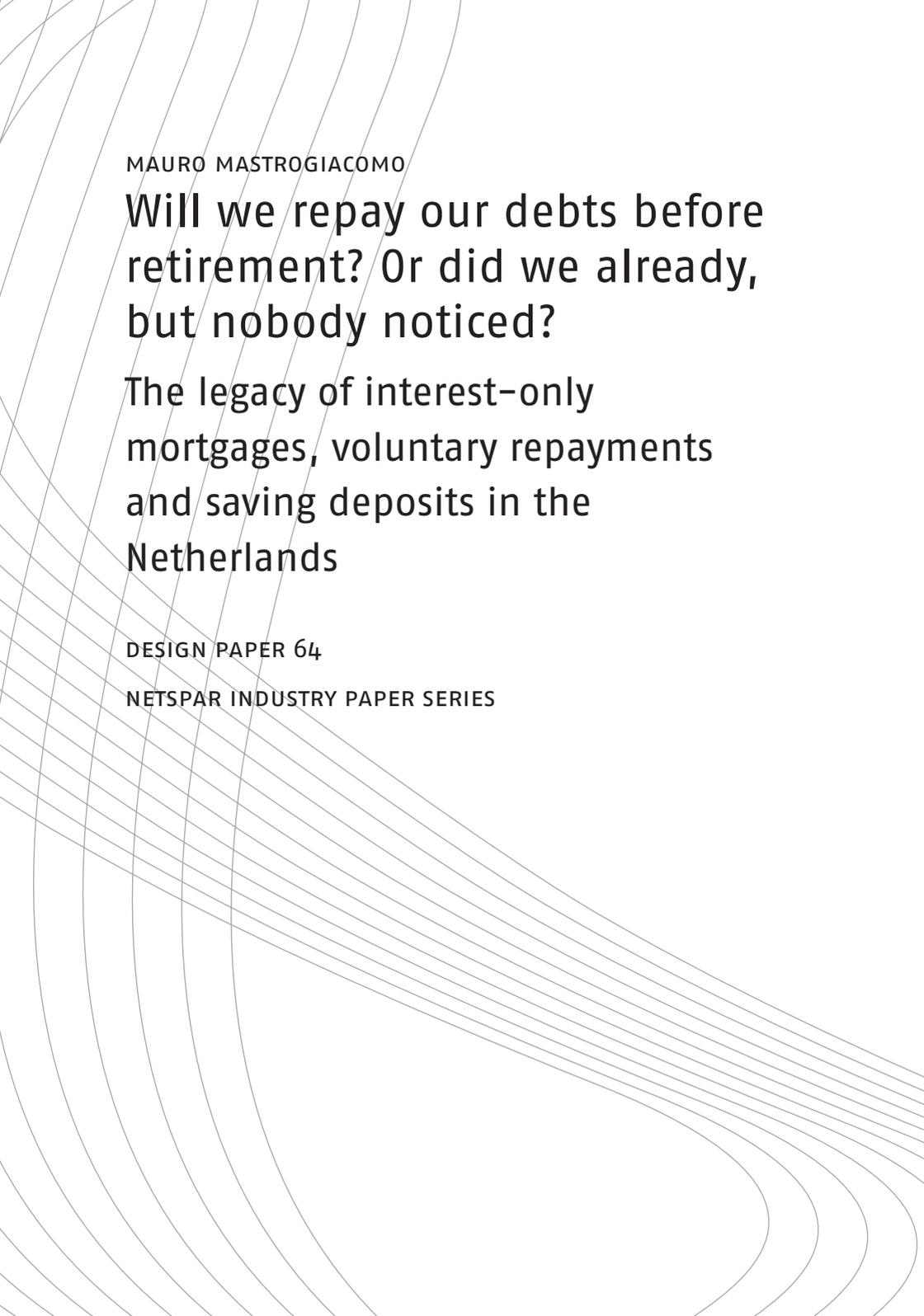


Will we repay our debts before retirement?

Or did we already,
but nobody noticed?

Mauro Mastrogiacomo





MAURO MASTROGIACOMO

Will we repay our debts before retirement? Or did we already, but nobody noticed?

The legacy of interest-only mortgages, voluntary repayments and saving deposits in the Netherlands

DESIGN PAPER 64

NETSPAR INDUSTRY PAPER SERIES

Design Papers, part of the Industry Paper Series, discuss the design of a component of a pension system or product. A Netspar Design Paper analyzes the objective of a component and the possibilities for improving its efficacy. These papers are easily accessible for industry specialists who are responsible for designing the component being discussed. Design Papers are published by Netspar both digitally, on its website, and in print.

