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# Decreasing house prices and household mobility: An empirical study on loss aversion and negative equity

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**Abstract**
This paper examines the effects of loss aversion and negative equity on household mobility. We stress the importance of studying these mechanisms simultaneously. By making use of a unique administrative data set of Statistics Netherlands, covering the period 2006-2011, we estimate the effects of loss aversion and negative equity. The results provide strong evidence for loss aversion, while less evidence is found for a lock-in effect of negative equity. The results indicate that moderately underwater households do have a lower mobility, but heavily underwater households do not. Additional results indicate that the particularly high mobility of heavily underwater households is not default-driven.

**Keywords**: Housing market, Household mobility, Loss aversion, Negative equity

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## 1. Introduction

House prices in the Netherlands have been rising from the early 1980s until prices peaked in 2008. The following drop in house prices led to a sharp decrease in transaction numbers, making the housing market come to a standstill. Loss aversion and negative equity can both explain how decreasing house prices affect household mobility. The decrease in house prices and its effects on household mobility have been debated widely, but there seems to be no agreement on the exact mechanisms. The relation between decreasing house prices and household mobility, therefore, deserves further attention.

We will study the effects of decreasing house prices in the owner-occupied market on sales rates and household mobility as it is not clear whether the decrease in transactions numbers is caused by financial constraints or by loss aversion. We will investigate whether households did not want to move or were no longer able to do so after prices started dropping. Studying the difference between the binding and non-binding constraints will lead to a better understanding on how the housing market functions.

Two main strands of literature exist within the study of reduced household mobility due to decreasing house prices. The first strand focuses on loss aversion. Loss averse households are not willing to sell their home for less than they paid themselves (Engelhardt, 2003; Genesove and Mayer, 2001). Facing a prospective loss thus reduces mobility. Even though these households could move from a financial point of view they are not willing to do so at a nominal loss. The second strand focuses on reduced mobility due to financial constraints (Chan, 2001; Ferreira et al., 2010, 2012; Henley, 1998; Schulhofer-Wohl, 2012). Negative equity may severely limit possibilities of obtaining a mortgage for a new home. Households with negative equity are locked-in as they are not able to move. Even though there is no formal downpayment constraint in the Netherlands, the residual debt causes a barrier in obtaining a new mortgage.

Most scholars have studied the effects of loss aversion and negative equity on household mobility individually. We argue, as did Engelhardt (2003), that loss aversion and negative equity effects should be studied simultaneously. We contribute to the existing literature by making a clear distinction between loss aversion and negative equity effects, while estimating the effects simultaneously. Besides, we provide estimates of negative equity effects conditional on household savings and look into voluntary and involuntary mobility. To the best of our knowledge, loss aversion and negative equity have not been investigated this extensively before.

Our analysis makes use of a unique administrative data set of Statistics Netherlands that contains the stock of Dutch owner-occupied houses and the traits of the households living in them. The period under investigation, 2006-2011, contains the peak in house prices and the following decline. Differences in contemporary housing duration combined with the price decreases provide the variation that we need for estimation and identification. This paper makes use of duration analysis to estimate the hazard rates of moving. The hazard rates are estimated with an extended Cox model.

The results suggest a strong effect of loss aversion. Households facing a prospective loss are over 50 percent less mobile than households not facing a loss. We find limited evidence for negative equity effects. Moderately underwater households seem to have a somewhat reduced mobility but heavily underwater households are the most mobile of all. Furthermore, the positive effect of household savings on mobility for underwater households provides evidence that the mobility is voluntary.

The remainder of this paper is organized as follows. Section 2 presents the theoretical background. Section 3 discusses the data set and variables. Section 4 describes the empirical model. Section 5 reports the estimates, while section 6 summarizes and concludes.

## 2. Theoretical background

### *2.1. Loss aversion*

Loss aversion is one of the mechanisms that explains how decreasing house prices can deter household mobility. Loss aversion describes how the nominal price that was originally paid for a house functions as a reference point in the household's selling decision; households are not willing to incur a nominal loss if they sell their house. Prospective losses thus deter residential mobility. Loss aversion was first introduced in prospect theory to describe the behavior that people give more importance to avoiding losses than obtaining gains (see Kahneman and Tversky, 1979; Tversky and Kahneman, 1991).

In their seminal paper Genesove and Mayer (2001) apply loss aversion to the housing market and study the effect of nominal loss aversion on asking prices, selling prices, and time-on-the-market. They corroborate that sellers use the transaction price that they originally paid as a reference point in their selling decision. Based on data of downtown Boston for the years 1990-1995 they conclude, as hypothesised, that facing a nominal loss leads to a higher selling price. The higher selling price is the result of a higher list price and a lower probability of sale. Genesove and Mayer (2001) do not study household mobility itself, but following their paper mobility studies have started to incorporate loss aversion into their studies.

Engelhardt (2003) studies the effect of equity constraints and loss aversion on household mobility in the United States. The focus is on the identification of these effects as both occur when prices start falling; periods of declining house prices are required for both binding equity constraints and nominal loss aversion. High equity households that are (financially) unconstrained are used for the identification of the nominal loss effect, while household potentially at risk of being constrained are used for the identification of negative equity effects. Engelhardt (2003) concludes that: "Household mobility is significantly influenced by nominal loss aversion. There is little evidence that low equity because of fallen house prices constrains mobility" (p. 171). Anenberg (2011) focuses on the effects of loss aversion and negative equity on house prices. He finds strong evidence that nominal losses and high loan-to-value (LTV) ratios have a positive effect on the selling price.

Loss aversion in the Dutch housing market has received almost no attention. Eichholtz and Lindenthal (2013) are a notable exception. They study loss aversion through the centuries based on housing transactions of the Herengracht in Amsterdam, spanning 324 years. They conclude that loss aversion has gotten more important over time. Still, a major concern of this paper is that it does not differentiate between loss aversion and equity effects. Financial constraints are even explicitly mentioned as an explanation for the psychological barrier that is loss aversion (Eichholtz and Lindenthal, 2013, p. 13).

### *2.2. Negative equity*

Negative equity is the second mechanism that relates decreasing house prices and household mobility. Decreasing house prices can lead to the mortgage being larger than the contemporary house value, that is, negative (housing) equity. Having negative equity, or being 'underwater' as it is also called, can make it impossible to obtain a mortgage for a new home. These households are said to be locked-in (Chan, 2001). Nonetheless, negative equity could also increase mobility through defaults and foreclosures.

Henley (1998) is one of the first to study the effects of negative equity on household mobility. He finds strong evidence that negative net housing equity deters residential mobility and labor market flexibility. The estimates suggest that owner-occupiers with negative equity encounter a down-payment constraint as they are no longer able to sell their house and make a down-payment on a next house, restricting geographical and labor market mobility.

Chan (2001) studies whether falling house prices reduce mobility of households with little equity (high LTV ratios). If such a household sells its house it is left with insufficient funds to repay its mortgage and make a down-payment on a new home, leading to a spatial lock-in. The household's contemporaneous LTV ratio is the variable of main interest. The crucial value for the LTV is set at 80 percent, as it is assumed that higher LTV ratios make a down-payment on a new house impossible. Chan (2001) recognizes that loss aversion may affect mobility and incorporates a cumulative house price change variable in the estimated models.[1] She does conclude that there is clear evidence of "severe constraints to mobility as a result of negative housing market shocks" (p. 584).

