Negative Home Equity and Household Mobility: Evidence from Administrative Data[*]

Sander van Veldhuizen, Benedikt Vogt, Bart Voogt

February 2016

Abstract

We investigate the impact of negative home equity on household mobility. We employ a unique administrative data set, which contains annual mobility and a large set of homeowner characteristics of more than two million Dutch households. We exploit the regional variation of the substantial and unanticipated housing market bust starting in 2008 until 2012 to identify the effect of negative home equity on mobility. We find that households falling into negative equity due to unanticipated declining house prices are 18 percent less likely to move compared to households maintaining positive home equity.

JEL CODES: D10, D14, H31

Keywords: Household mobility, negative home equity, LTV, administrative data

[*] We are especially thankful to Leon Bettendorf, Michiel Bijlsma, Jonneke Bolhaar, Sander Gerritsen, Sophie Kramer, Mauro Mastrogiacomo, Remco Mocking, Marielle Non, Ali Palali, Daan Struyven, Ulf Zoelitz and seminar participants at CPB and the NED 2015 for valuable comments. We are willing to share the Stata Do files which are used to construct the data set and to conduct the analysis. The data used for our analysis is confidential data and only available for personally registered users of Statistics Netherlands (CBS-remote access). All remaining errors are ours.

1. Introduction

Between the early nineties and the first half of 2008 the Netherlands faced aggregate house price increases. When the Great Recession hit the Netherlands in the fourth quarter of 2008, house prices started to decline. From the peak in 2008 until 2013, nominal house prices cumulatively declined by 20 percent. When house prices declined the fraction of households having negative home equity strongly increased. According to Statistics Netherlands (CBS) the number of households having a higher mortgage than the underlying property value, increased by 188 percent in the period 2008-2013. In the same period housing transactions plummeted by 65 percent[2], suggesting that the house price bust contributed to the decline in household mobility.

At least two explanations exist for this pattern of falling household mobility and falling house prices. One explanation is that households with negative home equity, so-called underwater mortgages, are unable to refinance the loss incurred when selling their house. These households are "locked" in their current property.[3] Hence, even if these households would want to move the economic situation prevents them from moving.

Another explanation is that households with negative home equity do not want to move, rather than not being able to move. In the Netherlands, negative home equity is not always the result of a decrease in house prices. On the contrary, mortgage origination with loan-to-value (LTV) ratio's over 100% are not unusual, since regulation allows to use the loan proceeds for financing transaction costs (e.g. stamp duty) as well as home improvements. Such households might be relatively immobile by choice, irrespective of the developments

[2] All numbers reported are retrieved from the official site of statistics Netherlands. http://statline.cbs.nl/Statweb/. Last access 20th October 2015.

[3] Stein (1995) provides a theoretical model for why households can be locked in. Henley (1998) provides empirical evidence for a strong "locked in" effect of households with negative home equity.

in the housing market. When testing the housing-lock-hypothesis, it is therefore important to control for potential self-selection into LTV-ratios.

The aim of this paper is to investigate the impact of negative home equity on household mobility. We first follow the conventional approach in the literature and study the relationship between negative home equity and mobility in general. Second, we distinguish between households which are underwater 'by choice' and households which are underwater involuntary due to the decline in house prices after 2008.

We find two effects of underwater mortgages on household mobility. First, negative home equity is associated with a lower probability of moving. Our estimates of a naïve estimation on the full sample period of 2006-2012 reveal a 26% - 32% lower annual mobility rate for households with negative home equity compared to households with positive home equity. Second, when we estimate the effects of negative home equity for those households who moved into negative equity after 2008, we only find a decline in mobility rate between 18 - 19%. Our results remain robust to various specifications.

To arrive at these main results, we construct a unique panel data set from various administrative data sets from Statistics Netherlands. The data contains, amongst others, information about the mobility of households, mortgage values and the underlying property value in the period from 2006 until 2012. This allows us to calculate LTV-ratios of homeowners and follow them over time.

The empirical strategy in this paper is twofold. In a first step, we follow the standard approach in the literature (see for instance Ferreira et al. 2010, Andersson and Mayock 2014, Struyven 2015). We compare household mobility between two groups: households having negative home equity and households with positive home equity. We employ panel regressions to estimate the effect of high LTV's on mobility, where we include postal code area - year fixed effects to control for unobserved heterogeneity. However, this approach has two caveats. First, it does not take into account potential self-selection in high LTV classes. Second, it ignores potential unobserved household characteristics such as education and financial literacy that determine LTV choice and hence mobility. We address this drawback in our second strategy. The second empirical strategy exploits the substantial (and unexpected) decline in house prices in the period 2008 to 2011 to identify households which went underwater involuntarily. This means that their home equity would have remained positive in absence of the decline in house prices. We make use of the panel structure of our data and compare the mobility of households who *got* into negative home equity to the mobility of households who remained with positive home equity after 2008. In our robustness checks we also employ household fixed effects to control for potential unobserved characteristics on the household level.

This study has two key contributions to the empirical literature on home equity and mobility. First, we construct a dataset which measures annual mobility patterns of *all* homeowners in the Netherlands, who bought a house since 1995.[4] This includes newly built property houses and existing houses. Most of the recent studies make use of selected samples, survey data or do not include newly built properties. Secondly, we aim to differentiate between households which select themselves in negative home equity and households which have negative home equity as a result of a decrease in house prices.

There are two recent papers which also investigate household mobility and negative home equity in the Netherlands. Struyven (2015) investigates the effect of negative home equity on household mobility using similar data. He finds a significant negative effect of negative home equity on household mobility. Our study is different in two aspects. First, we are able to incorporate newly built properties in our analysis. Secondly, we distinguish between

[4] We do not have data on addresses of the population prior to 1995. Therefore, we are unable to identify (with certainty) homeowners who bought a house prior to 1995 and haven't moved since then.

several channels through which home equity might influence household mobility. More specifically, we: (i) differentiate between households which are underwater due to the LTV-ratio at origination and households which went underwater due to housing market bust and (ii) we control for the effect of the housing price decline itself. Steegmans and Hassink (2015) investigate the effect of negative home equity for a selected sample of homeowners while controlling for loss aversion.[5] They find that both loss aversion and negative equity limit household mobility. However, they also do not differentiate between possible effects of becoming an underwater household versus selection effects into negative home equity.[6]

We also contribute to the international literature on negative home equity and mobility. Many studies use data from the US which differ substantially in the institutional settings from many European countries. More specifically, in the Netherlands lenders have full recourse and benefit from tax subsidies in the form of mortgage interest deductibility. Similar institutional settings existed for instance in Spain and Ireland and still exist in Denmark and Sweden (IMF, 2015 and Turk, 2015). Furthermore, the LTV-ratios at origination are on average substantially higher in the Netherlands than in the US, while default rates are relatively low. DNB (2015) provides a detailed overview on default rates and LTVs for the Dutch mortgage market making use of loan level data for the period 2014 and 2015.

The evidence from the international literature on household mobility and negative equity is mixed. Bricker and Bucks (2016) investigate household mobility in the US in the period from 2007-09 by making use of the Survey of Consumer Finance. They find a positive association between negative home equity and the probability of moving. They explain this

[5] More specifically, they select only owners of row houses which might lead to sample-selection effects.
[6] Moreover, they take the purchasing price of the house as reference point at which households evaluate their prospective loss. We take a different approach and introduce a change in house price dummy after 2008. Hence the reference price of the house price change is the house price in 2008.

finding with involuntary moves due to for instance foreclosure. Andersson and Mayock (2014) find a decline in household mobility of 25% due to reductions in home equity for homeowners in Florida. Ferreira et al. (2010) find that mobility of homeowners in the US with negative equity is almost 50% lower than the mobility of other owners. The results of this study are revised by Schulhofer-Wohl (2011) who finds that households with negative equity are more likely to move. This is more in line with the evidence presented by Coulson and Grieco (2013) who find that negative home equity is associated with higher levels of mobility for households in the US. Engelhardt (2003) finds little evidence that falling house prices constrain mobility using survey data from the US in the period between 1985– 1996. He explains that nominal loss aversion can be key driver for a decline in mobility. This explanation is supported by further empirical evidence of Einiö et al (2008). In our robustness checks we run specifications which control for this potential mechanism by taking the decline in house prices into account.

This study fits within the current policy debate in many OECD countries on the effects of household debt-overhang on economic outcomes (see for instance IMF, 2014). One topic of debate is on the re-profiling of underwater mortgages (on a large scale). A rationale for such a policy could be that negative home equity and household deleveraging can potentially generate negative externalities by (1) reducing mobility that affects the recovery of the housing market, and (2) reducing labor mobility.

The remainder of this paper is structured as follows. Section 2 gives an overview of the dataset, its construction and the most important descriptive statistics. Section 3 describes the empirical strategy. Section 4 reports the main results as well as several robustness checks. Section 5 concludes.