Colophon

November 2016

Editorial Board

Rob Alessie – University of Groningen

Roel Beetsma (Chairman) – University of Amsterdam

Iwan van den Berg – AEGON Nederland

Bart Boon – Achmea

Kees Goudswaard – Leiden University

Winfried Hallerbach – Robeco Nederland

Ingeborg Hoogendijk – Ministry of Finance

Arjen Hussem – PGGM

Melanie Meniar-Van Vuuren – Nationale Nederlanden

Alwin Oerlemans – APG

Maarten van Rooij – De Nederlandsche Bank

Martin van der Schans – Ortec Finance

Peter Schotman – Maastricht University

Hans Schumacher – Tilburg University

Peter Wijn – APG

Design

B-more Design

Lay-out

Bladvulling, Tilburg

Printing

Prisma Print, Tilburg University

Editors

Jeanne Bovenberg, etc editing

Netspar

Design Papers are publications by Netspar. No reproduction of any part of this publication may take place without permission of the authors.

CONTENTS

<i>Abstract</i>	7
<i>1. Introduction</i>	9
<i>2. Characteristics of the Dutch mortgage market</i>	14
<i>3. Data</i>	17
<i>4. Methodology</i>	30
<i>5. Results</i>	36
<i>6. Summary & conclusions</i>	52
<i>References</i>	54
<i>Appendix</i>	56

Affiliations

Mauro Mastrogiacomo – De Nederlandsche Bank, VU Amsterdam

This study is based on DNB research carried out and supervised by Mauro Mastrogiacomo. Some results of this project have already appeared in the *Overview Financial Stability 2014*, published by DNB, and in the master thesis of Jan Jakob Lameijer, who was supervised by Mauro Mastrogiacomo and Rob Alessie at DNB and Groningen University (Master's Thesis in Econometrics *s1904205*).

WILL WE REPAY OUR DEBTS BEFORE RETIREMENT? OR DID WE ALREADY, BUT NOBODY NOTICED?

Abstract

This paper uses a micro-simulation model to analyze the future housing debt position of specific groups of Dutch mortgage owners, such as starters and the self-employed, around the time of their future retirement. Our analysis shows that most household debt is in interest-only (IO) loans, which cease being fiscally deductible 30 years after origination— in most cases around the time of the mortgagor's retirement. These loans are often combined with amortizing loans in more complex mortgage structures, which are also explored in this study. We identify two assets that, due to data limitations of existing sources, are currently understudied: voluntary repayments, and the value of the saving accounts pledged to saving/investment mortgages. Using a novel dataset from the Dutch Central Bank (DNB) enables us to make detailed observations that lead to several projections. These account for current and future non-housing wealth of mortgagors, and show that individual mortgages, even if not completely redeemed, are in general not problematic for the borrowers' financial position around retirement. Costs will stay low if the IO part of debt is treated as a perpetuity, but might become burdensome, mostly to the self-employed, otherwise. Also, these debts are substantial at the macroeconomic level. In our most favorable simulations, one-third of the mortgage debt

existing at the beginning of 2014 will not be repaid in the next three decades, possibly exacerbating the banks' funding-gap problem.

1. Introduction

About 60% (7%) of the Dutch mortgage portfolio consists of interest-only (investment) loans (Mastrogiacomo and van der Molen, 2015). These loans were once popular because they allowed low monthly payments and because of the generous mortgage interest deduction (MID). Policymakers have in the past two decades attempted to limit their development— in 2001, by stopping the MID after 30 years, and then in 2013, by making interest-only (IO) loans no longer eligible for these fiscal rebates. Especially in the long run, the large amount of debt in this type of loan could impose a financial burden to households, in the event that the maximum number of years that owners are entitled to the MID is exceeded. Among the future 'unknowns' stands the possibility of treating IO loans as IO perpetuities (low financial burden for households) or transforming them into annuities with short maturity (higher financial burden). For households, this development in the treatment of IO loans could imply an increase of their debt-service-to-income ratio (DSTI); households potentially face not only an increase in net monthly costs, but also an income reduction (due to the fact that many will be about to retire). For specific groups, such as the self-employed (SE), this might become problematic; they are observed having larger debt and a lower projected future pension annuity, as they often did not provide for a private pension (Mastrogiacomo et al., 2014). Moreover, a substantial amount of debt could be left in the banks' books beyond maturity.

