly, our estimates suggest that for households that face negative home equity, job displacement does not function as a trigger for default. The double trigger theory of default predicts that households are likely to experience a default if two trigger events occur (Foote *et al.*, 2008). Our finding is in contrast with the study of Niu and Ding (2015), which shows that job displacement plays an important role in foreclosure decisions. For a sample of workers located in the State of Maryland, Niu and Ding (2015) show that negative equity directly increases the foreclosure rate. The disparity between the findings can be explained by the different context, as in the Netherlands the share of housing going into foreclosure is relatively low.

We show in Figures 2-8 that the context of changes over the entire pre- and post-displacement period in the outcomes of displaced and non-displaced workers depends on various workers' characteristics (see Eq. 7). Except for moving home, for all sources of worker heterogeneity we observe parallel pre-treatment paths in the outcome variables. Note that the pre-treatment trends in moving home are relatively stable given the low number of monthly movers (see the summary statistics on moving home in Table D3 presented in Appendix D). The importance of the housing state for the costs of job displacement is illustrated in Figure 2. Figure 2A shows that displaced tenants and outright owners experience in the entire post-displacement period a higher loss in employment than other displaced homeowners. Figure 2B illustrates that displaced workers who are in one of the three highest LTV groups experience a relatively high loss in wage. We do not find any significant three-way interaction effects on the commuting distance or moving home (see Figures 2C-2D). All in all, the results are in congruence with the estimates on the static model, and they indicate that the importance of workers' housing state for the costs of displacement is relatively persistent across time after displacement.

Figure 2: Housing state differential in displacement effects (Eq. (7)). All four fixed effects regression models include 1,959 parameters of which there are 36 are two-way interaction terms (base month is the twelfth month prior to job displacement). See Figure 1 and Table 2 for additional notes.

Figures 3-5 reflect the importance of demographic characteristics for the costs of job displacement. Figure 3 highlights the gender differential in the costs of employment. On the one hand, women experience a higher loss in employment than men. Importantly, the difference in the loss in employment diminishes over time. On the other hand, women experience a smaller gain in the commuting distance than men. Figures 4A-4C show that age directly increases the loss in employment, loss in hourly wage and gain in the commuting distance. These age differentials in the costs of displacement in employment, hourly wage and commuting distance are relatively persistent across time. Figure 5 shows that the nationality differential in the costs of displacement varies across time after displacement. The estimates show that displaced workers who have Dutch nationality experience relatively modest losses in employment but relatively high losses in wage.

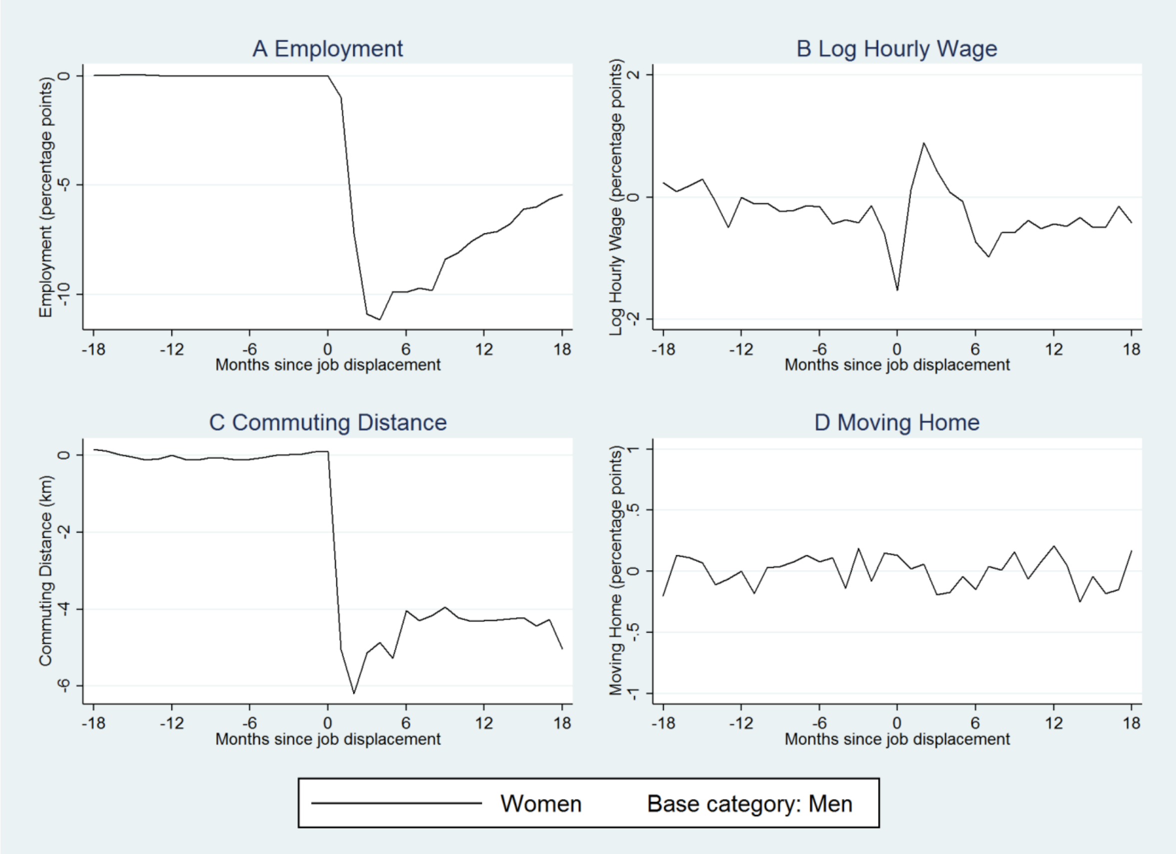

Figure 3: Gender differential in displacement effects (Eq. (7)). See Figs. 1-2 and Table 2 for additional notes.

Figure 4: Age differential in displacement effects (Eq. (7)). See Figs. 1-2 and Table 2 for additional notes.

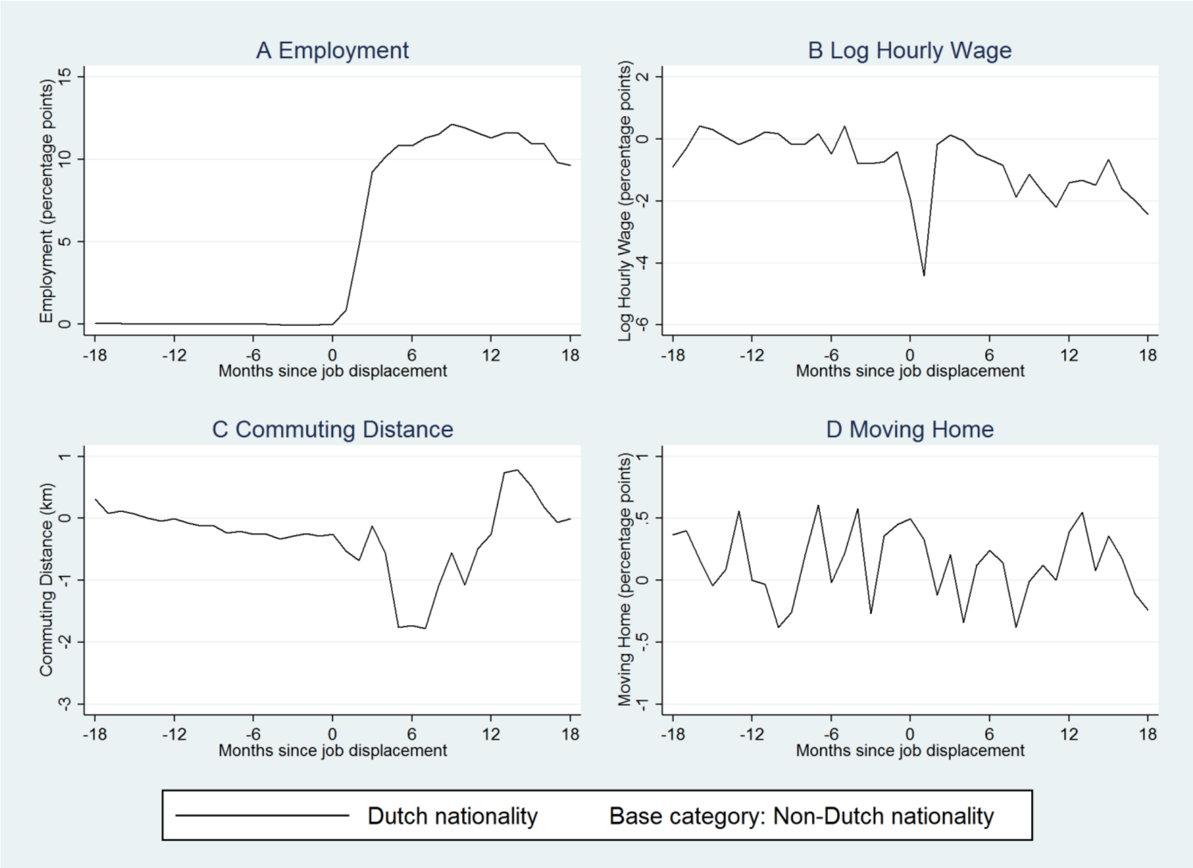

Figure 5: Nationality differential in displacement effects (Eq. (7)). See Figs. 1-2 and Table 2 for additional notes.