2. Data and descriptive statistics

2.1. Construction of the dataset

This section discusses the most important features of the data. A detailed description of the construction and the datasets that are used can be found in Appendix A. The data set is constructed by using nine administrative data sets from Statistics Netherlands. The starting point for our panel is the administrative dataset GBAADRESOBJECTBUS, which contains the address spells of all individuals since 1995. We merge this dataset with EIGENDOMWOZ(BAG)TAB and OBJECTWONINGTAB to distinguish between owner-occupied and rental houses. These datasets also provide the administrative house value (WOZ-value), which is determined annually by Dutch municipalities. We use the WOZ-value as proxy for the actual house price.[7]

For our analysis it is important to determine when a household purchased its current property. Therefore, we focus on transactions of owner-occupied houses, where transactions are determined based on movements. A movement is only considered as a transaction if certain criteria are met.[8] One important criterion is that the property must be vacant for at least one day. This criterion prevents that, for example, partners moving in are characterized as transactions. We only consider transactions since 1995, as we are unable to identify movements before 1995.

Since the composition of households changes over time, we construct the panel on the basis of household heads. To this end we use GBAHUISHOUDENSBUS, which contains

[7] Another common measure of the value of the property is the transaction price of a house. Unfortunately this data is not available to us. However, we used information from statistics Netherlands (CBS, 2014) to compare the differences between transaction prices and WOZ values. The key result is that in our sample period (2005-2011) there is hardly any difference between the WOZ values and the actual transaction prices (see this CBS (2014) report p.8 Table 2.3.2.2). For a further discussion on this evaluation method of house prices we also refer Beers et al. (2015).

[8] See for instance Figure A.1 the Appendix A for more detail.

information about the composition of households. We extract the following data: the size of the household, number of children, the household head and marital/partner status. Then, from GBAPERSOONTAB, we derive the age of the household head. For each transaction we identify a single household head and track his subsequent mobility. As balance sheet data is available on an annual basis we consider mobility on a yearly basis too. A person is considered to have moved if his address of 31st of December in year t differs from his address of 31st of December in year t-1. This implies that we consider movement from owner-occupied to owner-occupied dwellings as well as movement from owner-occupied to rental houses.[9]

We merge our panel of household heads with IVB to obtain balance sheet data, including mortgages. Next, we obtain household and personal income data from the datasets IHI and IPI, respectively. Finally, we use VSLGWBTAB and 'Code listing municipalities' to determine the geographical location of properties on the postal code area level.

Our sample is constricted for several reasons. More specifically, balance sheet data is (annually) available from 2006-2012 with reference date 1st of January of each year. Income data is available for 2005-2011, but with reference date 31st of December. Finally, house value data is available up to and including 2012, with a reference data 1st of January. For practical interpretation we chose 31st of December as the reference date for our panel. This implies that balance sheet data of 2006 is merged with income data of 2005, et cetera. The final panel consists of 2.2 million households with 2.4 million transactions, covering the period 2005-2012.[10]

The panel is unbalanced for several reasons. First, individuals can appear later than 2005 in the panel if they bought a house after 2005, but not before. Second, individuals drop out of

[9] To clarify, panel members are selected on the basis of movements into owner-occupied dwellings. Mobility of panel members is based on all their (subsequent) movements.
[10] Transactions of 2012 are excluded as we do not have LTV data for this year. However, for transactions prior to 2012 we can use the LTV of 2011 to explain mobility in 2012.

the panel if they move to a house in the rental sector. Finally, individuals who lose their position as household head, move abroad or die drop out of the panel too.

Our dataset is unique in the sense that we identify mobility patterns of all homeowners in the Netherlands, who bought a house since 1995. This includes moves from their current owner-occupied home into: newly built properties, other existing properties and rental houses. Recent studies are restricted to row houses (Hassink and Steegmans, 2015) or existing houses (Struyven, 2015). Many other studies analyze mobility patterns from survey data (see for instance Bricker and Bucks (2016) or Ferreira et al. (2010) and the references therein).

2.2. Descriptive statistics

Table 1 presents summary statistics for the full sample dataset. The average annual mobility between 2006 and 2012 is 3.6%.[11] This indicates that on average about 96 thousand households moved each year. The average LTV-ratio for all years is 73%. During 2005-2011, 28% of the households have negative home equity.[12]

--- Table 1 about here ---

In the period from 2006 until 2011 mobility of Dutch households declined by 70%. Figure 1 plots the development of Dutch homeowner mobility. Average annual mobility experienced its steepest decline from 2008 until 2009. In this period mobility decreases by 55% from 4.5% to 2.9%. Afterwards mobility further declined but at a much lower rate.

[11] The dataset contains LTV data for the period 2005-2011. However, we estimate the effect of the LTV in year t on the subsequent mobility in the year t+1. Therefore, the annual mobility is based on the period 2006-2012.

[12] Unfortunately, the data does not provide information about the type of mortgage. Certain mortgages include pledged accounts where capital is built up in the form of saving deposits. For this type of mortgages we overestimate the LTV-ratio (for more details see Struyven (2015)).

--- Figure 1 about here ---

The Netherlands experienced intense fluctuations in house prices in the period from 2006 until 2011. Figure 2 shows the average house price and the median house price of all owner-occupied houses in our data set. House prices peak in 2008 which is marked with a straight vertical line in the Figure. In the period from 2006 until 2008 house prices increased on average by 2.5% per year. From 2008 until 2011 house prices decreased on average by 2.9% per year.

--- Figure 2 about here ---

For our empirical strategy it is important that the shock is both random and independent of the value of the house. Figure 3 shows that there is no relationship between average house prices on the municipality level and the decrease in house prices from 2008 until 2011. The Netherlands is divided into 415 municipalities. We plot the average house price per municipality on the x-axis and the change in average house price from 2008 to 2011 on the y-axis. A linear regression reveals no significant relationship between the change in house prices and the average house price by municipality.[13]

--- Figure 3 about here ----

A key question is whether loan to value ratios also increased as a consequence of the house price shock. In our data the decrease in house prices went along with strong increases in LTV-ratios. Figure 4 shows the relationship between the change in LTV and change in house prices for each municipality in the period between 2008 and 2011. The figure shows that those municipalities with greater declines in house prices also experienced a greater

[13] The regression coefficient is -0.00000027 (p-value = 0.831).

increases in LTVs.[14] Since the house price shock was unexpected and random we conclude from these figures that the resulting increase in loan to value ratios was also random and unexpected (for additional evidence see for instance Beers et al. 2015, Ferreira et al. 2010 and Kerwin et al. 2015).[15]

--- Figure 4 about here ----

3. Empirical approach

In the first specification we consider the relationship between negative home equity and household mobility in general. We use a straightforward panel regression approach with postal code area-year fixed effects.[16] As balance sheet data is only available on an annual basis we consider annual mobility. [17] Our dependent variable, y_{it+1}, indicates if household i moves within the following year ($t+1$). If we used the current year t as the dependent variable, then the mortgage of the new home would already appear on the household balance sheet. Given that we have balance sheet data for 2005-2011 we estimate annual mobility for the period 2006 to 2012. We estimate the following model:

$$\mathrm{y}_{\mathrm{it+1}} = \delta \mathrm{U}_{\mathrm{it}} + \alpha_{\mathrm{tr}} + \mathrm{X}'_{\mathrm{it}}\beta + \epsilon_{\mathrm{it}} \qquad (1)$$

[14] Note that we restrict the sample here to non-movers in this period. The picture remains the same if we include households who moved in this period.

[15] In Appendix B we also provide two maps of the Netherlands. One map (Figure B.1) shows the average change in house prices in each municipality. The other map (Figure B.2) shows the average change in LTV. The picture that emerges from these two maps confirms the random distribution of house price shocks and the strong correlation between regions with decreasing house prices and increasing LTVs.

[16] Ideally we would like to include fixed effects on the household level. However, if we used fixed effects on the household level, identification is based on the variation of our underwater dummy on the household level. Since we have many households in the full sample who do not have negative equity at all, estimation on the full sample could lead to biased results of δ (Greene, 2011). We use fixed effects on the household level in our robustness checks.

[17] Note that we construct all variables in our data set such that they represent information about a household at the 31st of December in a given calendar year.