Given the high IO share in our mortgages, we must ask whether we are going to (be able to) pay back our debt before retirement. And if we do not/are not able to, how would mortgage costs increase if outstanding debt at maturity is then treated either

as an IO perpetuity or as an annuity? And, how much would the increase be for the SE?

We answer these questions using the loan-level data (LLD) gathered by DNB, which enable us to identify the self-employed, to disaggregate housing wealth, and to quantify for each household the accumulated savings and assets pledged as collateral for the mortgage in all periods preceding maturity. DNB's novel dataset allows us to observe detailed information on individual loan characteristics, where households typically have multiple loans to finance the house. More specifically, we aim to answer the following question: *What are the long-run risks associated with the large share of IO (and investment) loans in the Dutch mortgage portfolio, and how do these risks differ across specific groups in the population— specifically, the self-employed?* In order to provide a more specific answer to the rather broad question above, we formulate three sub-questions: 1. How are IO loans distributed across Dutch homeowners? 2. How much of the current mortgage debt will be redeemed in the upcoming 30 years? 3. Will different types of households with IO loans have saved enough to pay off their mortgage at maturity? If not, how large will housing costs be after maturity or retirement?

These questions, while broad in scope, also serve to delimit our research. We are not enquiring into the optimal allocation of debt over the life cycle. Such a discussion would involve consideration of the optimal path of retirement savings, including housing savings (Sun et al., 2007), as well as fiscal treatment of homes (Bovenberg and Jacobs, 2008), which in the Netherlands could be achieved by more often making use of reverse mortgages (Dillingh et al., 2015). We therefore do not suggest that one should pay back the whole mortgage, but we do want to understand

how large outstanding debt will be after mortgage maturity and around the time of retirement.

To answer the questions above, we build a micro-simulation model that simulates borrower-level mortgage debt up to 30 years in the future, where we use 2014 as the starting year and 2043 as the last year. We estimate a model for voluntary repayments and show that they contribute substantially to the redemption of the current mortgage debt. Furthermore, the contractual mortgage repayments and capital accumulation on accounts pledged to the mortgage are modeled deterministically, based on some quite undisputed assumptions. This reveals how part of the outstanding debt has already been repaid, while another part is very likely to be repaid soon.

In order to show the heterogeneity in our population, we highlight two specific dimensions. First, we separate different cohorts of borrowers. Second, we isolate those who were self-employed at mortgage origination, as these individuals are more likely to have low contributions in the second pillar (occupational pension). Also, we discuss the amortization of investment loans.

We find that, in 30 years' time, most interest-only loans are combined with amortizing loans— but also that still 36% of the borrowers have a full IO mortgage. The latter, however, are mostly older borrowers having substantial home equity. Starters are hardly represented in the 100% IO category. When we weight this share by household debt, we find no substantial differences between wage-employed and self-employed individuals. Mortgages that are currently underwater are typically amortizing mortgages (at least partially). We find that the share of negative equity mortgages will decrease even if house prices stay constant for the upcoming 30 years. Only when house prices decrease by more than 2% annually and no voluntary repayments are made

do we find that both the share of underwater mortgages and the average loan-to-value (LTV) ratio will increase. Problematic groups are the SE and the owners of investment loans. We observe for the SE a significantly higher LTV ratio. We also find that investment-loan owners have chosen to complete their mortgage combining the investment loan with an IO loan. They thus repay very little of their mortgage, and the performance of their investments has in the last decade been below the projections upon signing the loan. At the same time, we find that almost all mortgages will be above water at maturity and that most mortgages with high LTV ratios are backed by the government with a national guarantee (although the guaranteed amount diminishes over time, following an annuity scheme).

A further contribution of this study is the way it relates mortgage debt to non-housing wealth. Using a second administrative dataset, we estimate a model for wealth based on a subset of covariates that are observed in the LLD as well. We find that many borrowers with residual debt at maturity will not have saved enough to fully repay their mortgage at that time. Particularly those households with mortgages originating around the bursting of the housing bubble will have a remaining debt of roughly 90,000 euro on average, and financial wealth of about 30,000 euro. This figure is heterogeneous across the population. For instance, the SE will have a remaining debt of about 150,000 – 200,000 euro, although they will also have larger financial assets (60,000 euro). Moreover, as retirement is likely to occur soon afterwards, these borrowers may be confronted with a drop in income as well. This drop may be more severe for those self-employed workers who, excluded from second-pillar savings, did not prepare for their retirement by making additional savings.