The exact opposite results are found by Coulson and Grieco (2013). They find that underwater households are more mobile than households with positive equity. That is, moderately underwater households have the same mobility rate as above-water households, while heavily underwater households are the most mobile category. The results, therefore, go against the predictions of the lock-in mechanism. Coulson and Grieco (2013) give both increased mobility due to defaults and increased mobility in order to prevent an approaching default as possible explanations for the empirical findings. The results found by Coulson and Grieco (2013) indicate that lock-in may not be the only mechanism through which negative equity can affect household mobility.

It is regularly hypothesized that defaults and foreclosures may increase mobility (Chan, 2001; Ferreira et al., 2010; Schulhofer-Wohl, 2012). Andersson and Mayock (2013) explicitly differentiate between voluntary mobility and default-induced mobility (due to strategic behavior or the inability to pay), i.e. they disentangle the lock-in mechanism from the default mechanism. Their results show a U-shaped relationship between equity and house-

[1] In this specification the cumulative house price change measures more than only loss aversion, so no conclusive results of a loss aversion effect are presented.

hold mobility; at moderate debt levels an increase in debt decreases mobility, while at high debt levels an increase in debt increases mobility.[2] In other words, they find that for low levels of negative equity the lock-in effect dominates, while for high levels of negative equity the default mechanism dominates.[3]

That the effect of negative equity on mobility is still being debated is probably best illustrated by the polemic that developed between Ferreira et al. (2010, 2012) and Schulhofer-Wohl (2012). Ferreira et al. (2010) have found a negative effect of negative equity on household mobility while based on the same data Schulhofer-Wohl (2012) finds the contrary, i.e. that homeowners with negative equity are more mobile. Schulhofer-Wohl (2012) argues that Ferreira et al. (2010, 2012) underreport household mobility by excluding 'temporary moves', that is, moves by households that do return to their (unsold) original home. The conclusions in these three articles seem to be driven by the definition of moving that is used. However, more important than the discussion of what moves to include or exclude is the fact that neither of these articles distinguishes between negative equity and loss aversion effects.

### *2.3. Household mobility*

Both loss aversion and negative equity effects are driven by decreasing house prices, resulting in a positive correlation between them. The correlation between the two mechanisms seems to make it impossible to study one without the other. Estimating the effect of negative equity without incorporating loss aversion will overestimate the absolute effect of negative equity, that is,

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[2]Andersson and Mayock (2013) lump all LTV ratios between 0 and 0.8 together in a single group (over 53 percent of their sample). Equity effects for above-water households with LTVs under 0.8 can therefore not be distinguished, while Henley (1998) shows that household mobility increases with positive house equity. Coulson and Grieco (2013) also provide estimates that show that household mobility increases with positive house equity for above-water households, up to an LTV of 0.9.

[3]Ghent and Kudlyak (2011) study differences in default between recourse and non-recourse states in the US. The results indicate that having a recourse loan affects default through a decrease in the sensitivity to negative equity. In recourse states defaults are involuntary (due to liquidity constraints), while in non-recourse states defaults may also be strategic. In the Netherlands mortgages are recourse loans, leaving defaulting households with a residual debt if the mortgage debt exceeds the sale revenues. Default-induced mobility is thus expected to be substantially lower in the Netherlands than in countries with non-recourse loans.

the true effect of negative equity is likely to be less negative than found in studies that do not account for loss aversion.

Strong evidence exists that loss aversion has a negative effect on mobility whereas the evidence for a negative effect of negative equity is less conclusive. Prior studies that take loss aversion into account have found little evidence that negative equity hampers mobility (Engelhardt, 2003). Studies that do find a lock-in effect of negative equity have generally refrained from distinguishing between loss aversion and negative equity effects (Ferreira et al., 2010, 2012; Henley, 1998; Struyven, 2015).

In our analysis we will distinguish between loss aversion and negative equity effects. We will look into non-housing wealth of underwater households as being locked-in is conditional on household savings; it is not evident that negative housing equity hinders mobility if a household has additional sources of wealth. By taking into account non-housing wealth we are able to investigate the U-shaped relationship between negative equity and household mobility that is suggested by Andersson and Mayock (2013). To our knowledge this paper is the first to investigate the relationship between decreasing house prices and household mobility in such detail.

## 3. Data

### *3.1. Data set*

The data set, covering the period 2006-2011, consists of housing spells and characteristics of households living in the stock of owner-occupied existing row houses in the Netherlands.[4] Most of our observations have housing spells that started before our stock sampling date, January 2006. Houses and households are observed annually until 2011, or until the moment that the house is sold. The data set is extended with new housing spells beginning between 2006 and 2011. That is, houses and households can re-enter the data set after a sale. These latter observations have spells that started after the stock sampling date. The data set is thus constructed as a stock sample extended with an inflow sample. In total the data set consists of 2,474,839

[4]The housing stock is divided into existing homes and newly-build houses. Newly-build houses only enter the analysis after they have been sold, that is, after they have become an existing home.

observations of 574,145 unique spells.[5]

The data set has been constructed by making use of unique administrative data of Statistics Netherlands (CBS). The data set combines individual data from the Cadastre records (*Bestaande Koopwoningen*), the Housing Stock Register (*Woonruimteregister verrijkt*), the Population Register (*Adresbus, Huishoudensbus, Persoontab*), the Job Register (*Baankenmerkenbus, Baansommentab, Hoofdbaanbus*), the Integrated Capital Data Set (*Integraal Vermogensbestand*), and the Integrated Income Data Set (*Integraal Huishoudens Inkomen*).

The Cadastre records are matched with the Housing Stock Register to identify the owner-occupied houses in the Netherlands. The Cadastre records contain information on transactions of existing homes, thereby providing information on mobility and housing duration. The transaction records consist of both voluntary and involuntary sales.[6] The Population Register, based on information from the municipalities, contains information on household composition and demographic characteristics. The Job Register has been compiled by Statistics Netherlands out of administrative sources from the tax office and the Employee Insurance Agency (UWV). It provides information on all employment relationships in the Netherlands (see Schoonhoven and Bottelberghs, 2014). The Dutch tax authority is the main source of information for both the Integrated Capital Data Set and the Integrated Income Data Set. The former provides information on the assets and liabilities of the households, while the latter contains information on household income and the income composition.

The panel data set that we have constructed contains the stock of owner-occupied row houses in the Netherlands and the characteristics of the households living in these homes. It is due to data limitations that we restrict our analysis to owner-occupied row houses. Compared to the other types of family homes row houses have a major advantage: households in row houses tend to have shorter durations than households in corner houses, semi-detached houses, and detached houses. This implies that left-censoring, an unobserved spell start, is less of a problem for row houses (see section 4.3).

[5] Including the observations with an unobserved spell start the data set counts 2,612,267 observations of 627,515 unique spells.

[6] While forced sales are included in the data, it is not possible to distinguish them from the other sales.