U_{it} is a dummy variable which takes the value one if a household has a LTV-ratio which is equal or greater than 100 percent.[18] We include α_{tr} as a postal code area-year fixed effect.[19] The set of control variables, X_{it}, contains dummies for different age categories, household financial assets, disposable household income, size of the household, and changes in the composition of the household. Expected changes in the household composition (marriage, children) may trigger mobility prior to observing the change in composition. Therefore, we include dummies for composition changes in the current as well as the following year.[20]

The first specification is appropriate to test whether households with negative home equity are less mobile than households with positive home equity. However, LTV-ratios are to some extent endogenous as different type of households may select themselves in different LTV-ratio categories at origination. Suppose, for example, that relatively immobile households chose relatively high LTV-ratios. In this case model (1) will find a negative effect of negative home equity which is mainly caused by unobserved household characteristics rather than negative home equity. Therefore, our second specification aims to control for potential selection effects into LTV-ratios. We treat the housing market bust of 2008-2011 as a random and unexpected shock, which creates plausible exogenous variation in LTV-ratios independent of household characteristics. In the previous section Figure 3 shows that the decrease in house prices between 2008 and 2011 is substantial and independent of the value of the house and the region. We control for initial values of LTV-ratios by only selecting households with positive home equity. More specifically, we restrict the sample for the second specification to households with a LTV-ratio of 90-100

[18] There are hardly any observations with an LTV-ratio of exactly 100 percent. Therefore, it is irrelevant how we specify the zero home equity case.
[19] In the Netherlands there are about 4000 different postal code areas. Some of the areas change because of reforms during the years. We take the definition of postal code areas of the year 2012.
[20] This empirical strategy is similar to the ones which are used in recent papers by Ferreira et al. (2011), Struyven (2015) or Bricker and Bucks (2016). However, our specification contains more controls and fixed effects on a lower level.

in 2008.[21] The most important reason why we chose this group of households is that their LTVs are most likely to rise above 100 due to the shock in house prices and not because of other confounding factors. Hence this is the group which is most interesting for policy makers who are interested in the effect of increasing LTV ratios on household mobility. We estimate the following model for annual mobility in 2009-2012:

$$y_{it+1} = \delta U_{it} + \lambda S_{it} + \alpha_{tr} + X_{it}'\beta + \epsilon_{it} \qquad (2)$$

This specification differs from the first specification in two aspects. First due to the restricted sample, its interpretation is different. In this case the dummy U_{it} indicates whether a household went underwater relative to 2008, as in 2008 all selected households have positive home equity. Due to the shock in house prices, households experience increases in their LTV-ratios. This leads certain households to move underwater, while other households remain above water. However, households which receive a relatively large shock are more likely to go underwater. Therefore, we use an indicator variable, S_{it}, to control for the size of the shock. The shock is measured as the percentage difference in house value relative to 2008.

The main benefit of this approach is that we are able to compare households which went underwater due to a relatively large shock or a minor shock in their house price. Given the similar starting point in 2008 we are able to identify the effect of becoming an underwater household.

[21] As we only have balance sheet information since 2005 it is impractical to control for LTV-ratios at origination as this would require restricting the sample to homeowners who bought a house since 2005.

4. Results

4.1. Negative home equity and mobility between 2006 and 2012

Table 2 shows the regression results from equation (1), which explains annual household mobility between 2006 and 2012.

--- Table 2 about here ---

In all specifications in Table 2 we find a statistically and economically significant association between negative home equity in year t and the probability of moving within the following year ($t + 1$). Households with negative home equity are significantly less mobile compared to households with positive home equity. All estimates of δ are negative and significant. Column (1) shows the specification with only controls for the purchasing year and age of the household head. We then add additional control variables to our model. In columns (2) and (3) the coefficient of negative home equity decreases, but remains relatively stable. The interpretation of the results is that a household with negative home equity has a 0.95% - 1.16% lower probability of moving on a yearly basis. Given that annual mobility of households with positive home equity is on average 3.6%, mobility decreases by 26% - 32%.[22]

4.2. The effect of getting underwater

The previous analysis included all households with negative home equity. These are households with negative equity before the decrease in house prices and households which got into negative home equity due to the decrease in house prices after 2008. However,

[22] $-\frac{0.946}{3.6} * 100 = -26.28\%$ and $-\frac{1.157}{3.6} * 100 = -32.14\%$

getting into negative home equity due to a decrease in house prices can affect mobility differently than choosing to have negative home equity. In Table 3 we analyze the mobility of those households with a LTV between 90 and 100 in 2008. We then construct a dummy variable “got underwater” which takes the value one if the LTV of these households exceeded 100 after 2008. Table 3 shows regression results of household annual mobility from 2009 to 2012. The picture that emerges from the columns (1) - (3) of Table 3 is that, becoming an underwater household has a significant negative effect on mobility of around 1.44% to 1.47%. The baseline mobility of households with a LTV ratio of 90-100, which did not get into negative home equity is 4.44%. This implies that mobility of households which went underwater is 33% lower than households which remained with positive home equity.

--- Table 3 about here ---

In columns (4) – (6) we add controls for the size of the house price shock. The underlying idea is that not only the fact that households got underwater matters, but also to what extent the households were hit by the shock. The estimates of the “got underwater” dummy remain negative and significant but decrease in size compared to the previous specifications, see columns (4) – (6). Annual mobility of households which went underwater after 2008 is around 0.8% lower compared to households which remained above water. This a reduction of around 18% - 19% in annual mobility. One potential interpretation for the fact that shocks have an effect on mobility is that households experience loss aversion, where their reference point is their house value prior to the housing market bust. This is specification is different from studies such as Engelhardt (2003) and Hassink and Steegmans (2015) which use the price at the time of purchase of the house to check if households incurred a loss on their house.

4.3. Robustness checks

The results of the previous section depend on several key assumptions. In this section we present evidence that our results remain robust to (1) the choice of the LTV threshold, (2) adding household fixed effects, (3) choice of the LTV buckets, (4) endogenous increases in mortgages and (5) controlling for net wealth.

The choice of the LTV threshold might determine the effect size. We hypothesize that exceeding an LTV above 100 is crucial for household mobility since this threshold severely hampers financing possibilities of moving to a new home. The results in Table 4 confirm our assumption. The table shows regression results for 8 different LTV classes. Dependent variable is again yearly household mobility in the period 2009-2012. The variable “crossed boundary” takes the value one if a household exceeded the boundary. In column (1) it takes the value 1 if a household exceeded an LTV of 50 after 2008. The coefficient remains small but negative until a LTV boundary of 100.[23] After crossing that threshold, increases in LTVs have a substantial negative effect on household mobility.

--- Insert Table 4 here ---

In Table 5 we control for four other important confounding factors. For the ease of comparison we replicate the estimation results from column (6) of Table 3 against which we benchmark our results.

Column (2) contains household fixed effects. The main conclusion is that our estimate of negative home equity does not change significantly compared to the specification with postal code area-year fixed effects.[24] Household fixed effects allow us to control for

[23] Note that this is exactly the same regression as in column (6) in Table 3.
[24] We present the regressions with household fixed effects of all specifications of Table 3 in Table 1B in Appendix B.

unobserved household characteristics which might be correlated with the choice of debt and hence the fact that households become underwater households. The key identifying assumption is that the unobserved characteristics do not change over time. One unobserved characteristic is the mortgage type of the household.[25] However, it is quite unlikely that the mortgage type changes over time since such changes are extremely costly due to the high penalties banks will charge. Hence, household fixed effects capture this possible source unobserved of heterogeneity on the household level.

Next, the choice of the LTV-basket 90-100 might influence our estimates. The third column of Table 5 shows yearly household mobility for households who got underwater after 2008 for households with a LTV between 95 and 100. The coefficient slightly increases in size but remains in the range of the estimates which we obtain in Table 3.

--- Insert Table 5 here ---

Moreover, LTVs might increase not only due to a shock in house prices but also due to an increase in the mortgage. Therefore, we exclude all observations which experienced an increase in their mortgage after 2008 and run the same regression as in Table 3. Column (4) shows the result of this regressions and reveals that the coefficient of "getting underwater" does not change significantly.

Finally, in our specifications we control for (net) financial assets with dummy variables. However, there is a potential interaction between the LTV-ratio and the net financial assets of households. Underwater households, which are unable to finance their remaining debt after selling their house, might be less mobile than households with sufficient financial

[25] In the Netherlands banks usually offer four different types of mortgages: annuity mortgages, interest-only mortgages, savings mortgages and investment mortgages. Since we are not able to determine the mortgage type, this might lead to a potential overestimation of the LTVs (see also DNB (2015) for a discussion on that). However, this in turn means that our results present a lower bound of the effects of negative home equity on household mobility.

assets. Therefore, we calculate the net wealth position of households after a potential sale. More specifically, we define net wealth (W) of a household as: the value of their property minus the mortgage plus net financials assets.[26] Next, we consider four types of households: (i) above water households with positive wealth, (ii) above water households with negative W, (iii) underwater households with positive W and, (iv) underwater households with negative W. In the last column of Table 5 we present the results of this specification. The baseline group are households which remained above water and have positive wealth. The estimates reveal that households with negative home equity are more mobile if they have positive wealth. However, underwater households with positive wealth remain less mobile than above water household with positive wealth.

5. Discussion & Conclusion

In this paper we investigate the relationship between negative home equity, so called underwater households, and household mobility in the Netherlands. We use a unique administrative dataset from Statistics Netherlands which tracks annual mobility patterns of homeowners from 2006 to 2012. The dataset covers all homeowners who bought a house since 1995 and includes movements to newly built properties. Moreover, we merge mobility data with household balance sheet data.