It is thus unclear what the future housing costs will be of borrowers that do not repay in full at maturity, as it is by no means automatic that the remaining IO debt will always be treated as an IO perpetuity. If it is not, then the most exposed households may end up facing average increases of their monthly payments by amounts larger than the current social security benefit (AOW). Here, we focus on the period around maturity, as that is often close to retirement. However, the debt position of households before maturity is also relevant. Being underwater is a risk trigger that gets activated in association with several shocks that can easily be envisaged. Unemployment, bankruptcy, divorce and disability are the most relevant of these shocks, from an individual perspective, while an interest rate shock could affect all borrowers. When such shocks materialize, borrowers with negative equity mortgages become even more financially distressed. If their number is large (as it was in 2013, when a third of all mortgages were underwater in the Netherlands), the combination of these risks may result in additional defaults or in economic downturns. The former did not happen during the last crisis, but consumption dropped considerably (Verbruggen et al., 2015), which was one of the main causes of the recent recession (Mian and Sufi, 2015, quantified this for the US).

The remainder of this study is organized as follows. The next section discusses the most important features of the Dutch mortgage market. Section 3 describes the datasets. Section 4 presents the econometric models and estimation procedures, together with an overview of the design of the micro-simulation model. Next, Section 5 presents and interprets both the estimation and simulation results. Section 6 concludes the study.

2. Characteristics of the Dutch mortgage market

The Dutch housing market has undergone dramatic changes over the last two decades. An unprecedented growth in house prices in the latter half of the 1990s was associated with rising household leverage. This became possible when banks, supported by policymakers and public opinion, started to take the income of the partner into account when assessing the borrowing possibilities of households, thereby relaxing credit constraints. Banks allowed borrowers to increase their mortgages due to the expected increase in collateral value; households, in turn, used their extended borrowing capacity to accumulate debt (mainly for housing purposes).¹ The higher demand for housing and the loosening of credit constraints, along with the inelastic supply, caused house prices to escalate. This procyclical phenomenon, referred to as the collateral amplification mechanism or, more in general, the financial accelerator (Almeida et al., 2006; Bernanke et al., 1996) has been the root cause of credit crises worldwide (for further reading, see, for instance, Kiyotaki and Morre, 1997; Lorenzoni, 2008). Especially in the Netherlands, where the mortgage interest payments are fully tax-deductible, households were encouraged to finance their house with debt. The introduction in 2000 of the National Mortgage Guarantee (NHG [Nationale Hypotheek Garantie]), where government acts as guarantor for the mortgage payments, allowed banks to ease further the credit constraints for households. NHG can only be issued to mortgages for houses with transaction prices below a legislated threshold.

1 In 2000, mortgage interest deductibility was restricted to buying or renovating a house, thus encouraging households to use the credit mainly for housing and home improvements.

Eventually, the bursting of the housing bubble in 2008 revealed the vulnerabilities of the Dutch housing market. By 2013, house prices had decreased by more than 20% compared to the peak in August 2008. During the same period, the number of Dutch mortgages that were underwater increased from 10% to approximately 30% (DNB, 2014).

Both the decrease in house prices and the increase in mortgage debt have contributed to a higher loss given default (LGD), resulting in substantial credit risk for banks. A forced sale after the crisis is no longer enough to cover the outstanding mortgage debt (on average, the foreclosure value in the Netherlands is approximately 85% of the market value). Moreover, due to the shortage of savings deposits as a stable funding source, banks have become highly dependent on (short-term) market funding, which has resulted in a large deposit funding gap (DFG). This maturity mismatch between assets and liabilities becomes particularly troublesome when markets are not performing well, thereby making refunding more difficult. One way to overcome this problem is to securitize part of the mortgage portfolio via residential mortgage-backed securities (RMBS). Unfortunately, this type of funding has become much more expensive because investors have become aware of the risky mortgage portfolio (Jansen et al., 2013). The European Union is therefore now considering tightening the eligibility rules into the RMBS pool— by, for instance, allowing only those mortgages with an LTV below a conservative threshold (say 80%). Finally, part of the credit risks faced by banks are transmitted to the government via the NHG.