### *3.2. Spell length and mobility*

The Cadastre records (1995-2011) are the main source for our owner-occupied housing duration variable. For the stock-sampled observations house sales in the period 1995-2005 provide the beginning of the spell if a house is an existing home; the duration start of houses that were newly build in the period 1995-2005 is found in the Housing Stock Register. Durations of houses last sold before 1995 are not observed directly.[7] For the inflow-sampled observations the spell begins as soon as a house is bought after the stock sampling date. House sales in the period 2006-2011 provide, if a house is sold, the end of a spell for both the stock-sampled and the inflow-sampled observations. A move is thus defined as a house sale after the stock sampling date.

Table 1: Year of duration start

| | Frequency | Percent | Cum. percent |
|---|---|---|---|
| pre-1995 | 52399 | 11.47 | 11.47 |
| 1995 | 23486 | 5.14 | 16.61 |
| 1996 | 27339 | 5.99 | 22.60 |
| 1997 | 30799 | 6.74 | 29.34 |
| 1998 | 35371 | 7.74 | 37.09 |
| 1999 | 38311 | 8.39 | 45.47 |
| 2000 | 36755 | 8.05 | 53.52 |
| 2001 | 41761 | 9.14 | 62.66 |
| 2002 | 45486 | 9.96 | 72.62 |
| 2003 | 45712 | 10.01 | 82.63 |
| 2004 | 44274 | 9.69 | 92.32 |
| 2005 | 35065 | 7.68 | 100.00 |
| Total | 456758 | 100.00 | |

*Notes*: Statistics of stock-sampled row houses in 2006.

Table 1 shows the distribution of the starting years of the housing spells at the stock sampling date. The table shows that of the spells that started before January 2006 11.47 percent (52,399 observations) did start before 1995. For

[7]The Housing Stock Register provides the date that a (newly build) house is added to the housing stock. These addition dates go back until January 1992. However, as (re)sales between 1992-1994 are not observed the spell start of the houses that were newly build between 1992-1994 cannot be determined with absolute certainty.

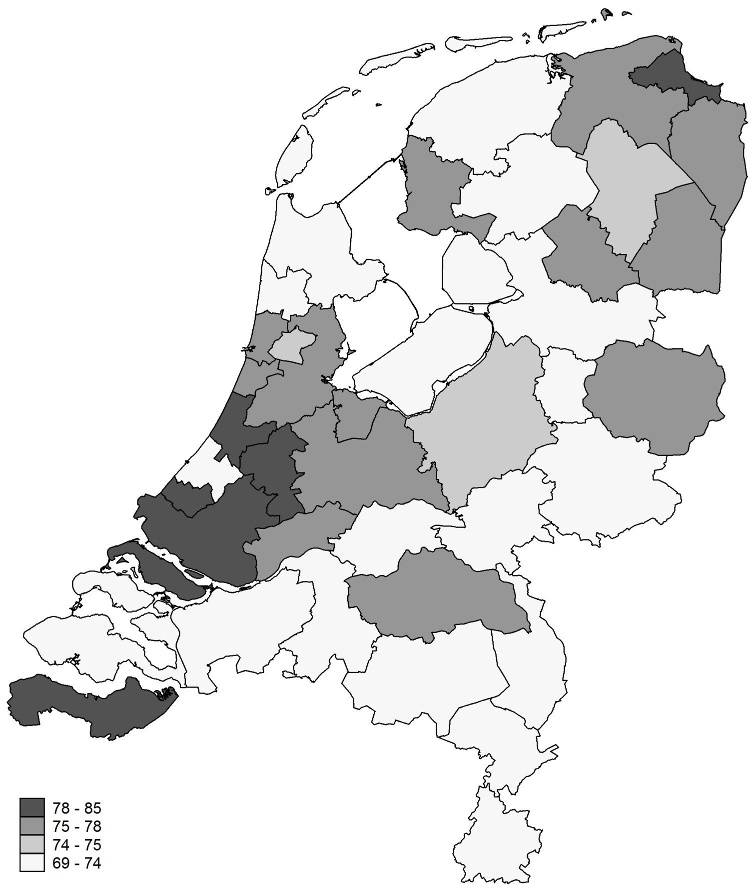


Figure 1: Median duration in months of stock-sampled row houses in 2006 at the COROP region level.

these observations the exact spell start is not observed, these observations are said to be left-censored. The way to handle left-censored observations is discussed in detail in section 4.3.

Figure 1 shows the regional distribution in median duration in the Netherlands. The economic core, the *Randstad*, has relatively long durations compared to the periphery. However, major differences are observed in the so-called shrinking regions: the south-west corner (Zeeuws-Vlaanderen) and the north-east corner of the Netherlands (Groningen) have relatively long durations, whereas the durations in the southernmost province (Limburg) are relatively short. Evidently, the regional differences in duration imply differ-

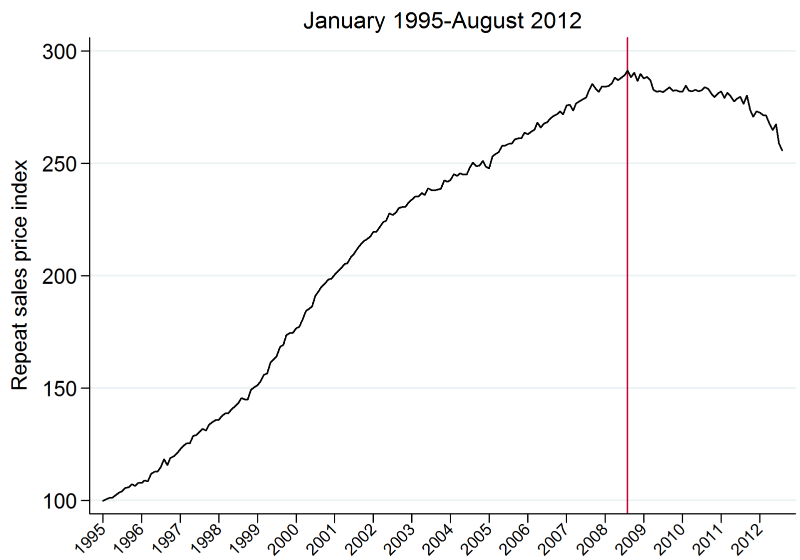


Figure 2: Repeat sales price index for row houses in the Netherlands.

ences in mobility as well.

### *3.3. Decreasing prices*

The price development of row houses in the Netherlands is presented in Figure 2. The repeat sales price index that we have estimated shows that house prices peaked in 2008.[8] Prices gradually increased up to 2008 and started decreasing afterwards; for row houses prices decreased 6.2 percent on average between August 2008 and December 2011. The price decreases are important as they are the main driver for both negative equity and loss aversion. In the following subsections we will look into the measures of negative equity and loss aversion. Summary statistics for the remaining covariates can be found in Appendix B.

### *3.4. Prospective losses*

Observed sale prices cannot be used to identify loss aversion as unsold houses are the likeliest to be affected by loss aversion and their sale prices are by

[8]The estimation of the repeat sales price index is discussed in Appendix A.

definition not observed. Instead of actual losses we have to resort to prospective losses. After all, whether a nominal gain or loss would occur depends on the price that could be obtained if the house was to be sold, while potential losses could result in transactions not taking place.