Figures 6-8 highlight the role of job characteristics in the costs of job displacement. Figures 6A, 6B and 6C show that the worker's tenure in the job in the month of displacement, especially in the case of job tenure higher than 18 years, increases the loss in employment and hourly wage and increases the gain in commute, respectively.[9] The role of job tenure in the costs of displacement is relatively persistent across time. Figure 7 shows that displaced workers who are active in the manufacturing sector, as compared with the service sector, experience a high persistent loss and gain in the hourly wage and commuting distance, respectively. The estimates shown in Figure 8A indicate that workers who are displaced later in time experience a higher loss in employment. The heterogeneity in the employment costs of displacement decreases over the period since job displacement.

[9] The strong effect of job tenure on losses in employment can be explained by the role of job tenure in the unemployment benefits duration. All displaced workers in our sample have a job tenure of at least 3 years and are therefore eligible for unemployment benefits for the first three months after displacement. For each additional year of work, displaced workers are eligible for another month of unemployment benefits. By having a minimum benefits duration and controlling for the job tenure of the terminated job, we distance ourselves from the effect of benefits duration on post-unemployment labour market outcomes (Katz and Meyer, 1990; Bover *et al.*, 2002).

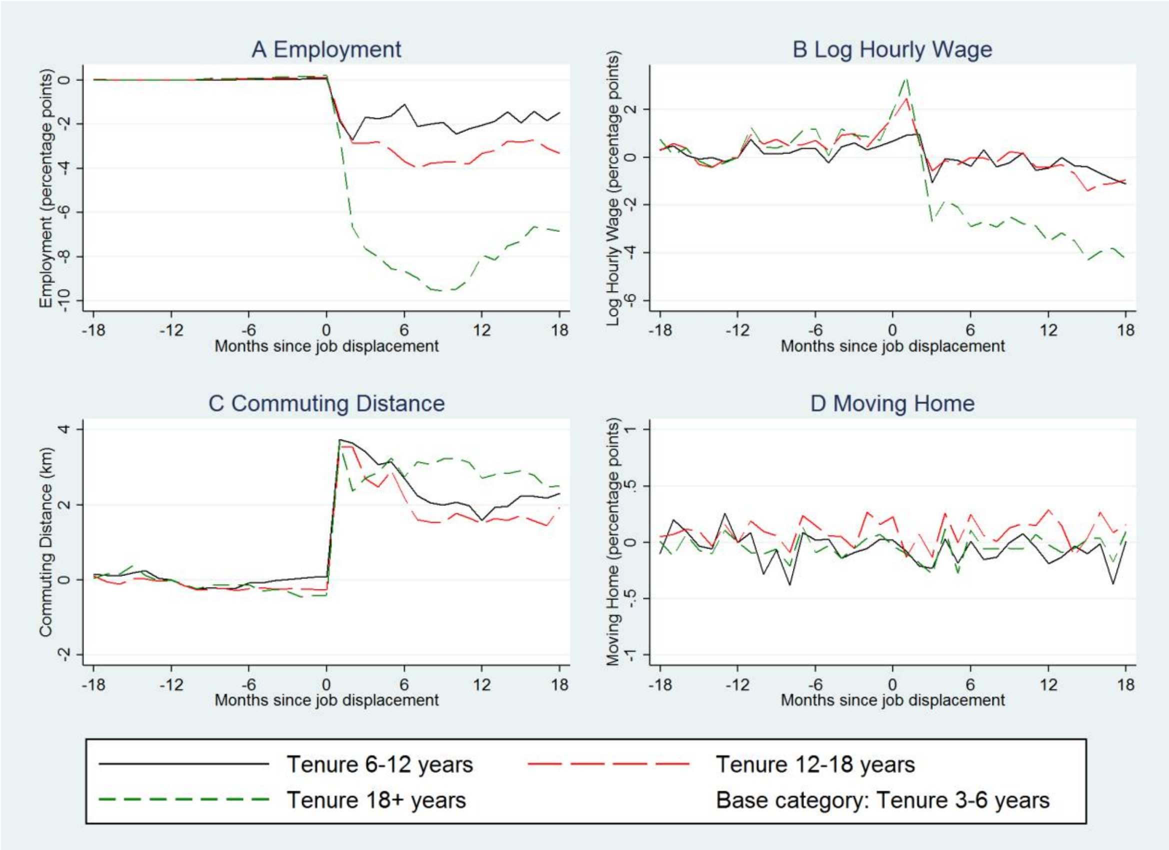

Figure 6: Job tenure differential in displacement effects (Eq. (7)). See Figs. 1-2 and Table 2 for additional notes.

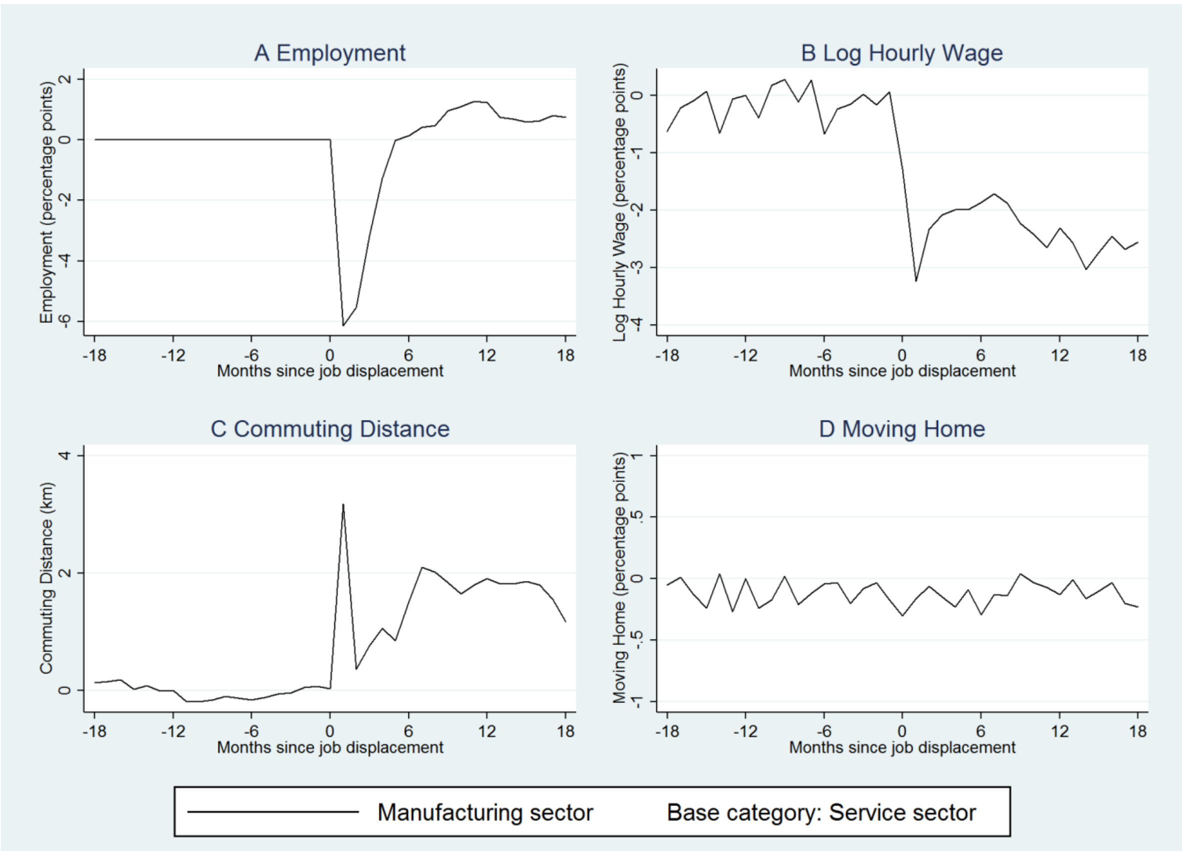

Figure 7: Industry differential in displacement effects (Eq. (7)). See Figs. 1-2 and Table 2 for additional notes.