In this situation, new regulations were implemented to reduce these risks and to prevent excessive credit growth. In 2013, the Dutch government introduced the rule that only new fully amor-

tizing mortgages are eligible for the interest deduction. The maximum tax-deductibility will be gradually reduced from 52% in 2014 to 38% in 2042, which also applies for existing mortgages. Furthermore, an upper limit to the LTV for home buyers was initiated. In 2015, this LTV cap was set to 103%, which will gradually reduce to 100% in 2018. Also, the Financial Stability Committee (FSC) advised lowering the limit even further, to 90%. One last regulation to keep in mind: from October 2013 until December 2014 the government temporarily raised the exemption from gift taxes to 100,000 euro— but only when the money was used for mortgage redemption or home improvements. At the same time, most lending institutions also increased the maximum amount that could be voluntarily repaid without incurring a penalty. This means that the Dutch government has chosen to use a strong fiscal stimulus to induce new borrowers to buy annuities rather than IO loans. Policy options for current mortgage owners, such as nudging them into choices that the government finds optimal, have not yet been attempted. For instance, with the recently falling interest rates, retirement saving programs like *Save More Tomorrow* could have been used on the mortgage market upon resetting mortgage contracts. This would have directed the gains of lower interest rates in the direction of higher repayments.

3. Data

3.1 Loan Level Data (LLD)

The LLD dataset is collected by DNB using the reporting template for Residential Mortgage-Backed Securities (RMBS) of the European Data Warehouse.² In order to use a securitized mortgage as collateral, each lending institution must agree to the ECB's 100% transparency policy and fill in the template. The DNB version of the LLD also includes the back-books on top of the securitized pool discussed above, which the institutions deliver on a voluntary basis. This is essential, as securitized mortgages in the Netherlands are not a random sample of the mortgage portfolio, and are typically rated AAA. Although the LLD meets the ECB reporting requirements, it is to some extent not designed for analytical purposes. Mastrogiamomo and van der Molen (2015) describe some limitations and advantages of the LLD.

The first wave was collected in 2012 Q4, and the last currently available wave is 2013 Q4. Table 1 testifies to the main advantages of the LLD. First, from the total number of borrowers and loans reported in the table we see that a mortgage typically consists of multiple loans (approximately two loans per mortgage, on average). Observing each loan and borrower separately makes it possible, for example, to accurately determine the repayment schemes of each loan, to ascertain the debt-weighted share of interest-only mortgages and to impute the saving deposits pledged to each loan. The table shows that roughly 60% of the loans are IO, in accordance with the aggregate figures reported in the literature. The granularity of our data allows us to nuance this large portion of IO loans. We observe in the table that only

2 The RMBS template can be found at <https://www.ecb.europa.eu/paym/coll/loanlevel/transmission/html/index.en.html> (accessed on 11-01-2014).

Table 1: Percentage of borrowers having a specific mortgage composition as reported in three waves of the LLD. Also, the share of each loan type at loan level is presented, together with the total number of observations on both borrower- and loan-level.

Mortgage composition	2012 Q4		2013 Q3		2013 Q4	
	borrowers	loans	borrowers	loans	borrowers	loans
<i>One loan type only</i>						
Annuity	1.35%	3.55%	1.98%	4.58%	2.36%	5.12%
Linear	0.61%	0.98%	0.70%	1.09%	0.72%	1.13%
IO	35.90%	60.99%	35.46%	59.59%	37.06%	60.34%
Savings	6.90%	15.52%	7.32%	16.45%	6.79%	15.59%
Life insurance	4.63%	11.15%	4.53%	10.22%	4.19%	9.59%
Investment	3.66%	5.52%	2.97%	4.84%	2.31%	4.49%
Other	0.18%	2.01%	1.01%	1.96%	1.15%	2.32%
Unknown	0.71%	0.28%	0.69%	1.28%	0.78%	1.42%
<i>Combination of loans</i>						
Including IO	44.98%	-	44.03%	-	43.08	-
Excluding IO	1.08%	-	1.31%	-	1.32	-
Total observations	3,040,976	5,828,982	2,928,214	5,641,773	2,915,542	5,611,558
Total population (CBS)	3,567,000		3,562,500		3,561,000	
Coverage	85.25%		82.20%		81.87%	
Reporting institutions	7		11		9 (preliminary)	

35% of the borrowers have a full IO mortgage, meaning that the remaining borrowers amortize— at least to some extent. In the next section we will also present the debt-weighted shares per loan type, which provides a more complete picture.