We employ panel data estimations with postal code area – year fixed effects and a large set of controls to estimate the effect of negative household equity on household mobility.

We obtain two main findings. First by making use of a conventional estimation strategy in the literature, households with negative home equity are 26% to 32% less mobile (on an annual basis) than households with positive home equity. In a second approach we

[26] We exclude non-financial assets as well as debt other than the mortgage. The reason is that we consider the possibility of households to finance their remaining debt with own assets. Non-financial assets are relatively illiquid for this purpose.

compare the mobility of households who went “underwater” due to the decline in house prices after 2008. Moreover, we take into account various other possible confounding factors in the period 2008 until 2011. Our main findings indicate a decrease in mobility of about 17-18%. A crucial point here is that it is important to control for the size of the house price shock. Our results remain robust when we control for (1) household fixed effects, (2) the choice of the LTV threshold, (3) choice of the LTV buckets, (4) endogenous increases in mortgages, and (5) negative financial assets.

Our findings are relevant for policy makers. Household mobility can affect the economy through various channels. A decrease in mobility can affect aggregate consumption, via a decrease in demand in the construction sector. Moreover, a lack of flexibility on the labor market can for instance lead to insufficient adaptations in local labor supply. An interesting avenue for further research is for instance to investigate commuting distances of underwater households.

References

Andersson, F. & Mayock, T. (2014). How does home equity affect mobility? *Journal of Urban Economics*, *84*, 23-39.

Beers, van N., Bijlsma, M., & Mocking, R. (2015). House Price Shocks and Household Savings: evidence from Dutch administrative data. *CPB Netherlands Bureau for Economic Policy Analysis Discussion paper*.

Bricker, J., & Bucks, B. (2016). Negative home equity, economic insecurity, and household mobility over the Great Recession. *Journal of Urban Economics*, *91*, 1-12.

CBS (2014). "Prijsindex bestaande koopwoningen: Methodebeschrijving", available at: http://www.cbs.nl/nl-NL/menu/themas/prijzen/methoden/dataverzameling/overigedataverzameling/2014-prijsindex-bestaande-koopwoningen-pub.htm (last access: 7-Jan-2016).

Coulson, N. E. & Grieco, P. L. (2013). Mobility and mortgages: Evidence from the PSID. *Regional Science and Urban Economics, 43*, 1-7.

DNB, (2015) Dutch mortgages in the DNB loan level data. *DNB Occasional studies Vol. 13 - 4.* Authors: Mauro Mastrogiacomo and Remco van der Molen

Einiö, M., Kaustia, M., & Puttonen, V. (2008). Price setting and the reluctance to realize losses in apartment markets. *Journal of Economic Psychology*, *29*(1), 19-34.

Engelhardt, G. V. (2003). Nominal loss aversion, housing equity constraints, and household mobility: evidence from the United States. *Journal of Urban Economics*, *53,* 171-195.

Ferreira, F., Gyourko, J., & Tracy, J. (2010). Housing busts and household mobility. *Journal of Urban Economics, 68,* 34-45.

Greene, W. H. (2011). *Econometric analysis*. (7 ed.) Prentice hall.

Hassink, W. & Steegmans, J. (2015). Decreasing house prices and household mobility: An empirical study on loss aversion and negative equity. *Utrecht University Discussion Paper Series nr: 15-12.*

Henley, A. (1998). Residential mobility, housing equity and the labour market. *The Economic Journal*, *108*(447), 414-427.

IMF (2014), "Kingdom of the Netherlands-Netherlands: 2014 Article IV Consultation-Staff Report; Press Release; and Statement by the Executive Director for the Netherlands", *Country Report No. 14/327*

IMF (2015), “IMF multi-country report housing recoveries: cluster report on Denmark, Ireland, Kingdom of the Netherlands—the Netherlands, and Spain”, *IMF Country Report No. 15/1*

Kerwin, K. C., Hurst, E., & Notowidigdo, M. J. (2015). Housing Booms and Busts, Labor Market Opportunities, and College Attendance. *NBER Working Paper Series,* 21587.

Mocking, R., & Overvest, B. (2015). Estimating the Impact of Forced Sales on House Prices (No. 304). CPB Netherlands Bureau for Economic Policy Analysis *Discussion paper*.

Schulhofer-Wohl, S. (2011). Negative equity does not reduce homeowners' mobility. *NBER working paper*.

Seek, N. H. (1983). Adjusting housing consumption: improve or move. *Urban Studies, 20,* 455-469.

Stein, J. C. (1995). Prices and Trading Volume in the Housing Market: A Model with Down-Payment Effects. *The Quarterly Journal of Economics*, 379-406.

Struyven, D. (2015). Housing Lock: Dutch Evidence on the Impact of Negative Home Equity on Household Mobility. *Working Paper*.

Turk, R. (2015). Housing Price and Household Debt Interactions in Sweden. *IMF Working Paper No. 15/276*

Tables and Figures

Table 1. Descriptive statistics of the variables of interest in the period from 2005 until 2011.

	Mean	Median	S.D.	N (x1000)
Households	-	-	-	2,182
Annual mobility 2006-2012 (%)	3.6	0	18.5	11,652
LTV-ratio (%)	73.2	77.84	35.6	11,652
Underwater Households (%)	27.6	0	44.7	11,652
Years since purchase	5.7	5	4.1	11,652
Age	45.0	43	13.0	11,652
Household size	2.8	2	1.3	11,652
Disposable Household Income (Euro)	40,580	36,512	26,215	11,652
Financial Assets (Euro)	91,685	20,326	719,668	11,652
Change in composition of HH (%)	7.5	0	26.3	11,652

Table 2. Negative home equity and household mobility in the period from 2006 to 2012

	(1)	(2)	(3)
Negative home equity	-0.946***	-1.014***	-1.157***
	(0.0170)	(0.0174)	(0.0168)
Years since purchase	YES	YES	YES
Age	YES	YES	YES
HH size, financial assets, disposable income		YES	YES
Change in HH composition			YES
Constant	3.951***	5.175***	2.499***
	(0.0260)	(0.0343)	(0.0335)
Observations	11,651,968	11,651,825	11,640,953
R-squared	0.009	0.011	0.051
Number of postcode-year FE	27,787	27,787	27,787

Note. The table reports results from linear probability models. The dependent variable is the probability of moving in the following year in percentage points. All regressions contain postal code – calendar year fixed effects. The variable 'Negative home equity' takes the value 1 if the loan to value ratio is equal to or greater than 100. "Years since purchase" are dummy variables for each year after the household purchased the house. "Age controls" are 5 categories for the age of the household head. The variables "HH size" (household size), "financial assets", "disposable income" are also dummy variables for different categories of the underlying variables. The variable change in HH composition takes the value one if the composition in the household changes in the current and/or following year. Robust standard errors are clustered on the postcode-area year level. *** p<0.01 , ** p0.05, *p<0.1.

Table 3. Probability of moving in 2009-2012 of households with LTV 90-100 in 2008

	(1)	(2)	(3)	(4)	(5)	(6)
Got underwater	-1.469***	-1.444***	-1.450***	-0.809***	-0.750***	-0.769***
	(0.0618)	(0.0619)	(0.0599)	(0.0646)	(0.0650)	(0.0626)
House price shock control	-	-	-	YES	YES	YES
Years since purchase	YES	YES	YES	YES	YES	YES
Age	YES	YES	YES	YES	YES	YES
HH size, financial assets, disposable income	-	YES	YES	-	YES	YES
Change in HH composition	-	-	YES	-	-	YES
Constant	5.489***	6.733***	3.477***	4.965***	6.145***	2.988***
	(0.157)	(0.190)	(0.183)	(0.222)	(0.244)	(0.236)
Observations	528,016	528,004	527,656	525,667	525,665	525,313
R-squared	0.008	0.011	0.058	0.013	0.015	0.062
# of postcode-year FE	10,960	10,960	10,960	10,945	10,945	10,945

Note. The table reports results from linear probability models. The dependent variable is the probability of moving in the following year in percentage points. All regressions contain postal code – year fixed effects. The variable 'Got underwater' takes the value 1 if the LTV ratio is equal to or greater than 100. The "House price shock control" are dummy variables for the decline/increase in house price relative to 2008. "Years since purchase" are dummy variables for each year after the household purchased the house. "Age controls" are 5 categories for the age of the household head. The variables "HH size" (household size), "financial assets", "disposable income" are also dummy variables for different categories of the underlying variables. The variable change in HH composition takes the value one if the composition of the household changes in the current and/or following year. Robust standard errors are clustered on the postcode-area year level. *** p<0.01, ** p0.05, *p<0.1.