Figure 8: Displacement year differential in displacement effects (Eq. (7)). See Figs. 1-2 and Table 2 for additional notes.

5. Conclusion

In this paper we have examined the role of the housing market in workers' resilience to job displacement after firm bankruptcy. We used administrative data, which were analysed with a quasi-experimental design. The conclusions of this paper are threefold.

First, we conclude that the spatial structure of the job reflects two key margins of adjustment in response to job displacement. A novel finding of this paper is that workers use two alternative margins of labour adjustment, next to losses in employment and wage, in response to job displacement. The results indicated that displaced workers experience gains in commute. Moreover, we found that the likelihood of moving home is lower after displacement, potentially due to difficulties in financing a new home after job displacement. This observation suggests that displaced workers are more able to use alternative margins of labour adjustment than home moving after job displacement.

Second, we conclude that the costs of job displacement vary across time after displacement. Specifically, the duration of the post-displacement period directly decreases the loss in employment, increases the loss in hourly wage and moving home, and decreases the gain in commute. The evidence suggests that displaced workers who have longer unemployment duration prefer lower gains in commute to higher losses in wage.

Third, we conclude that the worker-specific housing state is an important and persistent source of heterogeneity in the costs of displacement. We provided a comprehensive overview of the role of various worker characteristics in the costs of job displacement. A new finding is that displaced workers who have an LTV over 100% (i.e. underwater homeowners), compared with outright owners and tenants, experience a relatively low loss in employment but a relatively high loss in wage. Moreover, we are the first to demonstrate that the displacement effect on commute depends on gender, industry and tenure in the job. We showed that the importance of the worker-specific housing state for losses in employment and wage after displacement is substantial and comparable to that of various demographic and job characteristics.

We have conducted many robustness checks to assess the validity of our results. The external validity was positively evaluated based on models which indicate that the effects of job displacement on employment and wage are comparable to the effects that are observed in the literature on job displacement. This holds both for the displacement effects on employment and wage (Huttunen *et al.*, 2011; Schwerdt, 2011; Ichino *et al.*, 2016), and the role of demographic and job characteristics in the losses in employment and wage (Madden, 1987; Carrington, 1993; Carrington and Zaman, 1994; Chan and Stevens, 1999, 2001; Eliason and Storrie, 2006; Hijzen *et al.*, 2010; Tatsiramos, 2010; Hardoy and Schøne, 2014; Farber, 2015; Hellerstein *et al.*, 2016). This paper showed that the results are robust to the inclusion of indicators that represent four potential confounding variables, i.e. non-housing wealth, duration of home occupancy, loan-to-income ratio and skill level (see Appendix C). We conducted a final robustness check to assess the relationship between the housing state and search intensity (see Appendix F). By means of survey data we were able to use a direct measure of search intensity. We observed a positive correlation between the LTV and search intensity.

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Appendix A. Data Construction and Sample Selections

All individuals, firms and household addresses were uniquely identified on the basis of an encrypted Randomised Identification Number (RIN). We used the data set Bankruptcy Job Endings Register, which records the worker's RIN, the job's RIN and the date the firm entity is declared bankrupt for individuals who had a job at a firm where at least one entity of the firm experiences bankruptcy. Consequently, we possibly incorporated false-positives, i.e. we labelled voluntary job terminations in the bankrupted or non-bankrupted entity of a firm as a displacement due to firm bankruptcy. To limit the scope of false-positives we applied various data selections, which are discussed below.

Jobs that ended in year t or $t+1$ surrounding a bankruptcy of a firm entity were registered in the Bankruptcy Job Endings Register. The time span of year t to $t+1$ was chosen as jobs are recorded from firm payrolls that can continue after the verdict of bankruptcy. We included workers in the group of displaced workers if the date of the job ending was earlier than one year after the date of bankruptcy and later than six months prior to the date of bankruptcy. This restriction ensured that the early leavers, who may have anticipated the plant closure, were incorporated in the analysis (Schwerdt, 2011).

The Bankruptcy Job Endings Register was combined with multiple other registers. The Job Register was used to incorporate the date of job openings, the date of job endings and the RIN of the firm in which the worker was an employee. The Main Job Register was used to distinguish between the main job and secondary job of an individual. The worker's main job, observed on a monthly basis, is the job with the highest wage. The Job and Wages Register records monthly data based on income statements of employees to the tax office administration, including type of job (full-time or part-time), type of contract (fixed or temporary), number of hours worked and gross wage. We linked the worker's job with the highest monthly wage, i.e. the main job, to the aforementioned data sets. The data set Work Location Register was used to incorporate data on the municipality in which the worker works.[10] The number of municipalities changed over the last years as various municipalities merged. We used the set of 403 municipalities that existed in the year 2014. The Firm Register was used to incorporate annual data on firm size and firm sector. Firm sectors were classified in 21 sectors according to the five-digit Standaard Bedrijfs Indeling (SBI) code, which is based on the International Standard Industrial Classification of All Economic Activities (ISIC). The extraterritorial organisations and bodies sector was excluded as no displaced worker was employed in this sector.

[10] Work location is not complete nor consistent as the CBS has only data that is measured in December on the number of plants of a firm, the location of each firm plant and the number of employees at each specific plant. Work location is imputed by the CBS using data on the location of the workplace and residential home. Each resident is linked to the closest plant of a firm, conditional on not exceeding the number of workers at that specific plant. For workers who do not work in December at the firm, we do not observe the work location. We assessed the consequences of the incompleteness and inconsistency of the variable work location by applying two robustness checks. First, we excluded all workers whose firm location is not completely observed for all jobs in the period 2006-2013 (see Table E1). Second, we ran a robustness check with firms that consist of 49 employees at maximum to ensure a low number of firm plants (see Table E2). Our results are robust.

Registers that are based on municipal and tax office administration were used to incorporate personal, home and household information. The Population Register covers monthly data on the date of birth, gender, marital status, number of household members and moving home. The Address Object Register provides data on the location of the household at the level of the neighbourhood. The Integrated Household Income data set, which is based on data measured on the 31st of December and retrieved from the tax office, was used to incorporate data on housing tenure and household income. In the case of moving home, data on housing tenure was used from the year prior to that of moving. As an example, for household moves in 2006 we use data from 2005. The Integrated Capital data set, which consists of annual records from the tax office measured on the 1st of January, was used to incorporate data on the mortgage debt, non-housing wealth and property value of the home. The annual data on mortgage debt do not cover the asset side in endowment mortgages. Hence, the levels of the mortgage debt were likely to be overestimated and the effect of the housing state is likely to be biased towards zero. To limit the potential of the attenuation bias in the LTV ratio, we operationalised the LTV ratio as a categorical variable. In the case of moving home during the year, data were used on the mortgage debt and property value from the year after the move. As an example, for household moves in 2013 we use data from the year 2014.

The following selections were made to attain an appropriate sample for our analysis. To keep the employment history of a worker tractable, all job spells that were not identified as the main job were excluded. Moreover, we excluded groups of individuals for various reasons. First, we excluded all individuals who were not active in the labour market (e.g. disabled individuals, students and early retirees), who had no administered employment history (e.g. the self-employed and long-term unemployed), or who were aged below 21 or over 59 years old. Second, our data do not distinguish between a bankrupt or restarted firm. Hence, we excluded workers from the group of displaced workers if more than 40% of all displaced workers of each bankrupt firm became re-employed at the same firm. Third, all workers who had an LTV over 133.33% in the period under observation were excluded from the sample, as a higher LTV suggests an administrative error. Finally, all workers with three or more household moves in one calendar year were excluded from the sample, as this would create the problem that we could not observe data on all homes. We kept individuals that experienced two household moves in one year, as on many occasions households move to temporary accommodations following the sale of their home.

Prior to matching, individuals were excluded from the pool of displaced or non-displaced for various reasons. First, we excluded all workers whose hourly wage or housing state was not completely observed for all jobs and homes in the period 2006-2013. In multiple cases this was possible, as we did not perfectly link all the information of the Job Register to the Job and Wages Register and the Housing registers. In addition, we excluded individuals whose hourly wage is equal to or lower than one euro. Second, we excluded all workers with an employment spell shorter than three years. An employment spell of at least three years allows us to incorporate workers who had a stable job and who experienced an unexpected and involuntary job displacement. Thereby, the likelihood of false-positives was reduced. Moreover, this selection ensures that all workers were eligible for unemployment benefits for the first three months after job displacement. Third, we excluded all workers who, in the month prior to job displacement, worked at a firm with less than ten employees or who worked less than 64 hours in that month. Finally, we had to randomly exclude around 70% of the non-displaced workers due to computational limitations.