In this paper we define the market value of a house as the purchasing price adjusted by the cumulative change in the repeat sales price index.[9] In other words, the contemporary market value of a house is determined by the price at which the house was bought ($P_0$), the price index at the time the house was bought ($I_0$), and the contemporary price index ($I_t$).

$$P_{it} = P_{i0}\left(1 + \frac{I_{ct} - I_{c0}}{I_{c0}}\right) \tag{1}$$

where subscript $c$ of the price index denotes the region.

A household faces a prospective loss if the contemporary value ($P_t$) is less than the price that was initially paid ($P_0$). Given that $P_t$ is expressed in terms of $P_0$ this can be expressed in terms of the price index.

$$pros.\ loss = \begin{cases} 0 & \text{if } I_{ct} \geq I_{c0} \\ 1 & \text{if } I_{ct} < I_{c0} \end{cases} \tag{2}$$

We have estimated repeat sales price indices for 40 COROP regions in the Netherlands.[10] That means that loss aversion is identified through the use of the regional repeat sales price index.[11] The estimation of the repeat sales price index is discussed in Appendix A.

Figure 2 shows that only houses that were bought not that long before the stock sampling date are confronted with potential losses, while the magnitude of the prospective losses is relatively small. Consequently, no distinction in size is made within the prospective loss variable. Even though

[9]As we are interested in the (relative) price development only, the smoothed repeat sales price index fits our purpose very well. A comparison between various price indices for the Netherlands is done by de Vries et al. (2009) and Jansen et al. (2008).

[10]The COROP regions were defined in 1971 by a committee named *Coördinatiecommissie Regionaal Onderzoeksprogramma*, hence the name COROP. A COROP is an administrative region, in size between provinces and municipalities, that joins together regional labor markets based on commuting flows. Most COROPs, therefore, exist of a larger city and its periphery.

[11]The regional indices have been smoothed through (second degree) local polynomial smoothing in order to limit monthly fluctuations from the trend.

regional differences exist, it is only towards 2011 that prices had decreased until the price level of around 2006. This means that the lion's part of the households facing a prospective loss have spells that started after the stock sampling date. For the households with a spell starting before January 2006 0.2 percent of the observations (3,462 obs.) have a prospective loss, while for the households with a spell starting after January 2006 30.0 percent of the observations (107,808 obs.) have a prospective loss.

### *3.5. Loan-to-value ratios*

The effects of negative equity will be studied by making use of the household's LTV ratio, i.e. the value of the mortgage relative to the value of the house. A ratio of one indicates that the value of the mortgage equals the value of the house, while ratios larger than one indicate the existence of negative equity. It has to be noted though that the LTV ratios are overestimated as the asset side in endowment mortgages (in Dutch *beleggingshypotheek* and *spaarhypotheek*) are not taken into account.[12]

Table 2: Percentiles of loan-to-value ratios

| | Non-left-cens. | Left-cens. | Total |
|---|---|---|---|
| p1 | .000 | .000 | .000 |
| p5 | .255 | .000 | .122 |
| p10 | .398 | .000 | .288 |
| p25 | .596 | .167 | .529 |
| p50 | .831 | .341 | .786 |
| p75 | 1.016 | .553 | 1.001 |
| p90 | 1.153 | .836 | 1.142 |
| p95 | 1.282 | 1.087 | 1.271 |
| p99 | 1.641 | 1.662 | 1.643 |
| Observations | 404359 | 52399 | 456758 |

*Notes*: Statistics of stock-sampled row houses in 2006. Spells starting before 1995 are left-censored. The respective percentiles are given by p1 until p99.

The LTV ratios in the Netherlands are amongst the highest in the world

[12] Using Dutch survey data Schilder and Conijn (2012) exploit information on mortgage expenditures and interest payments to estimate the asset side of endowment mortgages and include endowment mortgage assets in the calculated potential residual debt. Nevertheless, as this information is not available in our data set we are not able to follow this approach.

(Dutch Central Bank and Netherlands Authority for the Financial Markets, 2009; Dröes and Hassink, 2014). The high LTV is explained by the existence of a fiscal policy that encourages mortgage debt through the full deductibility of mortgage interest payments (Rouwendal, 2007). Besides, there is no down-payment requirement as is the case in for instance the United States (Dröes and Hassink, 2014).

Table 2 shows the distribution of LTV ratios for left-censored and non-left-censored observations. The table shows that households with the longest spells, that is the spells that started before 1995, have lower LTV ratios. The median LTV for spells that started before 1995 is 0.341, whereas the median LTV for spells starting after 1995 is 0.831. The table also shows that within the left-censored observations many more households have paid off their mortgages than within the non-left-censored observations, between 10-25 percent and 1-5 percent respectively. These differences suggest that simply discarding the left-censored observations when analyzing equity effects might affect the results.

Table 3: Ratios of LTV groups with and without left-censored obs.

| | Non-left-cens. | Left-cens. | Total |
|---|---|---|---|
| LTV≤0.2 | .0396 | .2926 | .0686 |
| 0.2<LTV≤0.4 | .0613 | .2895 | .0875 |
| 0.4<LTV≤0.6 | .1533 | .2035 | .1590 |
| 0.6<LTV≤0.8 | .2113 | .1039 | .1990 |
| 0.8<LTV≤1.0 | .2592 | .0471 | .2349 |
| 1.0<LTV≤1.2 | .1993 | .0263 | .1794 |
| LTV>1.2 | .0759 | .0370 | .0715 |
| *Moderately underwater (subsgroups)* | | | |
| W<0 | .0040 | .0007 | .0036 |
| 0≤W<U | .1925 | .0245 | .1732 |
| W≥U | .0028 | .0011 | .0026 |
| *Heavily underwater (subsgroups)* | | | |
| W<0 | .0017 | .0011 | .0017 |
| 0≤W<U | .0729 | .0345 | .0685 |
| W≥U | .0013 | .0014 | .0013 |
| Observations | 404359 | 52399 | 456758 |

*Notes*: Statistics of stock-sampled row houses in 2006. Moderately underwater (1.0<LTV≤1.2). Heavily underwater (LTV>1.2). Additional wealth (W). Amount underwater (U).

The LTV ratios have been used to create seven LTV groups, which increase 0.2 (20 percent) per category (see Table 3). The latter two groups, LTV between 1.0 and 1.2 and LTV above 1.2 respectively, are so-called 'underwater' households as their mortgage is larger than their house value. In Table 3 the underwater households have also been subdivided into different groups based upon additional wealth, that is wealth excluding housing wealth. The table shows that the great majority of underwater households has additional wealth, but that the additional wealth is smaller than the amount that the household is underwater. This holds for both the moderately (1.0<LTV≤1.2) and the heavily (LTV>1.2) underwater households.

## 4. Empirical model

### *4.1. Specification of the hazard rate*

Duration analysis is particularly well-suited to study mobility in the housing market. Mobility is generally studied by estimating hazard rates, i.e. the probability that a household will move in a given period conditional on not having moved before. In order to analyse housing duration we will be estimating an extended Cox model. We will be applying a continuous time specification as the ratio of the interval length (duration is measured in months) to the typical housing duration is relatively small (Jenkins, 2005, p. 21).