Table 4. Robustness check: The effect of switching to a higher LTV class on mobility

LTV boundary	50	60	70	80	90	100	110	120
Crossed boundary	-0.0648	-0.103**	-0.145***	-0.232***	-0.219***	-0.769***	-1.014***	-0.808***
	(0.0546)	(0.0523)	(0.0533)	(0.0546)	(0.0594)	(0.0626)	(0.0572)	(0.0724)
Controls	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL
Constant	4.420***	3.707***	3.852***	3.630***	2.538***	2.988***	2.681***	2.569***
	(0.610)	(0.411)	(0.347)	(0.295)	(0.262)	(0.236)	(0.198)	(0.215)
Observations	344,570	400,713	425,627	438,019	480,344	525,313	595,487	376,111
R-squared	0.045	0.051	0.056	0.061	0.060	0.062	0.065	0.064
# of postcode-year FE	11,119	11,198	11,138	11,123	11,072	10,945	10,982	10,538

Note. The table reports results from linear probability models. The dependent variable is the probability of moving in the following year in percentage points. All regressions contain postal code – year fixed effects. The variable 'Crossed boundary' indicates if the LTV-ratio is above the relevant boundary. We include all control variables of Table 3. They contain the "House price shock control" which are dummy variables for the decline/increase in house price relative to 2008. "Years since purchase" which are dummy variables for each year after the household purchased the house. "Age controls" which are 5 categories for the age of the household head. Moreover, we control for household size, financial assets and disposable income, household composition changes in the current and/or following year. Robust standard errors are clustered on the postcode-area year level. *** p<0.01, ** p0.05, *p<0.1.

Table 5. Robustness check: household fixed effects, LTV buckets, loan increase and equity after sale

	Baseline	90-100 Household-FE	95-100	No increase in mortgage	Equity after sale
Got underwater	-0.769***	-0.801***	-1.109***	-0.734***	
	(0.0626)	(0.0756)	(0.105)	(0.0736)	
Remained above water, W≥0					Baseline
Remained above water, W<0					-1.620**
					(0.635)
Got underwater, W≥0					-0.579***
					(0.0660)
Got underwater, W<0					-1.082***
					(0.0843)
Controls	ALL	ALL	ALL	ALL	ALL
Constant	2.988***		2.689***	2.710***	3.068***
	(0.236)		(0.321)	(0.269)	(0.235)
Observations	525,313	532,879	266,730	425,361	532,879
R-squared	0.062	0.068	0.062	0.068	0.062
# of FE	10,945	186,876	10,369	10,776	10,950

Note. The table reports results from linear probability models. The dependent variable is the probability of moving in the following year in percentage points. All regressions in columns (1), (3) ,(4) and (5) contain postal code – year fixed effects. Column (2) contains fixed effects on the household level. The variable 'Got underwater' takes the value 1 if the LTV ratio is equal to or greater than 100. We include all control variables of Table 3. They contain the "House price shock control" which are dummy variables for the decline/increase in house price relative to 2008. "Years since purchase" which are dummy variables for each year after the household purchased the house. "Age controls" which are 5 categories for the age of the household head. Moreover, we control for household size, financial assets and disposable income, household composition changes in the current and/or following year. Robust standard errors are clustered on the postcode-area year level/ household level. *** p<0.01, ** p0.05, *p<0.1.

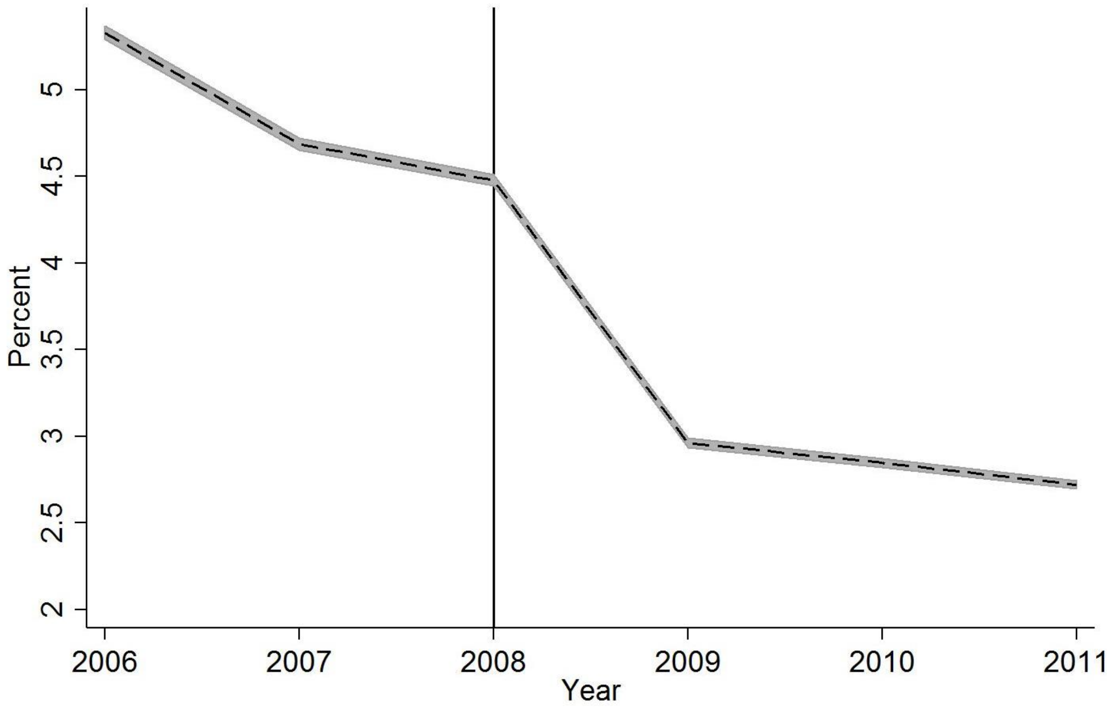


Figure 1. Average annual mobility.

Note. The figure shows the development of moves out of owner-occupied houses in the Netherlands in percentage points in the period from 2006 until 2011. Grey areas indicate 95% confidence bounds.

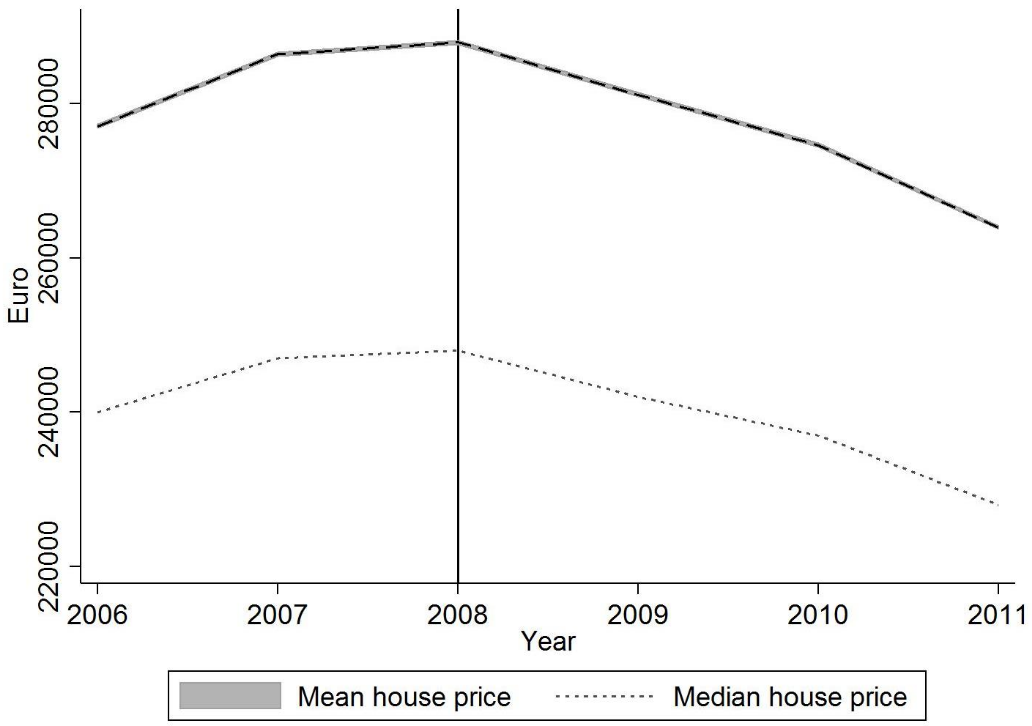


Figure 2. National house price development for the Netherlands.

Note. The figure shows the development of the mean and median house price of all owner-occupied houses in the Netherlands in the period from 2006 until 2011. The numbers are based on the “WOZ” values in our data set. Grey areas indicate 95% confidence bounds.