After the process of matching, if the displaced or non-displaced worker of a matched pair is not under observation for the entire period of thirty-seven months, the matched pair was excluded. The matched pairs were excluded as the incomplete data suggests data gaps, immigration, emigration or death. This ensured a weakly balanced sample.

Appendix B. Coarsened Exact Matching Procedure

In this Appendix we explain the "Coarsened Exact Matching" (CEM) procedure. We applied CEM to cope with observable heterogeneity, i.e. potential selection bias into displacement. Exact matching on coarsened observables ensured that the treated and control workers were observably equivalent. Workers displaced due to firm bankruptcy are referred to as treated. The non-displaced are referred to as controls.

In the month of job displacement, the treated were matched with a potential match in the group of controls. The controls were required to stay employed in the month of separation of the treated. Each treated was matched with a maximum of two controls. Note that the potential month of displacement of the matched control is equivalent to the actual month of job displacement of the matched treated. Except for job displacement due to firm bankruptcy, the controls were exposed to similar risks of labour turnover as the treated. These risks represent voluntary labour turnover and involuntary labour turnover. The treated or the matched controls were not allowed to be the counterfactual of another treated worker in the other months under observation. For this reason, the order of months in the period July 2007 to June 2012, in which we separately match treated workers with control workers, was taken randomly.

Before we applied CEM, the non-matched sample consisted of 41,372 treated workers. See Table D2 for individual summary statistics for the treated and controls based on the non-matched sample. The set of observables we incorporated in the matching process consists of indicator variables for gender, age (21-30; 31-35; 35-40; 41-45; 46-50; 51-59 years), children aged 18 or lower, spouse, Dutch nationality, tenancy, LTV (0; >0-33.33; 33.33-66.67, 66.67-100; 100-133.33 per cent), type of job (full-time or part-time), type of contract (fixed or temporary), job tenure (3-6, 6-12, 12-18, and over 18 years), work location (twelve provinces), firm size (10-49; 50-99; 100-499 and 500+ employed workers), firm industry (twenty-one ISIC sectors), calendar month and calendar year. The matched sample consisted of 28,067 treated workers, which implies a matching rate of 68%. See

Table D3 for individual summary statistics of the treated and controls based on the matched sample.

The matching procedure we applied, to balance treated and controls in covariates, was successful. Based on the comparison of Table D3 to Table D2, we observe that the difference in sample means between the treated and controls was smaller after matching. See Table D4 in Appendix D for an overview of the number of matched individuals by housing state and treatment group. See Table D5 for firm size and firm sector summary statistics in the month of job actual displacement. See Table D6 for individual summary statistics for workers distinguished by their housing state.

As a robustness check, we matched besides on the previous set of matching variables on the worker's categories of the non-housing wealth position (below 0; 0-5,000; 5,000-25,000; 25,000-75,000 and over 75,000 euro) and duration of home occupancy (0-60; 60-180 and over 180 months). In this case, the number of matched treated was 15,089. In a separate robustness check, we used both the loan-to-income (LTI) ratio and LTV as approximations of the financial incentive. For this robustness check, we matched besides on the = previous set of matching variables on the LTI ratio groups (0-1.5; 1.5-3.0, 3.0-4.5; 4.5-6.0; >6). Matching also on the LTI ratio resulted in 23,209 matched treated workers. As a final robustness check, we matched besides on the previous set of matching variables on the skill level (low, medium and high education). Matching on the skill level resulted in a relatively low number of 9,346 matched treated workers. The low number of matched treated individuals was caused by the selectivity of education data, as the education data were only available for individuals if they received their diploma after 1995. The three robustness checks are discussed in Appendix C.

In every matching algorithm there is the trade-off between efficiency and lower bias, i.e. the choice between exact matching and complete matching (Rubin, 2006; Caliendo and Kopeinig, 2008). Exact matching ensures a high quality of matching as the amount of imbalance between matched treated and controls is controlled and limited. Complete matching is achieved if all treated are matched with at least one control. We performed CEM of treated to controls as we prefer a lower bias to efficiency gains. Moreover, we applied CEM as we had the opportunity to exploit rich administrative data with a high number of controls. To assess the implications of incomplete matching, we matched on the work location at the NUTS 3 level (40 areas) instead of at the provincial level (12 areas). The matched sample consisted of 20,777 matched treated workers. The matching rate decreased from 68% to 50%. Table E3 shows that the results are robust to the difference in the matching rate.

Appendix C. Robustness checks for the empirical models on worker characteristics

As discussed in Appendix B, we created a new matched sample for each of the three robustness checks. The matched samples for each robustness check were created based on different matching algorithms, which include indicator variables for the non-housing wealth position and duration of home occupancy, loan-to-income (LTI) ratio and skill, respectively.

First, we assess whether the interaction effects between job displacement and the LTV are robust to the inclusion of approximations of non-housing wealth and duration of home occupancy. The non-housing wealth position of the displaced worker can be of importance for the labour market outcomes, as it can aid job search through increased mobility or deter job search through decreased job search activity (Henley *et al.*, 1994; Goss and Phillips, 1997). The duration of home occupancy is an approximation of the willingness to move and an important driver behind the ability to become employed in a distant labour market. Moreover, we aim to capture any further unobserved heterogeneity in human capital by controlling for non-housing wealth and duration of home occupancy. Human capital is expected to be positively correlated to non-housing wealth and negatively correlated to duration of home occupancy, as high-skilled workers earn a relatively high income and are characterised by a relatively high geographical mobility (Bowles, 1970).

The non-housing wealth is represented by five zero-one indicator variables that equal one for non-housing household wealth below 0 (base category), between 0-5,000; 5,000-25,000; 25,000-75,000 and over 75,000 euro, respectively. The duration of home occupancy is represented by three zero-one indicator variables that equal one if the period in the home equals 0-60 (base category), 60-180 and over 180 months, respectively.

Table C1 shows the three-way interaction effects of the indicator variables that represent the LTV, non-housing wealth and duration of home occupancy. The three-way interaction effects of non-housing wealth and duration of home occupancy indicate that non-housing wealth and duration of home occupancy increase the losses in employment and wage, respectively. The three-way interaction effects of the LTV on employment are remarkably similar to the parameter estimates of the model in which we do not control for non-housing wealth and duration of home occupancy provided in Table 2. Note that by simultaneously controlling for the housing state, non-housing wealth and duration of home occupancy, the fixed effects coefficients of the two highest LTV groups on hourly wage become slightly higher.

Table C1

Static three-way interaction model: Housing state, non-housing wealth and duration of home occupancy (Eq. (6))

	Employment (=1)	Hourly wage (log)	Commuting distance (km)	Moving home (=1)
	(1)	(2)	(3)	(4)
Housing state:				
DISPLACED × POST ×				
LTV 0%	0.0266	-0.0091	1.6811	-0.0013
	(0.0190)	(0.0127)	(1.7643)	(0.0015)
LTV 0-33%	0.0194*	-0.0021	-0.9745	0.0010
	(0.0115)	(0.0075)	(1.1011)	(0.0008)
LTV 33-66%	0.0182*	-0.0153**	-0.8566	0.0004
	(0.0101)	(0.0070)	(0.9540)	(0.0007)
LTV 66-100%	0.0209**	-0.0246***	-0.1640	-0.0004
	(0.0101)	(0.0067)	(0.9805)	(0.0008)
LTV 100-133%	0.0687***	-0.0265***	-0.6441	0.0000
	(0.0120)	(0.0083)	(1.2265)	(0.0013)
F-Value joint significance of three-way interaction terms on LTV	6.76***	4.31***	0.69	1.52
Non-housing wealth:				
DISPLACED × POST ×				
WEALTH 0-5,000	0.0414**	0.0185	-3.4245**	-0.0041**
(in euro)	(0.0178)	(0.0142)	(1.4273)	(0.0020)
WEALTH 5,000-25,000	0.0584***	0.0237*	-3.4839**	-0.0030
(in euro)	(0.0179)	(0.0143)	(1.4281)	(0.0020)
WEALTH 25,000-75,000	0.0641***	0.0238	-2.9842*	-0.0032
(in euro)	(0.0186)	(0.0148)	(1.5324)	(0.0020)
WEALTH 75,000+	0.0318*	0.0052	-4.0246**	-0.0025
(in euro)	(0.0193)	(0.0155)	(1.5928)	(0.0020)
F-Value joint significance of three-way interaction terms on WEALTH	5.83***	2.70**	1.88	1.51
Duration of home occupancy:				
DISPLACED × POST ×				
DURATION 60-180	-0.0202**	-0.0065	1.2229	-0.0015
(in months)	(0.0087)	(0.0059)	(0.8480)	(0.0010)
DURATION180+	0.0138	-0.0090	1.3240	-0.0021*
(in months)	(0.0124)	(0.0084)	(1.0959)	(0.0013)
F-Value joint significance of three-way interaction terms on DURATION	8.46***	0.71	1.08	1.44
Number of parameters	233	233	233	233
Number of individuals	38,063	38,063	38,063	38,063
Number of observations	1,408,331	1,297,445	1,283,424	1,408,331