The Cox proportional hazard model (Cox, 1972, 1975) has empirically been very successful (Cameron and Trivedi, 2005). The Cox proportional hazard is a semiparametric method; non-parametric regarding the baseline hazard, parametric regarding the effects of the set of covariates. The starting point is the standard proportional hazards framework. The hazard rate is given as follows (see Cameron and Trivedi, 2005):

$$\lambda(t|\boldsymbol{x}, \beta) = \lambda_0(t)\phi(\boldsymbol{x}, \beta) \tag{3}$$

where $t$ is duration, $\boldsymbol{x}$ is the set of covariates, and $\lambda_0$ is the baseline hazard. The baseline hazard is a function of $t$ alone and $\phi(\boldsymbol{x}, \beta)$ is a function of $\boldsymbol{x}$ alone. As $\phi(\boldsymbol{x}, \beta)$ is generally specified in an exponential form, i.e. $exp(\boldsymbol{x}'\boldsymbol{\beta})$, the conditional hazard rate becomes:

$$\lambda(t|\boldsymbol{x}, \beta) = \lambda_0(t)exp(\boldsymbol{x}'\boldsymbol{\beta}) \tag{4}$$

The hazard functions $\lambda(t|\boldsymbol{x})$ are all proportional to the baseline hazard, hence its name. Differences in characteristics simply imply a scaling of the baseline hazard. The scaling factor is given by $exp(\boldsymbol{x}'\boldsymbol{\beta})$. In other words, the hazard ratios depend on the covariates but not on $t$. Cox (1972, 1975) suggested a partial likelihood approach that allows for estimation of the parameters without estimating the baseline hazard.

The Cox proportional hazard model can easily be extended to include time-varying covariates.

$$\lambda(t|\boldsymbol{x}(t)) = \lambda_0(t)\phi(\boldsymbol{x}(t), \beta) \tag{5}$$

However, as $\boldsymbol{x}$ depends on $t$ the proportionality factor now varies with survival time, that is, the proportional hazard assumption is no longer satisfied. Still, as long as the partial likelihood is adjusted accordingly, the model can be estimated (Cameron and Trivedi, 2005; Jenkins, 2005). It is the Cox model with time-varying covariates that is called the extended Cox model. Even though it is not a proportional hazard model in a strict sense, it is often referred to as a proportional hazard with time-varying covariates (Cameron and Trivedi, 2005, p. 991).

### *4.2. Left truncation*

The above model could directly be estimated if one uses an inflow sample, that is, a random sample of all households starting a (housing) spell in a given time interval. However, a large part of our data set consists of a stock sample: a random sample of all households that had already started their spell at our stock sampling date. The spell start date is found before the moment of observation. The problem here is that the probability of observing a short duration is smaller than observing a longer duration; the longer the typical spell length, the greater the proportion of long spells in a stock sample.

The best way to understand this is with an illustration from our data. We have information on housing spells that started in the period 1995-2011. If we look at the stock of owner-occupier households in January 2006 the average expected spell length – expected because these spells have not ended yet by definition – is longer than the expected spell length of *all* the spells that started before 2006. After all, most of the short spells that occurred between 1995 and 2005 are not observed in our stock sample as they ended before 2006; only short spells that started close to our (stock) sampling date can be observed. Thus, if our population comprises all households that bought a house after 1995 our random stock sample causes a sample selection problem as observations are missing non-randomly.

This sample selection problem is known as left truncation (Cameron and Trivedi, 2005). Kiefer (1988) uses the term length-biased sampling to describe it. It is also referred to as delayed entry as the individuals in the sample are not 'at risk' from the beginning of their spells. They survive until the sampling date per se and become at risk at the moment that they are sampled (Jenkins, 2005). Nevertheless, the sample selection problem is easy to deal with as long as we observe the starting dates of the spells and have observations of some spells after the sampling date (Cameron and Trivedi, 2005). We can correct for the sample bias by taking into account the time between the start of the spell and the moment of sampling. Put differently, we can analyse the observations conditional on surviving up to the sampling date (Jenkins, 2005, pp. 64-66).

*4.3. Left-censoring*

Some of the houses in our stock sample have not been sold between 1995 and 2005. The exact starting dates of these housing spells remain unobserved. These observations are said to be left-censored. Left-censoring could lead to a selection bias as the longest durations are excluded from the analysis (Iceland, 1997). The possibility of a selection bias leads us to investigate the methods that are used to handle left-censored data even though the proportion of left-censored spells is relatively small: 11.47 percent at the stock sampling date. Ex ante there is no reason to assume that households who bought before 1995 react differently to prospective losses or to being underwater than households with shorter durations.[13]

Left-censoring is most commonly handled by discarding the left-censored data altogether. Although Allison (1984, p. 57) calls this the "safest approach" – claiming that "it should not lead to any biases" – the contemporary view is that discarding the left-censored observations could cause serious selection bias (Gottschalk and Moffitt, 1994; Iceland, 1997; Moffitt

[13]Following Stevens (1999) we have run a regression with an artificial stock sampling date, that is excluding durations that started in 1995 and 1996 from the sample of non-left-censored observations. The estimates of the standard (left-censored) sample and the artificially left-censored sample are virtually the same, suggesting no effect of a sample selection bias due to left-censoring.

and Rendall, 1995; Stevens, 1999).[14] Consequently we consider it necessary to investigate whether excluding left-censored spells causes selection bias in our results.

The simplest way to include the left-censored observations is to substitute the left-censoring moment as the beginning of the spell (Guo, 1993). An empirical application of this approach can be found in Lawrance and Marks (2008). However, this approach is only optimal if the hazard rate is constant, which is generally not the case (Allison, 1984; Guo, 1993; Iceland, 1997). For obvious reasons we will call this the naive approach. A more elaborate approach is 'integrating out' over all possible durations (see Gottschalk and Moffitt, 1994; Moffitt and Rendall, 1995). This approach, however, is not feasible with time-varying covariates as is the case in our analysis (Gottschalk and Moffitt, 1994; Stevens, 1999). The remaining approaches estimate the durations of the left-censored spells through additional assumptions on the distribution of the durations (e.g. Guo, 1993).

Our preferred way of handling the left-censored data makes optimal use of a not yet exploited feature of the left-censored observations in our data set. That is, for a part of our left-censored observations we observe the date that the house has been added to the housing stock. While the transaction records of the Cadastre records do not go back further than 1995, the Housing Stock Register goes back until 1992 providing likely starting dates for houses that have been added to the housing stock between 1992 and 1994. While the spell start is not observed directly, it is not likely that these 'left-censored homes' have been sold twice in a very short period. The date (in the period 1992-1994) that the newly build house has been added to the housing stock can serve as a proxy for the beginning of the housing spell.

Furthermore, these observed 'left-censored' durations can be matched with the remaining left-censored observations. Given the strong correlation between the age of the owner and the duration of the left-censored observations, age is used to match the proxied observations with the left-censored observations lacking this proxy. Even though the majority of the left-censored observations is likely to have started between 1992 and 1994 (see Table 1), the estimated left-censored durations will be an underestimation of the ac-

[14]Apart from simply discarding the left-censored data one could also refine the research question to exclude the left-censored observations (Iceland, 1997). In our paper that would have meant restricting the research question to exclude the longest durations from our analysis.

tual durations as no matched spells start before 1992. The main advantage of this approach, however, is that we do not need any further distributional assumptions while optimally using the available information.