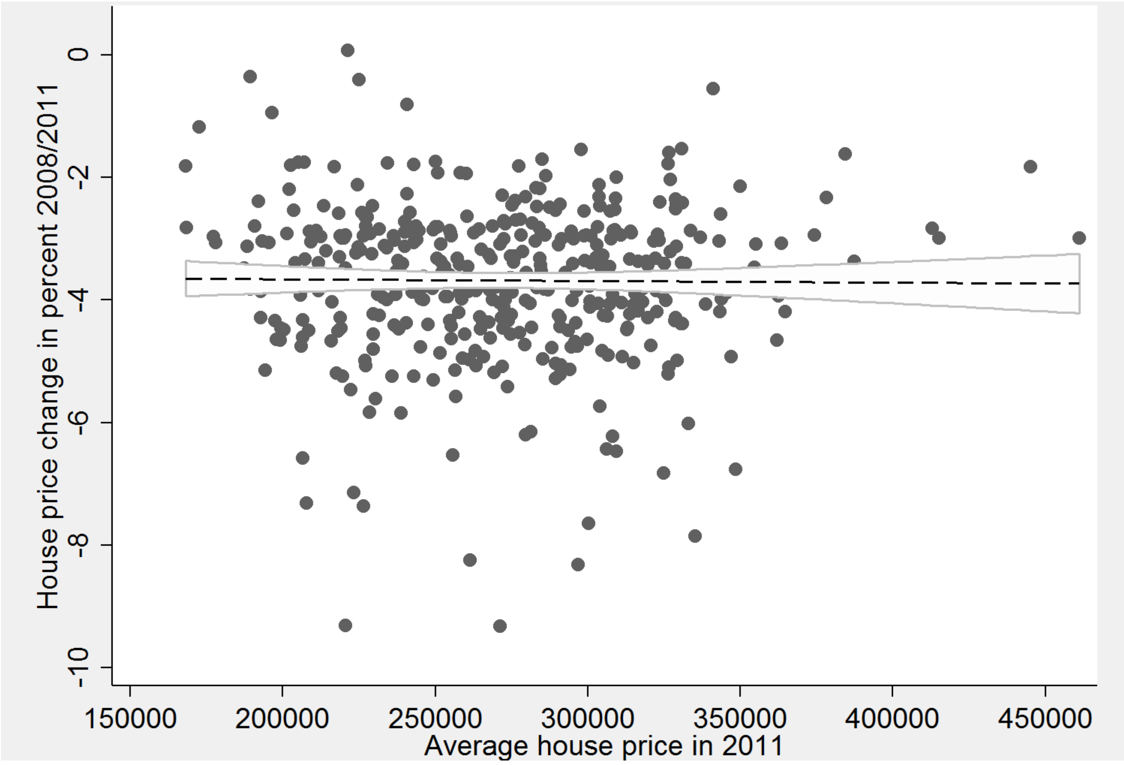


Figure 3. Relation between house price and house price change between 2008 and 2011.

Note. The Figure shows the average house price in each municipality in 2011 and the change in the house price in percentage points from 2008 until 2011. The regression coefficient is -0.00000027 (p-value = 0.831).

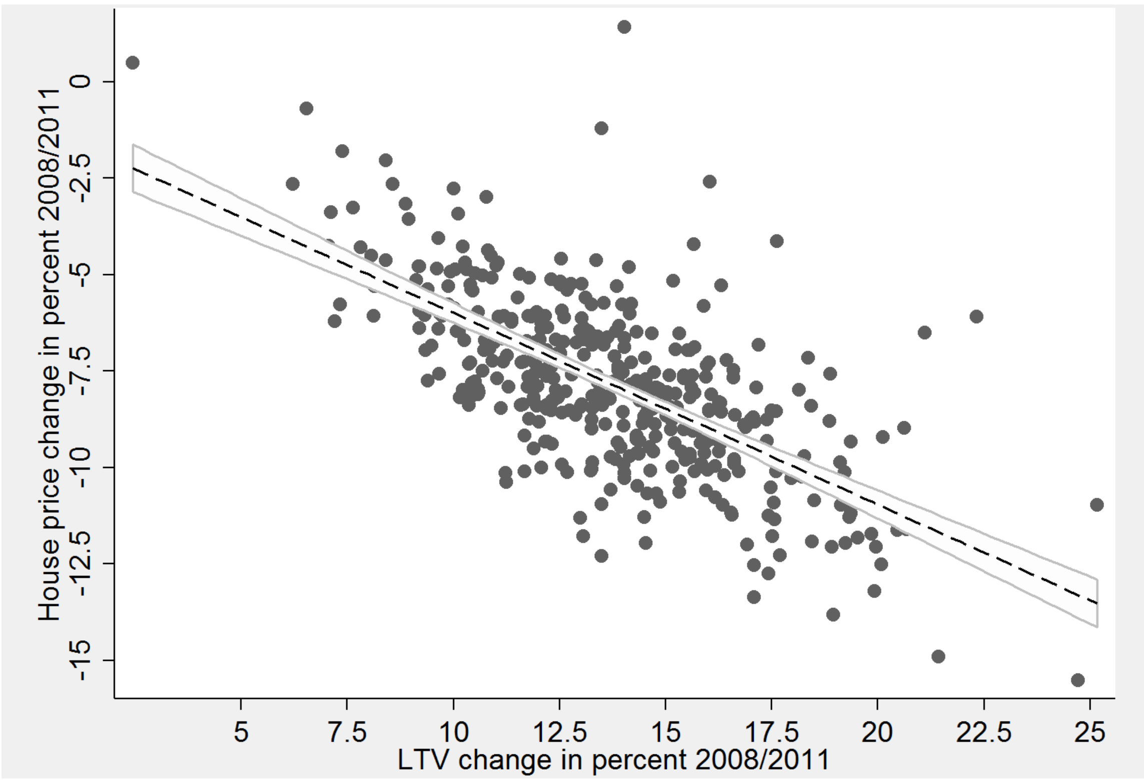


Figure 4. Relation between LTV change and house price change for non-movers.

Note. The Figure shows the average house price in each municipality in 2011 and the change in the house price in percentage points from 2008 until 2011. The regression coefficient is -0.5 (p-value <0.01).

Appendix

A. Construction of the data set

There are two main challenges when constructing a panel of homeowners. First, we cannot directly observe the ownership of properties. More specifically, we do not know when and if transactions of properties take place. Secondly, properties can be owned by households rather than individuals. As the composition of households can change over time, due to for example divorces, it is not straightforward to construct a panel on the basis of households. On the other hand, constructing a panel on the basis of individuals requires us to specify ownership on the individual level.

In A.1. we explain how we select the panel members in light of aforementioned challenges. Then, in A.2. we describe how we construct the dataset for these members. In total we combine the following 15 different administrative datasets: EIGENDOMWOZTAB, EIGENDOMWOZBAGTAB, OBJECTWONINGTAB, GBAADRESOBJECTBUS, GBAHUISHOUDENSBUS, GBAPERSOONTAB, IVB, IPI, IHI, VSLGWBTAB, Code listing municipalities.

A.1. Selection of panel members

Identification of transactions of properties

A typical transaction has the following implications:

(i) the current owners will move out of the property

(ii) the new owners will move into the property and

(iii) the current owners will move out before the new owners move in.

By tracking the movement of all individuals it is therefore possible to identify potential transactions. The dataset GBAADRESOBJECTBUS contains all address spells of every individual who was officially registered in the Netherlands in the time period from 1995 – 2013. For each movement of each individual we check whether the property is vacant at the moment of moving in. If this is the case then we flag this as a potential transaction. Next, we merge the list of all potential transactions with the datasets EIGENDOMWOZ(BAG)TAB and OBJECTWONINGTAB, which contain information about the type of building (residential building, recreational building, et cetera) and whether the property is a rental or owner-occupied house. We only keep (potential) transactions that in the year and following year of the transaction are specified as residential *and* owner-occupied dwellings.[27]

Furthermore, we drop all transactions in 2013, as we are unable to track subsequent mobility. This leaves us with 3,399,704 transactions. Finally, we remove 9,988 transactions where the person moving in moves out again within 30 days.[28] We remain with a total of 3,389,716 transactions over the period 1995-2012.

Identification of household heads

We first remerge the list of transactions with GBAADRESOBJECTBUS and for each transaction we identify all persons moving into the selected property within 30 days of the first person moving into the property. For mainly administrative reasons, individuals from a household do not always appear to move simultaneously. We therefore allow for a ‘grace’ period of 30 days.

[27] The relevant characteristics of a property are determined once a year. Therefore, we must allow for a delay of one year for properties which, for example, shift from an owner-occupied house to a rental house in the year of interest.

[28] It is unlikely that an actual transaction took place in these cases.

Next, we identify the relationship between all individuals who have moved into a property within the grace period. For this purpose we merge with the dataset GBAHUISHOUDENSBUS, which contains household data. We drop 1,515 transactions that we cannot merge to any household data, leaving us with 3,388,201 transactions. If members of a household do not move simultaneously, then the composition of the household may change during the grace period. Therefore, we consider the position of individuals within a household at the day the grace period ends. We chose to track household heads in our panel. The benefit of having a panel based on individuals, rather than households, is that we do not have to eliminate households which alter in composition over time.