Notes: The regression analyses include, besides the covariates, multiple three-way interaction terms. Three-way interaction terms are included among the variables DISPLACED, POST and LTV, among the variables DISPLACED, POST and WEALTH position, among the variables DISPLACED, POST and DURATION and among the variables DISPLACED, POST and all other covariates. Loan-to-value (LTV) represents five indicator variables for homeowners' LTV expressed as a percentage. The reference category of each LTV indicator consists of workers who are tenant. The reference category of WEALTH consists of workers who have negative non-housing wealth. The reference category of DURATION consists of workers who live between zero and sixty months in their home. See Table 2 for additional notes.

Second, we assess whether our results are robust to the inclusion of the loan-to-income (LTI) ratio as an additional approximation of the financial incentive to work. The LTI ratio is constructed by the mortgage loan of year t relative to the gross household income of year $t-1$. The LTI ratio is time-invariant to prevent the situation that a large share of variation in the LTI ratio is caused by changes in the household income in the aftermath of job displacement. The LTI ratio is operationalised as five zero-one indicator variables, which equal one if the LTI ratio ranges between 0-1.5 (base category), 1.5-3.0, 3.0-4.5, 4.5-6.0 and over 6.0, respectively. The LTV and LTI are highly correlated: the correlation coefficient of the categorical variables LTV and LTI is around 0.88.

Table C2 shows the interaction effects of both the LTV and job displacement and the LTI ratio and job displacement. We find that the coefficients of the LTV become higher if we include variables that represent the LTI ratio. Compared with displaced workers who have an LTI ratio between 0-1.5, displaced workers with an LTI ratio over 6.0 experience a higher loss in the hourly wage. We show that our results are robust to the inclusion of variables that represent non-housing wealth, duration of home occupancy and the LTI ratio.

Table C2
Empirical model with three-way interaction terms using LTV and LTI

	Employment (=1)	Hourly wage (log)	Commuting distance (km)	Moving home (=1)
	(1)	(2)	(3)	(4)
Housing state:				
DISPLACED × POST ×				
LTV 0%	0.0153	-0.0171*	0.8926	-0.0005
	(0.0141)	(0.0088)	(1.3975)	(0.0008)
LTV 0-33%	0.0482***	-0.0073	-0.9543	0.0002
	(0.0096)	(0.0059)	(0.9207)	(0.0005)
LTV 33-66%	0.0423***	-0.0159*	0.0848	0.0009
	(0.0144)	(0.0093)	(1.4070)	(0.0007)
LTV 66-100%	0.0400**	-0.0381***	0.7445	-0.0005
	(0.0166)	(0.0109)	(1.6407)	(0.0009)
LTV 100-133%	0.0559***	-0.0362***	-0.3077	0.0014
	(0.0185)	(0.0122)	(1.8178)	(0.0012)
F-Value joint significance of three-way interaction terms on LTV	5.75***	3.67***	0.79	2.39**
Loan-to-income:				
Three-way interaction term DISPLACED × POST ×				
LTI 1.5-3.0	-0.0030	-0.0097	-0.5201	-0.0009*
	(0.0121)	(0.0075)	(1.1694)	(0.0005)
LTI 3.0-4.5	-0.0116	-0.0037	-1.5131	0.0004
	(0.0149)	(0.0097)	(1.4776)	(0.0007)
LTI 4.5-6.0	0.0016	0.0178*	-1.1242	0.0003
	(0.0167)	(0.0108)	(1.6364)	(0.0009)

$\mathrm{LTI} > 6$	-0.0070	0.0237**	-1.0475	-0.0002
	(0.0174)	(0.0117)	(1.7013)	(0.0010)
F-Value joint significance of three-way interaction terms on LTI	0.58	5.01***	0.32	2.81**
Number of parameters	208	208	208	208
Number of individuals	60,498	60,498	60,498	60,498
Number of observations	2,238,426	2,067,929	2,045,376	2,238,426

Notes: Parameter estimates of the three-way interaction terms among $\mathrm{DISPLACED}, \mathrm{POST}$ and LTI, and among $\mathrm{DISPLACED}, \mathrm{POST}$ and LTI are displayed. The reference categories of LTI and LTI consist of workers who are tenant and who have an LTI ratio between 0 and 1.5, respectively. The parameter estimates of the covariates and the two-way interaction terms are not reported. See Table 2 for additional notes.

Third, we assess whether our results are robust to the inclusion of the worker's skill level. The impact of skill on the post-displacement losses is ambiguous. On the one hand, high-skilled workers have a higher job offer arrival rate. The higher job offer arrival rate is driven by the higher willingness to commute and relocate (Zax, 1991). Consequently, the distribution of job offers and the market power of employers is increasing and decreasing, respectively, in the skill level of the displaced worker. Hence, the costs of job displacement for high-skilled displaced workers are likely to be relatively low. On the other hand, high-skilled workers have a relatively high wage premium due to their firm-specific human capital. If high-skilled workers invested more in human capital than low-skilled workers, the displacement effect on wage would be higher for high-skilled workers. Hijzen *et al.* (2010) show that skilled workers have higher initial losses in wage than unskilled workers, but two years after job displacement the skill difference in wage losses becomes statistically insignificant. Farber (2015) shows that a higher number of years in education decreases the losses in employment and earnings.

The skill level is based on the international standard classification of education 1997, and is represented by three variables that equal one if the skill level is low (base category), medium, and high, respectively. We only incorporated the skill level in a robustness check, because the education data is highly selective as it is only available for individuals who received their diploma after the year 1995.

The fixed effects coefficients of LTV on employment that are shown in Tables C3 and C4 are based on the sample in which we matched on, among other covariates, the housing state and skill level. The coefficients of the three-way interaction effects based on the LTV without the indicator variables that represent the skill level (see Table C3) are similar to the coefficients based on the LTV with the indicator variables that represent the skill level displayed in Table C4. Hence, we argue that the results are robust to the inclusion of variables that represent the skill level.

Compared to the parameter estimates provided in Table 2 of the model in which we do not match and control for the skill level, the coefficients shown in Tables C3 and C4 are different. Specifically, by matching on and controlling for the housing state and skill level, the coefficients of the two highest LTV groups on hourly wage become smaller. Importantly, the difference in results is completely driven by the difference in the sample.

Table C3

Static three-way interaction model: Housing state, sample of Table C4 (Eq. (6))

	Employment (=1)	Hourly wage (log)	Commuting distance (km)	Moving home (=1)
	(1)	(2)	(3)	(4)
Housing state:				
DISPLACED × POST ×				
LTV 0%	0.0200	0.0251	1.4911	-0.0014
	(0.0248)	(0.0158)	(2.5745)	(0.0026)
LTV 0-33%	0.0178	0.0061	-0.1915	0.0013
	(0.0143)	(0.0096)	(1.3097)	(0.0011)
LTV 33-66%	0.0005	-0.0013	-1.1895	0.0018
	(0.0126)	(0.0087)	(1.3035)	(0.0011)
LTV 66-100%	0.0183	-0.0094	0.2853	0.0007
	(0.0122)	(0.0081)	(1.2193)	(0.0012)
LTV 100-133%	0.0541***	-0.0028	-1.1474	0.0044***
	(0.0136)	(0.0088)	(1.4268)	(0.0016)
F-Value joint significance of three-way interaction terms on LTV	3.93***	1.17	0.55	2.44**
Number of parameters	209	209	209	209
Number of individuals	23,015	23,015	23,015	23,015
Number of observations	851,555	774,248	763,518	851,555

Notes: The regression analyses include, besides the covariates, multiple three-way interaction terms. Three-way interaction terms are included among the variables DISPLACED, POST and LTV and among the variables DISPLACED, POST and all other covariates. See Table 2 for additional notes.