To make sure that our results are not driven by selection bias due to the exclusion of the left-censored observations we will provide estimation results with and without the left-censored spells. The left-censored data will be incorporated by employing both the naive approach – substituting the left-censoring date as the spell start – and the proxy/matching approach. The comparison of the results with and without the left-censored spells will show whether omitting the left-censored spells leads to selection bias (Iceland, 1997; Stevens, 1999).

### *4.4. Covariates*

The variables of main interest are the loss indicator, indicating whether the regional house price index at the time the house was purchased was higher than the contemporaneous house price index, and the LTV indicators. The other covariates that will be used to estimate equation (5) include a loan-to-income (LTI) indicator (six categories), an age indicator (ten categories), a household type indicator (seven categories), a labor market indicator (five categories), a gender indicator, a divorce indicator, and a region indicator (40 COROPs).

The LTV categories are LTV below 0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8, 0.8-1.0 (reference category), 1.0-1.2, and LTV above 1.2. The LTI categories are LTI below 1.0 (reference category), 1.0-2.0, 2.0-3.0, 3.0-4.0, 4.0-5.0, and LTI above 5.0. The age groups are under 25 (reference category), 25-30, 30-35, 35-40, 40-45, 45-50, 50-55, 55-60, 60-65, and over 65. The household types are single person household (reference category), unmarried couple without children, married couple without children, unmarried couple with children, married couple with children, one parent household, and other household types. The labor market categories are no job, no change in job or jobs (reference category), loss of a job, getting a (or an extra) job, and losing a job while getting another.

## 5. Estimates

The estimation results of equation (5) can be found in Table 4. The table presents the estimated hazard ratios of the semi-parametric extended Cox model. A ratio of one indicates that the effect is the same as the baseline

Table 4: Hazard ratios of households mobility: regression results of equation (5)

| | (1) Left-censored | | (2) Matching | | (3) Naive | | (4) Left-cens | | (5) Matching | | (6) Naive | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Prospective loss | 0.497*** | (0.012) | 0.467*** | (0.011) | 0.464*** | (0.011) | 0.499*** | (0.012) | 0.469*** | (0.011) | 0.466*** | (0.011) |
| LTV≤0.2 | 0.428*** | (0.012) | 0.813*** | (0.015) | 0.850*** | (0.016) | 0.434*** | (0.012) | 0.822*** | (0.015) | 0.860*** | (0.016) |
| 0.2<LTV≤0.4 | 0.826*** | (0.016) | 1.058*** | (0.015) | 1.078*** | (0.015) | 0.833*** | (0.016) | 1.067*** | (0.015) | 1.087*** | (0.015) |
| 0.4<LTV≤0.6 | 1.009 | (0.013) | 0.952*** | (0.010) | 0.935*** | (0.010) | 1.014 | (0.013) | 0.957*** | (0.011) | 0.940*** | (0.010) |
| 0.6<LTV≤0.8 | 1.056*** | (0.011) | 0.977* | (0.009) | 0.960*** | (0.009) | 1.058*** | (0.011) | 0.980* | (0.009) | 0.963*** | (0.009) |
| 1.0<LTV≤1.2 | 0.836*** | (0.008) | 0.890*** | (0.009) | 0.898*** | (0.009) | | | | | | |
| LTV>1.2 | 2.117*** | (0.025) | 2.488*** | (0.026) | 2.553*** | (0.026) | | | | | | |
| 1.0<LTI≤2.0 | 0.602*** | (0.011) | 0.740*** | (0.009) | 0.700*** | (0.009) | 0.605*** | (0.011) | 0.741*** | (0.009) | 0.701*** | (0.009) |
| 2.0<LTI≤3.0 | 0.347*** | (0.007) | 0.497*** | (0.007) | 0.467*** | (0.007) | 0.351*** | (0.007) | 0.501*** | (0.007) | 0.470*** | (0.007) |
| 3.0<LTI≤4.0 | 0.274*** | (0.006) | 0.428*** | (0.007) | 0.403*** | (0.007) | 0.277*** | (0.006) | 0.432*** | (0.007) | 0.407*** | (0.007) |
| 4.0<LTI≤5.0 | 0.338*** | (0.008) | 0.556*** | (0.010) | 0.522*** | (0.010) | 0.342*** | (0.008) | 0.562*** | (0.010) | 0.528*** | (0.010) |
| LTI>5.0 | 0.687*** | (0.015) | 1.124*** | (0.019) | 1.065*** | (0.018) | 0.695*** | (0.016) | 1.133*** | (0.020) | 1.075*** | (0.018) |
| Age 25-30 | 0.767*** | (0.038) | 0.778*** | (0.039) | 0.781*** | (0.039) | 0.768*** | (0.038) | 0.778*** | (0.039) | 0.782*** | (0.039) |
| Age 30-35 | 0.659*** | (0.033) | 0.676*** | (0.033) | 0.678*** | (0.033) | 0.658*** | (0.033) | 0.676*** | (0.033) | 0.677*** | (0.033) |
| Age 35-40 | 0.518*** | (0.026) | 0.512*** | (0.025) | 0.499*** | (0.025) | 0.517*** | (0.026) | 0.510*** | (0.025) | 0.497*** | (0.025) |
| Age 40-45 | 0.358*** | (0.018) | 0.343*** | (0.017) | 0.341*** | (0.017) | 0.356*** | (0.018) | 0.341*** | (0.017) | 0.338*** | (0.017) |
| Age 45-50 | 0.257*** | (0.013) | 0.271*** | (0.014) | 0.276*** | (0.014) | 0.256*** | (0.013) | 0.269*** | (0.013) | 0.274*** | (0.014) |
| Age 50-55 | 0.210*** | (0.011) | 0.256*** | (0.013) | 0.265*** | (0.013) | 0.209*** | (0.011) | 0.254*** | (0.013) | 0.263*** | (0.013) |
| Age 55-60 | 0.200*** | (0.011) | 0.273*** | (0.014) | 0.289*** | (0.015) | 0.199*** | (0.011) | 0.270*** | (0.014) | 0.286*** | (0.014) |
| Age 60-65 | 0.212*** | (0.011) | 0.281*** | (0.014) | 0.309*** | (0.016) | 0.211*** | (0.011) | 0.278*** | (0.014) | 0.306*** | (0.016) |
| Age >65 | 0.208*** | (0.011) | 0.279*** | (0.014) | 0.332*** | (0.017) | 0.206*** | (0.011) | 0.276*** | (0.014) | 0.328*** | (0.017) |
| Male | 0.949*** | (0.015) | 0.995 | (0.013) | 1.017 | (0.013) | 0.950** | (0.015) | 0.996 | (0.013) | 1.018 | (0.013) |
| Unmarried w/o children | 0.824*** | (0.012) | 0.887*** | (0.012) | 0.871*** | (0.011) | 0.825*** | (0.012) | 0.887*** | (0.012) | 0.871*** | (0.011) |
| Married w/o children | 0.763*** | (0.011) | 0.922*** | (0.010) | 0.916*** | (0.010) | 0.764*** | (0.011) | 0.923*** | (0.010) | 0.917*** | (0.010) |
| Unmarried with children | 0.736*** | (0.011) | 0.754*** | (0.010) | 0.741*** | (0.010) | 0.736*** | (0.011) | 0.754*** | (0.010) | 0.741*** | (0.010) |
| Married with children | 0.662*** | (0.008) | 0.716*** | (0.007) | 0.705*** | (0.007) | 0.662*** | (0.008) | 0.716*** | (0.007) | 0.705*** | (0.007) |
| One parent household | 1.019 | (0.020) | 1.025 | (0.017) | 1.027 | (0.017) | 1.019 | (0.020) | 1.025 | (0.017) | 1.027 | (0.017) |
| Other household type | 0.556*** | (0.056) | 0.593*** | (0.053) | 0.578*** | (0.051) | 0.558*** | (0.056) | 0.596*** | (0.053) | 0.581*** | (0.051) |
| Divorced | 4.433*** | (0.080) | 3.258*** | (0.054) | 3.423*** | (0.054) | 4.440*** | (0.080) | 3.264*** | (0.054) | 3.429*** | (0.055) |
| No job | 1.019 | (0.011) | 1.007 | (0.009) | 1.009 | (0.009) | 1.018 | (0.011) | 1.007 | (0.009) | 1.009 | (0.009) |
| Job plus | 1.176*** | (0.028) | 1.162*** | (0.025) | 1.149*** | (0.025) | 1.173*** | (0.028) | 1.158*** | (0.025) | 1.144*** | (0.025) |
| Job minus | 1.123*** | (0.018) | 1.114*** | (0.015) | 1.114*** | (0.015) | 1.122*** | (0.018) | 1.114*** | (0.015) | 1.114*** | (0.015) |
| Job plus and minus | 1.162*** | (0.012) | 1.141*** | (0.011) | 1.139*** | (0.011) | 1.163*** | (0.012) | 1.142*** | (0.011) | 1.140*** | (0.011) |
| 1.0<LTV≤1.2 & W<0 | | | | | | | 0.731*** | (0.037) | 0.748*** | (0.036) | 0.752*** | (0.036) |
| 1.0<LTV≤1.2 & 0≤W<U | | | | | | | 0.827*** | (0.009) | 0.877*** | (0.009) | 0.885*** | (0.009) |
| 1.0<LTV≤1.2 & W≥U | | | | | | | 1.536*** | (0.074) | 1.869*** | (0.080) | 1.880*** | (0.081) |
| LTV>1.2 & W<0 | | | | | | | 1.636*** | (0.099) | 1.848*** | (0.096) | 1.866*** | (0.097) |
| LTV>1.2 & 0≤W<U | | | | | | | 2.098*** | (0.025) | 2.459*** | (0.026) | 2.523*** | (0.027) |
| LTV>1.2 & W≥U | | | | | | | 4.374*** | (0.260) | 5.305*** | (0.254) | 5.538*** | (0.263) |
| Number obs. | 2,474,839 | | 2,612,267 | | 2,612,267 | | 2,474,839 | | 2,612,267 | | 2,612,267 | |
| Log-likelihood | -1120652 | | -1555687 | | -1576926 | | -1120493 | | -1555398 | | -1576630 | |