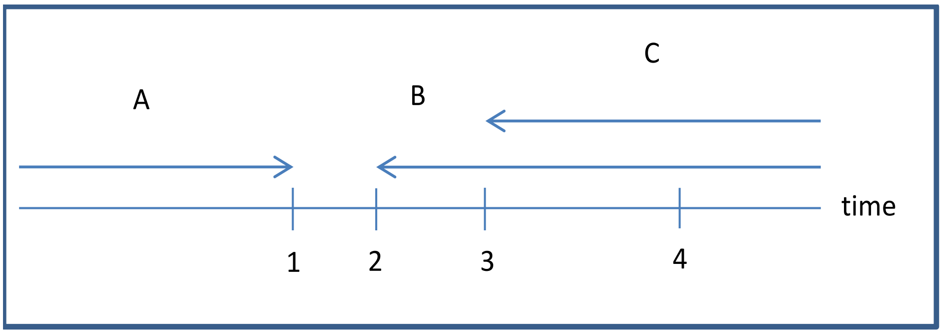
We use the definition of Statistics Netherlands (CBS) to identify the household head. The variable household head is created by CBS according to the following rules. In case of a couple, the male member is the head. If the couple has the same gender, then the oldest person is selected. For a single-parent household, the parent is the head. In multiple-generation households, the head is selected on basis of the youngest couple. For other type of households, the head is in general the oldest male (at least 15 years or older) and oldest female otherwise.

In a few cases there is more than one household head for a given transaction. We remove these transactions (41,633), leaving us with 3,346,568 transactions. Furthermore, we remove all household heads and corresponding transactions if the household head has more than one transaction for a particular address. We remain with 3,310,256 transactions. Certain individuals have multiple transactions in a single year. As we build an annual panel we only consider the last transaction within a year, thereby removing 13,591 transactions. At this point our panel consists of 3,296,665 transactions and 2,663,387 unique individuals.

Example

In Figure A.1 we present an example of the selection of a panel member. First, the previous owner, A, moves out and the property becomes vacant. Then, B moves in and automatically becomes the head of the household. C moves in at t=3 and now the head of household may change to C. Finally, at t=4, which is 30 days after t=2, we check who is the head of the household and we select that person for our panel.

Figure A.1: selection of panel members



A.2. Building the dataset

We build an annual panel for the 2,663,387 individuals, which contains their address on December 31 of each year for the period 1995-2013. Due to memory constraints we drop 50 individuals who have more than 50 addresses during this period. Furthermore, we remove 43,255 transactions for which the individual has already moved out of the transaction property by the end of the transaction year.[29]

Next, we merge the panel with the dataset GBAPERSOONTAB , which contains information about the age of our panel members. We drop 47 individuals (with 57 corresponding transactions) for which no personal data is available. Then we remerge the data with the GBAHUISHOUDENSTAB to gain household data on an annual (December 31) basis.

[29] We only have balance sheet data on an annual basis. Therefore, we are unable to determine the LTV-ratio for these observations.

Balance sheet data, value of houses and income

Balance sheet data is only available for 2006-2013, with reference date January 1. The latest available reference date for the value of houses is January 1, 2012. As our panel is based on December 31 addresses, we merge balance sheet and house value data of January 1, 2006, with the address of December 31, 2005, et cetera. This implies that we can derive the LTV-ratio for the period 2005-2011, with reference date December 31.

Due to memory constraints we first remove all observations that are not relevant for the econometric analysis. More specifically, we remove all transactions of 2012 and all observations prior to 2005. Note that we retain the addresses of 2012 in order to track mobility of households who bought a house prior to 2012. Furthermore, we drop all observations for which the address is missing. The main reasons for missing addresses is that people may have died or moved abroad. This leaves us with 2,296,540 individuals with 2,536,842 transactions and 12,711,735 observations.

We now merge the smaller dataset with the following datasets:

- (i) IVB to acquire balance sheet data
- (ii) IPI and IHI to acquire data about household and personal income
- (iii) EIGENDOMWOZ(BAG)TAB to acquire the value of houses

We drop 2,119 individuals who have more than two missing observations for the value of their mortgage. We remove 29,556 transactions (corresponding to 25,729 individuals) as the value of the property is missing. Next, we remove 1,059 individuals who have a mortgage that changes exactly by a factor 10 or 1/10, which is most likely due to a typo in the number of zeros. In certain cases the mortgage value increases by a relatively large amount in a single year. One reason for this is that sometimes the mortgages of multiple properties are (mistakenly) added. As we are unable to accurately measure the LTV-ratio in these cases we drop all individuals who increase their mortgage by more than 100,000 Euro without an identifiable transaction in the corresponding year. We remove 86,170 individuals and 134,994 transactions.

Finally, we merge with VSLGWBTAB and ‘Code listing municipalities’ to obtain data about the geographical location of addresses. We remain with 2,181,913 individuals/households with 2,368,858 transactions and total of 11,972,822 observations. Table 4 presents an overview of the selections.

Table 1A: Overview

Selection	Transactions	Households
Transactions before selections	3,399,704	-
Moving out within 30 days	3,389,716	-
Missing household data (at transaction)	3,388,201	-
More than one household head per transaction	3,346,568	-
Multiple transactions same property	3,310,256	-
Multiple transactions within year	3,296,665	2,663,387
More than 50 addresses	3,296,606	2,663,337
Moved again in purchasing year	3,253,351	2,633,234
Missing personal data	3,253,294	2,633,187
Panel 2005-2011	2,536,842	2,296,540
Missing mortgage data	2,534,607	2,294,421

Missing value of property	2,505,051	2,269,142
Obvious mistakes mortgages	2,503,852	2,268,083
Large increase mortgages	2,368,858	2,181,913

A.3. Data imputations

For several key variables we cleaned the data and imputed certain missing values.

Type of building

The variable indicating whether a building is rental or owner-occupied has quite some missing values. The main reason is that before 2007 the reference data was not on a yearly basis, but on a two, three or four year basis. As there is little variance over time in the type of building we use an intuitive imputation. If the type of building is identical prior and after the missing entry, we assume that the type of building has not changed over time. If the type of building is not identical, then we are uncertain in which year the change took place. Therefore, we leave the entry missing in these cases. Finally, if the first (last) entry is missing then we impute on the basis of the following (previous) entry.

Property value (WOZ-value)

Similar to the type of building variable, the WOZ-value does not have a yearly reference date before 2007. This implies that we have the WOZ-value for 2005 and 2007, but do not have any data for 2006. We use a linear extrapolation based on 2005 and 2007 to estimate the values for 2006. For values missing in a year other than 2006 we use a regression based on the current and previous year to estimate the change in value and we impute accordingly. Finally, in certain cases the WOZ-value is 0 or negative, which we put at missing.

Mortgages

The variable indicating the mortgage has for certain households unlikely fluctuations over time. The main reasons are administrative mistakes and missing entries which are automatically put at a value of zero. First, we put negative mortgages at missing. Next, to filter out rounding errors, we impute the mortgage of the previous year if the mortgage in the current year differs by a single Euro. In the next step we identify fluctuations which revert back to a value that is close (maximum difference of 100 Euro) to the original value. In these cases we put the mortgage on the original value for all relevant entries. For example: the mortgage in year t is 200.000, in year t+1 it is 50.000 and in year t+2 it is 199.950. We impute the value 200.000 for year t+1 and t+2.

Next, we impute missing entries. If we have three or more missing entries, we remove the mortgage and corresponding transaction from our panel. For one or two missing entries, we use a linear extrapolation based on the entry prior and after the missing entries. If the first entry is missing we impute based on the following observation.

Finally, we identify relatively large fluctuations that do not revert back to a certain value. We consider increases (decreases) in the mortgage of at least 20%, followed by a decrease (increase) of at least 17% (25%) in the following year. In these cases we impute using a linear extrapolation based on the entry prior and after the entry that caused the large fluctuation.

LTV-ratio

Even after the imputations of the WOZ-value and the mortgages, certain LTV-ratios took very unlikely values. We put all LTV-ratios above 150% at missing. Even after a substantial shock to the value of the property it is unlikely to have a LTV-ratio of this magnitude.