Table C4

Static three-way interaction model: Housing state and skill level (Eq. (6))

	Employment (=1)	Hourly wage (log)	Commuting distance (km)	Moving home (=1)
	(1)	(2)	(3)	(4)
Housing State:				
DISPLACED × POST ×				
LTV 0%	0.0196	0.0234	1.0166	-0.0015
	(0.0249)	(0.0156)	(2.5993)	(0.0026)
LTV 0-33%	0.0176	0.0059	-0.4890	0.0013
	(0.0144)	(0.0096)	(1.3303)	(0.0012)
LTV 33-66%	0.0002	-0.0028	-1.6871	0.0018
	(0.0128)	(0.0088)	(1.3387)	(0.0011)
LTV 66-100%	0.0185	-0.0124	-0.5028	0.0006
	(0.0125)	(0.0083)	(1.2653)	(0.0012)
LTV 100-133%	0.0545***	-0.0083	-2.1962	0.0042***
	(0.0139)	(0.0090)	(1.4704)	(0.0016)
F-Value joint significance of three-way interaction terms on LTV	3.88***	1.44	0.82	2.31**

Skill:				
DISPLACED × POST ×				
SKILL MEDIUM	0.0020	-0.0033	0.8570	-0.0003
	(0.0101)	(0.0065)	(0.9907)	(0.0007)
SKILL HIGH	-0.0011	0.0236**	4.5921***	0.0008
	(0.0144)	(0.0098)	(1.5414)	(0.0011)
F-Value joint significance of three-way interaction terms on SKILL	0.05	5.23***	4.85***	0.77
Number of parameters	213	213	213	213
Number of individuals	23,015	23,015	23,015	23,015
Number of observations	851,555	774,248	763,518	851,555

Notes: The regression analyses include, besides the covariates, multiple three-way interaction terms. Three-way interaction terms are included among the variables DISPLACED, POST and LTV, among the variables DISPLACED, POST and SKILL and among the variables DISPLACED, POST and all other covariates. The reference category of SKILL consists of workers who are of low skill. See Table 2 for additional notes.

Appendix D. Summary statistics

Table D1 provides multiple statistics that improve our understanding of the within change in hourly wage and commuting distance for the displaced and non-displaced. The within change is calculated by taking the difference between the values of each variable eighteen months after job displacement and the month of potential or actual job displacement.

Table D1
The within change in hourly wage and commuting distance for displaced and non-displaced workers

	Hourly wage (log)		Commuting distance (km)	
	Displaced	Non-displaced	Displaced	Non-displaced
	(1)	(2)	(1)	(2)
Mean	-0.0299	0.0381	3.8863	0.2913
St. Dev.	0.3080	0.1831	32.4209	14.8087
Variance	0.0948	0.0335	1,051.1125	219.2979
Skewness	-1.1467	1.8761	1.1807	0.8068
Kurtosis	30.1173	73.4905	14.4334	57.2154
1th percentile	-0.9637	-0.5050	-94.8127	-48.5023
5th percentile	-0.4590	-0.1555	-37.2684	-6.2129
25th percentile	-0.1289	-0.0043	-1.6361	0
50th percentile	-0.0010	0.0309	0	0
75th percentile	0.0933	0.0832	9.1485	0
95th percentile	0.3233	0.2389	52.8610	8.8410
99th percentile	0.7145	0.5530	130.6124	52.0451
Number of observations	20,487	46,690	19,613	46,405

Notes: The individual summary statistics are based on the within change, measured by the difference in the values of each variable between the eighteenth month after job displacement and the month of job displacement.

The displaced have a negative within hourly wage change while the controls have a positive within hourly wage change. Half of all displaced workers experience no or a modest decline in commuting distance. For the displaced, the within hourly wage change follows a distribution with a long tail to the left. For the non-displaced, the within hourly wage change follows a distribution with a long tail to the right.

Half of all displaced workers experience a sharp increase in commuting distance after job displacement. The mean within change in the commuting distance for the controls is close to zero. Only the bottom and top 5% experience a relatively small decrease and increase, respectively. The within commuting change has a substantial skewness and follows an asymmetrical distribution with a long tail to the right, especially for the displaced.

Table D2

Individual summary statistics using the non-matched sample

	Displaced		Non-displaced		
	Mean	St. Dev.	Mean	St. Dev	t-statistic
Employment[a] (=1)	1	0	1	0	
Hourly wage (log)	2.8673	0.3823	2.8037	0.4152	33.83***
Hourly wage (€)	19.0829	11.8790	18.6686	37.2715	7.06***
Commuting distance (km)	14.8012	21.1221	17.4054	24.4851	-25.06***
Moving home (=1)	0.0040	0.0632	0.0044	0.0660	-1.16
LTV[b] (%)	60.3364	33.5770	61.1907	34.3969	-4.42***
LTI ratio	2.9839	31.5792	2.8798	3.3806	0.67
Mortgage debt[b] (€)	121,363	116,377	111,488	113,598	17.25***
Property value[b] (€)	214,683	217,997	196,659	262,524	16.80***
Non-Housing Wealth (€)	44,344	21,368	41,989	21,583	22.40***
Annual household income (€)	67,777	295,066	56,493	214,775	7.78***
Age (in years)	44.3824	8.9533	43.7214	9.1803	15.01***
Female (=1)	0.4397	0.4963	0.2600	0.4386	73.59***
Dutch (=1)	0.9119	0.2834	0.9054	0.2927	4.69***
Spouse (=1)	0.6241	0.4844	0.6023	0.4894	9.13***
No child (=1)	0.5390	0.4985	0.5534	0.4971	-5.84***
Household members (#)	2.9652	1.3023	2.9496	1.3010	2.44**
Fixed contract (=1)	0.9531	0.2114	0.9176	0.2750	34.18***
Full-time job (=1)	0.6005	0.4898	0.7227	0.4477	-50.74***
Tenure in the job (in months)	151.7854	96.9591	134.5800	89.9990	36.08***
Manufacturing sector (=1)	0.2462	0.4308	0.4908	0.4999	-115.40***
Duration of home occupancy (in months)	108.9448	59.7565	110.4477	61.2194	-5.11***
Number of individuals (#)	41,372		39,532,897		

Notes: The individual summary statistics, provided for the month of actual or potential displacement, are based on the sample prior to matching. The time period under observation is from July 2007 to June 2012. Sample means with standard deviations are provided for the treatment group and control group. The t-statistic is provided to assess whether the mean and standard deviation of each variable for the groups of displaced and non-displaced workers are statistically different from each other. ***,**,*, correspond to the significance level of 1%, 5%, 10%, respectively.

[a] By construction, all displaced and non-displaced were employed in the month of actual or potential displacement.

[b] The LTV and property value was observed if the worker is a homeowner and not if the worker is a tenant. Tenants can have a mortgage debt if they owned a home prior to their current rental home.

Table D3
Individual summary statistics using the matched sample

	Displaced		Non-displaced		
	Mean	St. Dev.	Mean	St. Dev	t-statistic
Employment[a] (=1)	1	0	1	0	
Hourly wage (log)	2.8493	0.3698	2.8349	0.4073	4.99***
Hourly wage (€)	18.6579	10.5727	19.1353	33.8003	-2.88***
Commuting distance (km)	15.2014	21.6747	17.1187	24.1474	-11.32***
Moving home (=1)	0.0040	0.0633	0.0040	0.0628	0.13
LTV[b] (%)	60.0975	33.0162	60.2507	33.2253	-0.53
LTI ratio	2.8476	3.5155	2.8618	3.2339	-0.55
Mortgage debt[b] (€)	115,502	112,330	112,974	113,040	3.00***
Property value[b] (€)	205,499	166,108	202,714	298,290	1.66*
Non-Housing Wealth (€)	43,194	20,386	42,674	22,126	3.30***
Annual household income (€)	62,833	325,497	55,611	206,553	3.35***
Age (in years)	44.1032	9.2292	44.2006	9.1774	-1.41
Female (=1)	0.2043	0.4032	0.2101	0.4074	-1.89*
Dutch (=1)	0.9518	0.2142	0.9450	0.2281	4.17***
Spouse (=1)	0.6435	0.4790	0.6366	0.4810	1.92*
No child (=1)	0.5393	0.4985	0.5507	0.4974	-3.06***
Household members (#)	3.0266	1.3093	2.9869	1.2947	4.06***
Fixed contract (=1)	0.9755	0.1545	0.9688	0.1740	5.60***
Full-time job (=1)	0.7933	0.4050	0.7803	0.4140	4.23***
Tenure in the job (in months)	144.1697	92.6080	143.6421	93.7002	0.76
Manufacturing sector (=1)	0.5391	0.4985	0.5324	0.4990	1.81*
Duration of home occupancy (in months)	112.7043	60.9245	113.2692	61.0827	-1.24
Number of individuals (#)	28,067		48,785		