Table 1 reveals that the LLD covers approximately 80% of the total population. Each loan record in the LLD is comprised of several attributes. Each record includes a unique loan and

borrower identifier, which permits tracking them over time if (and only if) the borrowers stay within the same bank.

Further, some banks apparently observe the assets pledged to the mortgage and subtract this from the outstanding debt. This is different from monetary statistics practices, where the two accounts are kept separately. Distinguishing between voluntary and contractual repayments when amortizing loans are present is therefore not straightforward. In order to break this observational equivalence, we make use of the panel nature of the data. By looking at the difference in loan balance over all five waves, we are able to identify the flow into the accumulated capital (AC) pledged to the mortgage.³ This means that we are dealing simultaneously with two definitions of mortgage debt: a gross definition (where the AC is not considered) and a net definition (which subtracts the AC). Fortunately, the large number of attributes in the LLD allows to estimate the AC for each loan, such that we are able to approximate both gross and net mortgage debt.

Since several value concepts could be used to determine the value of the property, care must be taken when comparing LTV ratios in the literature. The fair market value might differ from the actual transaction price due to market distress and inefficiencies. Other commonly used value concepts that differ from the fair market value are, for example, the tax-assessed value (WOZ-value [Waardering Onroerende Zaken])⁴ determined by the fiscal authority and the liquidation value.⁵

- 3 Specifically, the flow is identified by regularity in the reduction of the outstanding debt. Everything on top of this qualifies as a voluntary repayment.
- 4 Historically, the WOZ-value was an underestimation of transaction prices; in recent years, the two have become more aligned.
- 5 In the Netherlands, a foreclosure auction results on average in a liquidation value of 80% of the market value.

Table 2: Different property valuation methods used in the LLD (2013 Q4)

<i>Valuation method</i>	<i>Property value</i>			
	<i>Share</i>	<i>Median</i>	<i>Mean</i>	<i>Std. Dev</i>
Internal and external expert inspection	46.63%	203,168	249,290	168,512
External expert inspection only	5.40%	198,592	225,027	110,522
Drive-by/desktop	0.01%	391,815	541,098	523,400
Estate agent	14.44%	209,785	261,502	202,092
WOZ value	17.52%	225,979	257,842	151,608
Other/unknown	16.00%	242,084	318,079	232,931

The LLD does not necessarily allow for a consistent definition of the valuation amount, as different value measures are used across observations. From Table 2 we observe that the appraised value is reported for more than 50% of the properties, where the appraisal is performed by an expert. The purpose of the appraisal, however, is not indicated, but we may learn more by comparing the average property values resulting from the different valuation methods. As can be seen, the average property value determined by expert inspection is somewhat smaller compared to the WOZ-value and the value determined by an estate agent. This might indicate that experts indeed are valuing the property as collateral for the mortgage, where in the event of foreclosure the sale needs to occur quickly, leading to a more conservative valuation. However, here we make the assumption that the valuation method is chosen randomly, which does not have to be the case.

Mortgage debt concepts are also slightly different in both datasets. First, the IPO reports only a gross definition. The approximated gross mortgage debt in the LLD is possibly an underestimation. Second, the IPO reports only the fiscal debt,

which is the part of the mortgage debt used to finance the prime residence and for which the interest payments can be deducted from taxable income. Our LTV definition uses net mortgage debt, as it provides a more complete picture of the financial position and risks of the households.

3.1.1 Descriptive statistics

This subsection presents some descriptive statistics based on the 2013 Q4 wave. After removing borrowers with missing or highly unrealistic values for the relevant variables, we are left with 2,375,545 borrowers having 4,521,284 loans in total (for 472,991 of the removed borrowers the birth-year was missing). Using this restricted sample, we estimate the aggregate gross mortgage debt in the Netherlands to be approximately 639 billion euro. Subtracting the estimated 30 billion euro AC (which may be an underestimation, as will be discussed below) yields an estimate of the net mortgage debt of 609 billion euro.