*Notes*: Exponentiated coefficients (hazard ratios) with clustered standard errors in parentheses. The estimated coefficients for the COROP effects are excluded from the table. Models are estimated for row houses. Additional wealth (W). Amount underwater (U). Reference categories: LTV between 0.8-1.0, LTI below 1.0, age below 25, single person household, and no job change(s). For details on the matching and naive approach see section 4.3. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

hazard. Coefficients below one indicate a probability lower than the baseline, whereas coefficients above one indicate a higher probability.

The first column of Table 4 shows the results where the left-censored observations have been discarded.[15] The coefficient for the *prospective loss* variable is 0.497, indicating that a prospective loss results in a probability of selling that is only 49.7 percent of the situation where there is no such loss. The probability of selling is thus 50.3 percent lower in case of a prospective loss.

Compared to households that have a mortgage between 80 and 100 percent of the house value (the reference category), those with a mortgage between 100 and 120 percent of the house value have a 16.4 percent lower probability of moving (the coefficient is 0.836). These moderately underwater households thus have a lower probability of moving than the group that has a slightly better financial position. Note, however, that the moderately underwater households have a higher probability of moving than do households with LTVs between 0 and 40 percent.[16] The coefficient for households with mortgages over 120 percent of the house value is 2.117, meaning that these heavily underwater households have a 111.7 percent higher probability of moving than the reference category ($0.8<\text{LTV}\leq 1.0$). The heavily underwater households, therefore, have the highest mobility of all LTV categories.[17]

The results in column 1 also show that, overall, mobility decreases with age; people under 25 (the reference category) have by far the highest mobility. There are just significant differences between men and women, while divorced people have a 343.3 percent higher probability of selling/moving than non-divorced people. Job mobility is also related to housing duration and hazard rates: getting a job (or an additional job for that matter) increases the

[15] All results are robust to the inclusion of cohort dummies (i.e. year dummies indicating the spell start) and municipality fixed effects (instead of COROP fixed effects).

[16] The results indicate that for above-water households mobility is lowest for the lowest LTV groups. This corresponds to the findings of Henley (1998) and Coulson and Grieco (2013), who find that (positive) house equity decreases mobility. This result is consistent, for instance, with low LTV households taking larger steps on the property ladder, resulting in less moves over a life-time.

[17] An additional regression confirms that dropping the prospective loss variable from the regression leads to smaller coefficients for the negative equity categories (see the discussion in section 2.3). In other words, not including the measure of loss aversion in the regression model indeed leads to an overestimation (in absolute terms) of the effect of negative equity on mobility.

probability of selling by 17.6 percent, while losing a job (possibly out of multiple jobs) increases mobility by 12.3 percent (both compared to the group without any job changes).[18] Losing one job and getting another increases selling probability by 16.2 percent. Furthermore, the coefficients of the loan-to-income ratios show a U-pattern; households with a moderate LTI have the lowest mobility.

The second and third column of Table 4 show the estimates when the left-censored observations have been included. Column 2 shows the results for the matching approach, column 3 shows the results for the naive approach (see section 4.3). Facing a prospective loss is estimated to decrease mobility by 53.3 percent in the matching approach and 53.6 percent in the naive approach. Compared to the reference category being moderately underwater reduces mobility by 11.0 and 10.2 percent respectively, while being heavily underwater increases mobility by 148.8 and 155.3 percent. Overall the patterns and the magnitudes of the estimated effects are very similar for all three approaches, that is, the inclusion or exclusion of the left-censored observations does not drive our results.

In the estimates that are presented in the columns 4, 5, and 6 of Table 4 the moderately underwater households ($1.0<\text{LTV}\leq 1.2$) and the heavily underwater households ($\text{LTV}>1.2$) have been divided into three different groups based on wealth excluding net housing wealth (savings, etc.). The first group has negative wealth/savings, that is, the household has additional debt. The second group has positive wealth/savings but the total is smaller than the amount that the household is underwater, while the third group has positive wealth/savings that is larger than the amount that it is underwater.