Notes: The individual summary statistics, provided for the month of actual or potential displacement, are based on the sample after matching. The time period under observation is from July 2007 to June 2012. Sample means with standard deviations are provided for the treatment group and control group. The t-statistic is provided to assess whether the mean and standard deviation of each variable for the groups of displaced and non-displaced workers are statistically different from each other. ***,**,*, correspond to the significance level of 1%, 5%, 10%, respectively.
[a] By construction, all displaced and non-displaced were employed in the month of actual or potential displacement.
[b] The LTV and property value was observed if the worker is a homeowner and not if the worker is a tenant. Tenants can have a mortgage debt if they owned a home prior to their current rental home

Table D4
Number of matched individuals

	Number of individuals		
	Displaced	Non-displaced	All
	(1)	(2)	(3)
Housing state			
Tenant	7,318	12,551	19,869
LTV 0%	911	1,437	2,348
LTV 0-33%	4,176	7,424	11,600
LTV 33-66%	6,526	11,528	18,054
LTV 66-100%	6,237	10,973	17,210
LTV 100-133%	2,899	4,872	7,771
Total	28,067	48,785	76,852

Notes: The number of matched individuals is provided for each housing state and treatment group.

Table D5
Firm summary statistics in the month of job displacement

	Firms			
	Bankrupt firms		Non-bankrupt firms	
	Mean	St. Dev.	Mean	St. Dev.
Firm size:				
1-9 employees (=1)	0	0	0	0
10-49 employees (=1)	0.7298	0.4441	0.6443	0.4787
50-99 employees (=1)	0.1133	0.3170	0.1437	0.3508
100-499 employees (=1)	0.1045	0.3060	0.1602	0.3668
500+ employees (=1)	0.0524	0.2228	0.0519	0.2217
Firm sector:				
Agriculture, forestry and fishing (=1)	0.0095	0.0971	0.0044	0.0662
Mining and quarrying (=1)	0	0	0	0
Manufacturing (=1)	0.2302	0.4210	0.3317	0.4708
Electricity, gas, steam and air conditioning supply (=1)	0	0	0	0
Water supply; sewerage, waste management and remediation activities (=1)	0.0015	0.0390	0.0005	0.0217
Construction (=1)	0.2081	0.4060	0.2257	0.4180
Wholesale and retail trade; repair of motor vehicles and motorcycles (=1)	0.1944	0.3958	0.2082	0.4060
Transportation and storage (=1)	0.0720	0.2585	0.0530	0.2241
Accommodation and food service activities (=1)	0.0141	0.1179	0.0055	0.0740
Information and communication (=1)	0.0369	0.1886	0.0181	0.1334
Financial and insurance activities (=1)	0.0288	0.1671	0.0229	0.1496
Real estate activities (=1)	0.0051	0.0715	0.0013	0.0364
Professional, scientific and technical activities (=1)	0.0823	0.2748	0.0566	0.2311
Administrative and support service activities (=1)	0.0655	0.2474	0.0336	0.1802
Public administration and defence; compulsory social security (=1)	0	0	0	0
Education (=1)	0.0057	0.0754	0.0048	0.0689
Human health and social work activities (=1)	0.0331	0.1790	0.0292	0.1684
Arts, entertainment and recreation (=1)	0.0044	0.0660	0.0014	0.0368
Other service activities (=1)	0.0084	0.0912	0.0032	0.0561
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use (=1)	0	0	0	0
Activities of extraterritorial organisations and bodies (=1)	0	0	0	0
Number of firms (#)	5,252		38,354	

Notes: Means and standard deviations are provided at the firm level. Bankrupts firms consist of all distinct firms of which an entity is declared bankrupt and a worker is displaced in the month of actual displacement. Non-bankrupt firms consist of all distinct firms where matched non-displaced workers work in the month of potential displacement.

Table D6
Individual summary statistics using the matched sample for each housing state

	Housing State					
		LTV				
	Tenant	0%	0-33%	33-66%	66-100%	100-133%
Employment[a] (=1)	1	1	1	1	1	1
Hourly wage (log)	2.6624	2.8597	2.8964	2.9305	2.9308	2.8799
Hourly wage (€)	15.0489	18.7715	19.3148	20.2091	20.2824	19.5913
Commuting distance (km)	12.6395	13.8002	14.2600	16.0523	17.0940	17.3726
Moving home (=1)	0.0081	0.0063	0.0016	0.0023	0.0025	0.0041
LTV[b] (%)	/	0	20.0143	49.9469	83.3867	110.4669
LTI ratio	0.0392	0	1.4670	3.3251	5.3333	6.3039
Mortgage debt[b] (€)	1,480	0	62,541	141,047	213,857	242,046
Property value[b] (€)	/	319,560	322,340	283,972	257,800	219,735
Non-Housing Wealth (€)	34,497	52,771	48,529	47,187	44,531	42,187
Annual household income (€)	24,963	221,394	98,895	69,580	61,672	45,320
Age (in years)	43.1437	48.0416	49.3004	46.7595	41.7191	36.5787
Female (=1)	0.2269	0.1308	0.1459	0.2088	0.2174	0.2167
Dutch (=1)	0.8772	0.9951	0.9946	0.9806	0.9666	0.9647
Spouse (=1)	0.4167	0.6347	0.8303	0.7859	0.6707	0.5476
No child (=1)	0.7117	0.7328	0.5686	0.4624	0.4126	0.4606
Household members (#)	2.4813	3.0383	3.3625	3.3206	3.1596	2.9210
Fixed contract (=1)	0.9581	0.9847	0.9840	0.9853	0.9818	0.9680
Full-time job (=1)	0.8058	0.8309	0.8000	0.7664	0.7847	0.8229
Tenure in the job (in months)	127.9304	181.0424	176.5913	163.9481	132.9686	104.1533
Manufacturing sector (=1)	0.5063	0.7084	0.6560	0.5537	0.4924	0.4667
Duration of home occupancy (in months)	104.2958	148.4447	153.8858	130.8799	92.2686	64.0915
Number of individuals (#)	7,318	911	4,176	6,526	6,237	2,899

Notes: Sample means, based on the sample after matching, are provided for each housing state of the treatment group in the month of actual displacement. The time period under observation is from July 2007 to June 2012.
[a] By construction, all displaced and non-displaced are employed in the month of actual or potential displacement.
[b] The LTV and property value was observed if the worker is homeowner and not if the worker is tenant. Tenants can have a mortgage debt if they owned a home prior to their current rental home

Appendix E. Robustness checks for models on margins of adjustment

Table E1
Static two-way interaction model for sample of workers who have no missing information on the firm location (Eq. (4))

	Employment (=1)	Hourly wage (log)	Commuting distance (km)	Moving home (=1)
	(1)	(2)	(3)	(4)
Two-way interaction term				
$\mathrm{DISPLACED} \times \mathrm{POST}$	-0.3562***	-0.0399***	4.7337***	-0.0005***
	(0.0028)	(0.0017)	(0.2549)	(0.0002)
Number of parameters	149	149	149	149
Number of individuals	57,668	57,668	57,668	57,668
Number of observations	2,133,716	1,978,233	1,978,233	2,133,716

Notes: Each column gives the dependent variable. Clustered (by individual) standard errors are in parentheses. $***,**,*$, correspond to the significance level of 1%, 5%, 10%, respectively. The reference category of $\mathrm{DISPLACED}$ and POST, consists of the non-displaced workers and pre-displacement period, respectively. The regression analyses include indicator variables for housing state (5), age (3), children aged 18 or lower, spouse, the number of household members (3), the NUTS 3 location of the household (39) and calendar month (95). The period under observation is from January 2006 to December 2013. The parameter estimates of the covariates and the main effect of POST are not reported.