B. Additional Figures & Tables

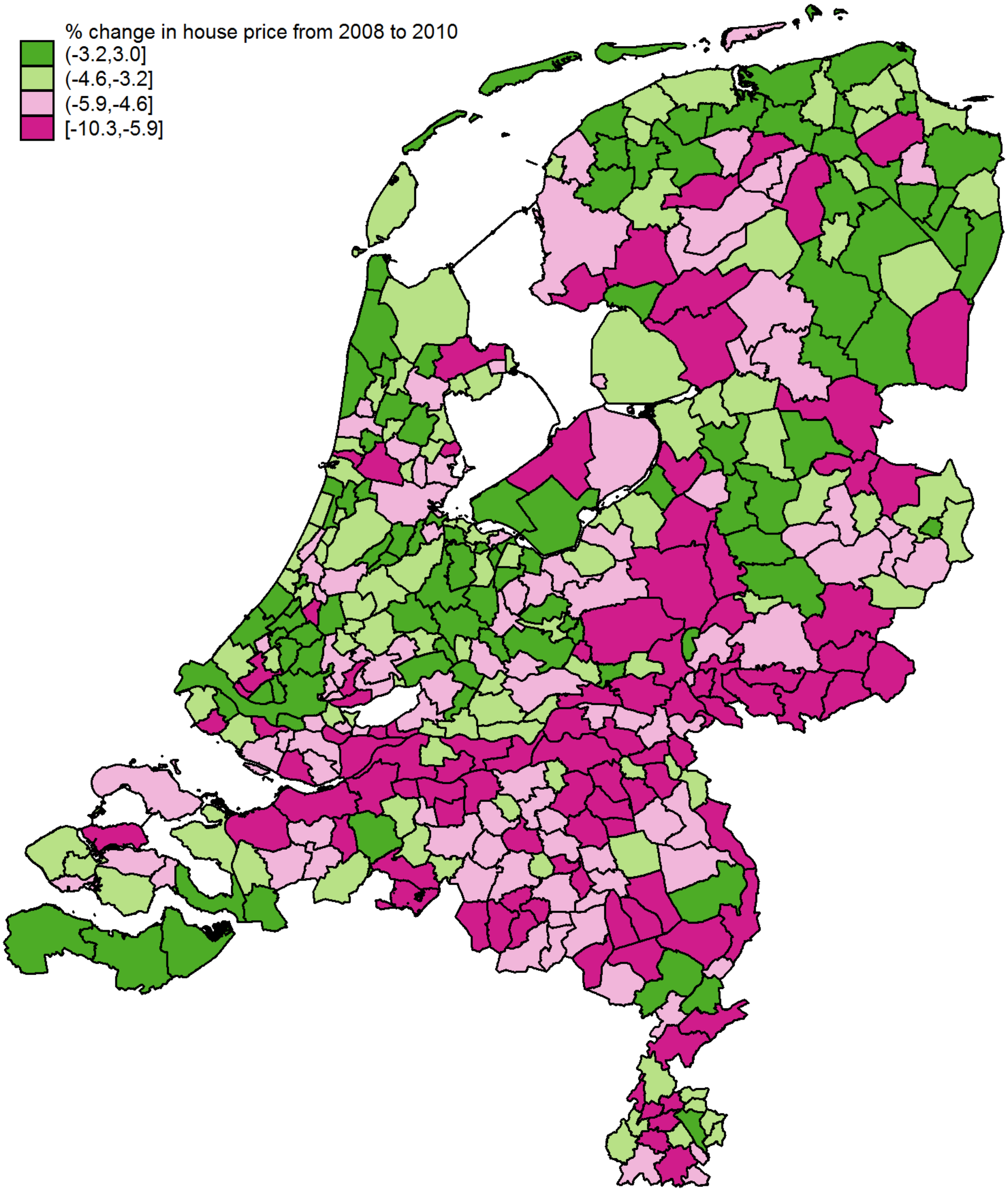


Figure B.1. % Change in house price by region.

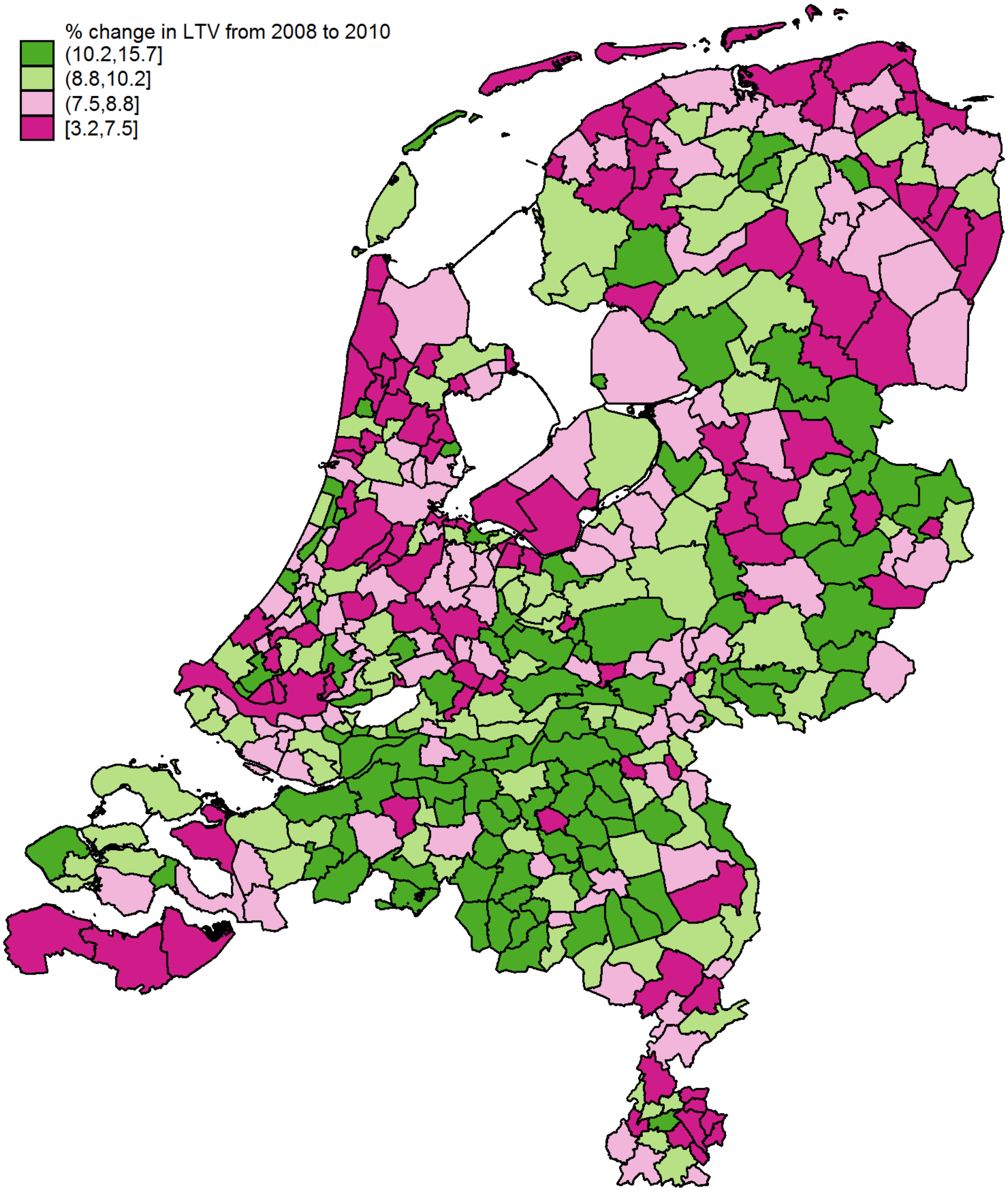


Figure B.2. Percentage change in LTV of households who did not move.

Table 1B. Household fixed effects: Probability of moving in 2009-2012 of households with LTV 90-100 in 2008

	(1)	(2)	(3)	(4)	(5)	(6)
Got underwater	-1.790***	-1.806***	-1.750***	-0.839***	-0.858***	-0.801***
	(0.0706)	(0.0705)	(0.0693)	(0.0770)	(0.0770)	(0.0756)
House price shock control	-	-	-	YES	YES	YES
Years since purchase	YES	YES	YES	YES	YES	YES
Age	YES	YES	YES	YES	YES	YES
HH size, financial assets, disposable income	-	YES	YES	-	YES	YES
Change in HH composition	-	-	YES	-	-	YES
Observations	535,586	535,574	535,222	533,237	533,225	532,879
R-squared	0.040	0.041	0.064	0.044	0.045	0.068
# of Households	187,282	187,280	187,122	187,035	187,033	186,876

Note. The table reports results from linear probability models. The dependent variable is the probability of moving in the following year in percentage points. All regressions contain postal code – year fixed effects. The variable 'Got underwater' takes the value 1 if the LTV ratio is equal to or greater than 100. The "House price shock control" are dummy variables for the decline/increase in house price relative to 2008. "Years since purchase" are dummy variables for each year after the household purchased the house. "Age controls" are 5 categories for the age of the household head. The variables "HH size" (household size), "financial assets", "disposable income" are also dummy variables for different categories of the underlying variables. The variable change in HH composition takes the value one if the composition of the household changes in the current and/or following year. Robust standard errors are clustered at the household level. *** p<0.01, ** p0.05, *p<0.1.