The results in the columns 4, 5, and 6 of Table 4 confirm that the mobility of the moderately underwater households is lower than the mobility of the heavily underwater households. The estimates also show that the moderately underwater households with additional debt are the least mobile subgroup. These households are between 24.8 and 26.9 percent less mobile than the group with an LTV between 80 and 100 percent. Another important observation is that the coefficients for the subgroups increase with additional wealth, thereby showing that mobility of households with negative equity rises with additional (non-housing) wealth. This holds for both the moderately and heavily underwater households. Apparently the high mobility

[18] Note that this latter group might very well identify past job transitions.

for the heavily underwater households is not caused by involuntary mobility. After all, the heavily underwater households with additional debt are the likeliest to be confronted with forced house sales.

## 6. Conclusions

In this paper we make a clear distinction between loss aversion and negative equity. The prospective loss indicator is used to identify loss aversion, while loan-to-value (LTV) ratios larger than one indicate the existence of negative equity. The paper has shown that a prospective loss decreases mobility in the owner-occupied housing market by more than 50 percent. Being moderately underwater (LTV between 1.0 and 1.2) reduces mobility by about 15 percent compared to the group that has a mortgage that is not larger than its house value (LTV between 0.8 and 1.0). Nevertheless, the mobility rate of the moderately underwater households remains higher than the households with the lowest LTVs. The analysis shows that heavily underwater households have the highest mobility: over 100 percent higher than those with an LTV between 0.8 and 1.0. The analysis also shows that additional wealth/savings increases mobility for underwater households. The effects are similar for moderately and heavily underwater households, the difference being that mobility is roughly 2.5 times higher for the heavily underwater households.

The conclusions are threefold. First, our results – consistent with the findings of Engelhardt (2003) – indicate the existence of loss aversion as prospective losses decrease mobility substantially. Second, there is much less evidence for negative equity effects; moderately underwater households are less mobile than households with mortgages between 80 and 100 percent of their house values, but moderately underwater households are more mobile than households with very low LTV ratios. This finding is similar to the findings of Schulhofer-Wohl (2012) and Coulson and Grieco (2013). Moderately underwater households might have encountered some negative effects – especially households with additional debt – but heavily underwater households have the highest mobility. Third, non-housing wealth increases mobility for underwater households, suggesting that the high mobility for heavily underwater households is not default-driven. If the higher mobility for heavily underwater households was default-driven then we would have seen higher mobility rates for the households with negative wealth/savings. After all, households with positive wealth are likelier able to make their mortgage payments even if their house is underwater. The high mobility of heavily underwater households is an interesting phenomenon that needs attention in future research. Possibly heavily underwater households use their financial means to move instead of continuing mortgage payments on their underwater home.

This paper has presented evidence that decreasing house prices have hampered household mobility through loss aversion. There is less evidence that negative equity limits household mobility even though some particular groups with negative equity are indeed less mobile. All in all, it seems that households did not want to move in a market with decreasing prices, while they generally could have from a financial perspective.

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## Appendix A. Repeat sales price index

The repeat sales index makes use of repeated sales of houses or pairs of transactions as Bailey et al. (1963) call them in their seminal paper. Under the assumption that house quality is constant, house price changes over time can be estimated without house characteristics being observed (e.g. Wang and Zorn, 1997). The starting point for the repeat sales index is a standard hedonic pricing model with a time indicator for the moment of sale.

$$ln(P_{it}) = \beta_0 + \sum_{k=1}^{K} \beta_k z_{ik} + \sum_{t=2}^{T} \gamma_t D_{it} + \mu_{it} \tag{A.1}$$

where $P$ is the price of property $i$ at time $t$, $z$ is the $k^{\text{th}}$ house characteristic, $D$ is the sale time indicator, and $\mu$ is a random error term.

The price change for a house that is sold twice is easily found by subtracting the price at time $t_1$ from the price at time $t_2$ (where $0 \leq t_1 < t_2 \leq T$). It follows that the difference in price between sale and resale is given by:

$$\begin{aligned} ln(P_{it_2}) - ln(P_{it_1}) &= ln\left(\frac{P_{it_2}}{P_{it_1}}\right) \\ &= \sum_{t=2}^{T} \gamma_{t_2} D_{it_2} - \sum_{t=2}^{T} \gamma_{t_1} D_{it_1} + (\mu_{it_2} - \mu_{it_1}) \qquad \text{(A.2)} \\ &= \sum_{t=2}^{T} \delta_t D^{\star}_{it} + \epsilon_{it} \end{aligned}$$

where $D^{\star}_{it}$ is a time indicator that is equal to one in the period of the resale, minus one in the period of the (original) sale, and zero otherwise. The random error term is given by $\epsilon$.

The repeat sales index $I_t$ is found by exponentiating the Ordinary Least Squares regression results of equation A.2. By multiplying the coefficients with 100 we set the base for $I_0$ at 100.

$$I_t = 100exp(\widehat{\delta_t}) \tag{A.3}$$

We have estimated a separate price index, $I_{ct}$, per COROP region. Thus, we have estimated a total of 40 regional repeat sales price indices.

## Appendix B. Summary statistics

Table B.5: Household summary statistics

| | Non-left-cens. | Left-cens. obs. | Total |
|---|---|---|---|
| Age | 41.2 | 55.1 | 42.8 |
| | (10.5) | (12.7) | (11.6) |
| Male | 0.917 | 0.873 | 0.911 |
| | (0.277) | (0.333) | (0.284) |
| Single person household | 0.129 | 0.176 | 0.134 |
| | (0.335) | (0.381) | (0.341) |
| Unmarried couple w/o children | 0.136 | 0.035 | 0.125 |
| | (0.343) | (0.183) | (0.330) |
| Married couple w/o children | 0.157 | 0.324 | 0.176 |
| | (0.364) | (0.468) | (0.381) |
| Unmarried couple with children | 0.095 | 0.028 | 0.087 |
| | (0.293) | (0.164) | (0.282) |
| Married couple with children | 0.446 | 0.390 | 0.439 |
| | (0.497) | (0.488) | (0.496) |
| One parent household | 0.036 | 0.046 | 0.037 |
| | (0.187) | (0.209) | (0.189) |
| Other household types | 0.001 | 0.001 | 0.001 |
| | (0.035) | (0.032) | (0.035) |
| Divorced | 0.009 | 0.018 | 0.010 |
| | (0.096) | (0.134) | (0.101) |
| No job | 0.157 | 0.394 | 0.184 |
| | (0.363) | (0.489) | (0.387) |
| Same job | 0.673 | 0.499 | 0.653 |
| | (0.469) | (0.500) | (0.476) |
| Job plus | 0.018 | 0.012 | 0.017 |
| | (0.133) | (0.109) | (0.130) |
| Job minus | 0.036 | 0.034 | 0.035 |
| | (0.185) | (0.182) | (0.185) |
| Job plus and min | 0.117 | 0.060 | 0.110 |
| | (0.321) | (0.238) | (0.313) |
| Loan-to-income | 3.1 | 1.7 | 3.0 |
| | (39.8) | (5.0) | (37.5) |
| Observations | 404359 | 52399 | 456758 |

*Notes*: Statistics of stock-sampled row houses in 2006. Standard deviations are shown under the means. Age and loan-to-income have been divided into different groups in the analysis.