Table E2
Static two-way interaction model for sample with firms which have 49 employees at maximum (Eq. (4))

	Employment (=1)	Hourly wage (log)	Commuting distance (km)	Moving home (=1)
	(1)	(2)	(3)	(4)
Two-way interaction term				
$\mathrm{DISPLACED} \times \mathrm{POST}$	-0.3274***	-0.0432***	5.2372***	-0.0009***
	(0.0031)	(0.0018)	(0.2701)	(0.0002)
Number of parameters	149	149	149	149
Number of individuals	39,898	39,898	39,898	39,898
Number of observations	1,476,226	1,372,192	1,356,664	1,476,226

Notes: Each column gives the dependent variable. Clustered (by individual) standard errors are in parentheses. $***,**,*$, correspond to the significance level of 1%, 5%, 10%, respectively. The reference category of $\mathrm{DISPLACED}$ and POST, consists of the non-displaced workers and pre-displacement period, respectively. The regression analyses include indicator variables for housing state (5), age (3), children aged 18 or lower, spouse, the number of household members (3), the NUTS 3 location of the household (39) and calendar month (95). The period under observation is from January 2006 to December 2013. The parameter estimates of the covariates and the main effect of POST are not reported.

Table E3
Static two-way interaction model for sample of workers who are matched on 40 NUTS 3 areas (Eq. (4))

	Employment (=1)	Hourly wage (log)	Commuting distance (km)	Moving home (=1)
	(1)	(2)	(3)	(4)
Two-way interaction term				
DISPLACED × POST	-0.3533***	-0.0522***	4.6608***	-0.0007***
	(0.0027)	(0.0017)	(0.2634)	(0.0002)
Number of parameters	149	149	149	149
Number of individuals	53,153	53,153	53,153	53,153
Number of observations	1,966,661	1,812,051	1,792,504	1,966,661

Notes: Each column gives the dependent variable. Clustered (by individual) standard errors are in parentheses. ***,**,* , correspond to the significance level of 1%, 5%, 10%, respectively. The reference category of DISPLACED and POST, consists of the non-displaced workers and pre-displacement period, respectively. The regression analyses include indicator variables for housing state (5), age (3), children aged 18 or lower, spouse, the number of household members (3), the NUTS 3 location of the household (39) and calendar month (95). The period under observation is from January 2006 to December 2013. The parameter estimates of the covariates and the main effect of POST are not reported.

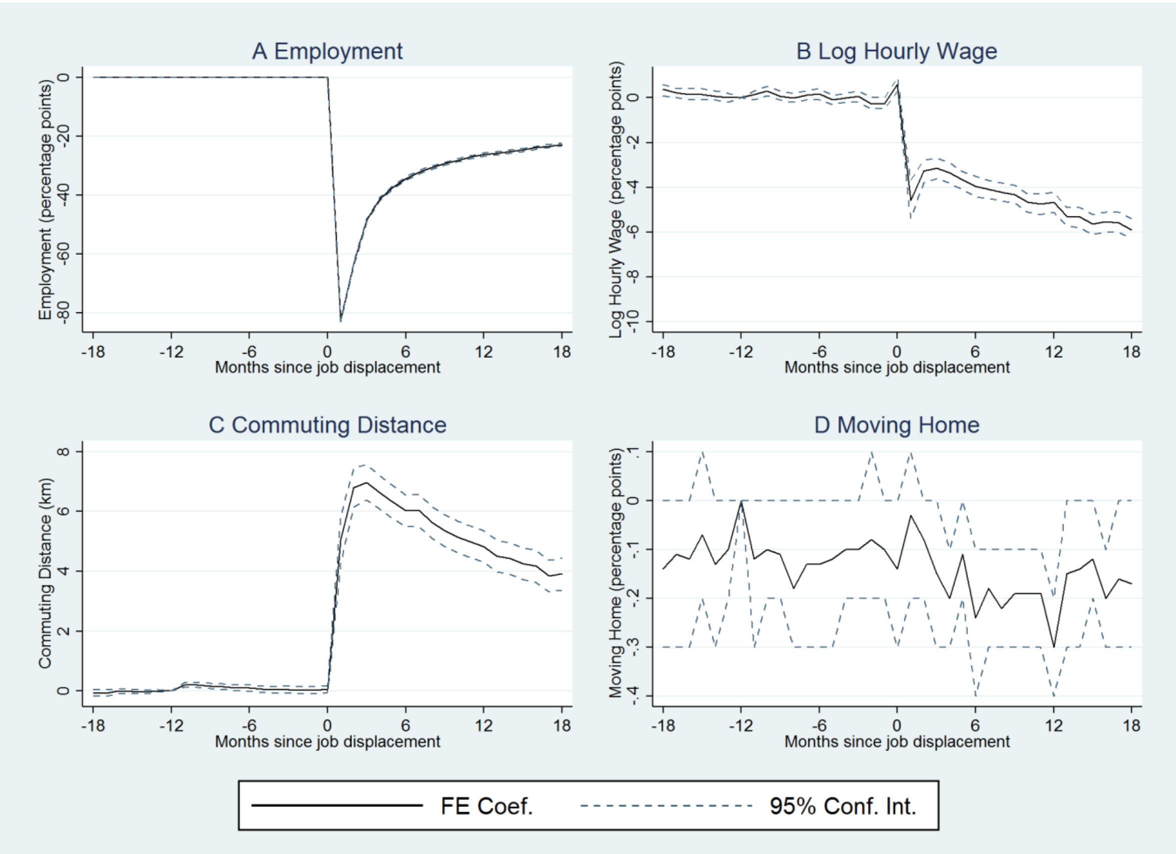

Figure E1: Displacement effects on employment (*A*), log hourly wage (*B*), commuting distance (*C*) and moving home (*D*) (Eq. (5)). For B and C, the post-displacement observations are included conditional on being in the first post-displacement job. The 95% confidence intervals are computed using standard errors clustered by individual. All four fixed effects regression models include 218 parameters of which there are 36 two-way interaction terms (base month is the twelfth month prior to job displacement). See Table 1 for additional notes and statistics.

Appendix F. Search intensity

In this appendix we assess the effect of tenancy and owners' LTV on search intensity. We tend to get a clearer view on whether the LTV determines job search intensity, because we found evidence suggesting that search intensity plays a role in post-displacement labour market outcomes. The administrative data are not sufficient to examine this as the data do not cover approximations of workers' search intensity.

This additional analysis makes use of survey data that consists of pooled cross-sections administered by centERdata (LISS, 2015). The annual data cover the period 2008-2015. The two dependent variables are approximations of the search intensity. The indicators are measured by the number of applications sent over the previous two months and the number of channels used to seek work over the previous two months. The main independent variables are four approximations of the housing state, indicated by housing tenure and three LTV groups. Tenancy is an indicator variable that equals one if the individual is a tenant, and zero otherwise. The LTV is expressed as a percentage and measured by the self-reported mortgage loan relative to the self-reported property value. We chose to construct three LTV groups from 0 to 150% in increments of 50%, because of the low number of observations.

We made various selections. First, we excluded all workers who reported that they were employed. Second, we excluded individuals who were not active in the labour market, for example as they were disabled, students or early retirees. Third, we excluded all workers who had an LTV over 150%. Fourth, we normalised the number of applications sent by unemployed workers to employers to a maximum of thirty applications.

Table F1
Effect of the housing state on unemployed search intensity[a]

	Applications sent (#)	Channels used (#)
	(1)	(2)
Effect by housing state		
LTV 0-50%	-1.3216*	-0.6008**
	(0.7397)	(0.2437)
LTV 50-100%	-0.4621	0.0926
	(0.9869)	(0.2333)
LTV 100-150%	0.2823	0.1971
	(1.5000)	(0.2917)
Number of parameters	35	35
Number of individuals	664	738
Number of observations	1,073	1,221

Notes: Clustered (by individual) standard errors are in parentheses. ***,**,*, correspond to the significance level of 1%, 5%, 10%, respectively. The reference category of the housing state consists of workers who are tenant. The estimates of the covariates are not reported. The regression analyses include indicator variables for gender, age (4), number of children (4), spouse, widowed, divorced, separated, the number of household members (3), the degree of urbanisation of the place of residence (4), education (5) and calendar year (7).

Table F1 shows the parameter estimates of the OLS regression models. Column (1) and Column (2) display the estimates of the number of applications sent and number of channels used, respectively. Compared with tenants (the reference category), low LTV owners have a significantly lower number of applications sent and a lower number of channels used. The difference between tenants and unemployed owners with an LTV between 50-150% is not statistically significant. The parameter estimates suggest that tenants have a higher search intensity than owners who have a low LTV. Moreover, the results indicate a positive correlation between the LTV and search intensity.