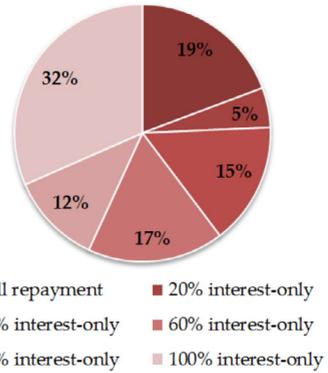
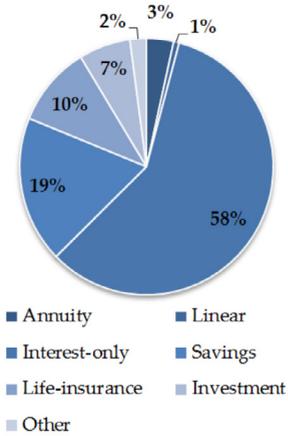
The pie chart on the left-top in Figure 1 presents the debt-weighted share of each mortgage type. Similar to Table 1, we find that almost 60% of the net mortgage debt comes from IO loans⁶. The bottom of the figure is dedicated to those who are self-employed at origination. It shows that there the IO shares and mortgage types of this sub-group do not differ from those of the rest of the population.

From Figure 1, we observe that 32% of the net mortgage debt comes from borrowers having a 100% IO mortgage, which is even less than the 35% from Table 1. This result therefore shows that the majority of IO mortgages are often combined with other amortizing mortgages. Descriptive statistics for the relevant vari-

6 The difference between the 50% indicated in Table 1 can be attributed to the difference in net and gross mortgage debt (CPB, 2014).

Figure 1: Debt-weighted share of each mortgage type (left) and the debt-weighted share of borrowers per interest-only category (right), both based on net mortgage debt in 2013 Q4.

Whole sample:



Self-employed:

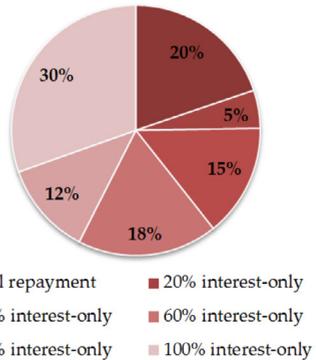
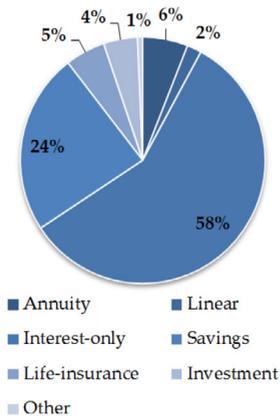


Table 3: Descriptives LLD 2013 Q4 on borrower-level per IO category

Variable	0% IO			20% IO			40% IO		
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	Mean	Std. dev.	Median
Age	45.4	12.5	45.0	44.4	9.6	44.0	41.5	10.0	41.0
House value (€)	235,537	159,719	200,994	249,325	140,356	215,214	226,241	131,914	196,399
Net debt (€)	146,662	125,367	133,251	192,079	172,190	119,908	198,454	111,618	180,332
LTV (%)	68	42	75	81	33	85	93	32	103
Interest rate (%)	4.6	1.1	4.7	4.7	0.8	4.7	4.6	0.7	4.7
NHG (%)	38			35			54		
Underwater (%)	30			33			54		
Observations	535,830			104,323			314,786		
Variable	60% IO			80% IO			100% IO		
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	Mean	Std. dev.	Median
Age	46.3	10.0	46.0	51.3	10.9	51.0	60.4	12.3	61.0
House value (€)	261,968	159,964	221,530	292,854	195,023	242,008	300,081	212,823	247,548
Net debt (€)	215,640	140,022	188,288	227,015	170,039	189,750	142,995	145,629	106,000
LTV (%)	86	32	92	81	34	83	48	30	44
Interest rate (%)	4.6	0.8	4.7	4.5	0.9	4.6	4.4	1.0	4.5
NHG (%)	26			10			4		
Underwater (%)	38			34			5		
Observations	323,206			204,976			892,425		

ables are presented in Table 3, where descriptives are given per IO category.⁷ The statistics are given at the borrower level, where the interest rate is the average debt-weighted interest rate of all mortgage loans of the borrower.

We observe that the relationship between the IO share and LTV is not linear. On average, the youngest borrowers fall into the

7 The table does not contain the variable *income*, which might be considered a relevant variable, as it likely has a strong effect on both savings and voluntary repayments. Unfortunately, income is reported for only 50% of the borrowers, and a comparison of means tests strongly rejects the hypothesis that these observations are missing at random.

40% IO category, where the average LTV is no less than 93% and where 54% of the mortgages are underwater. These borrowers do contractually amortize on more than half of their mortgage debt. Also, we find that a large share of underwater mortgages is often accompanied by a large share of mortgages that are NHG-guaranteed.

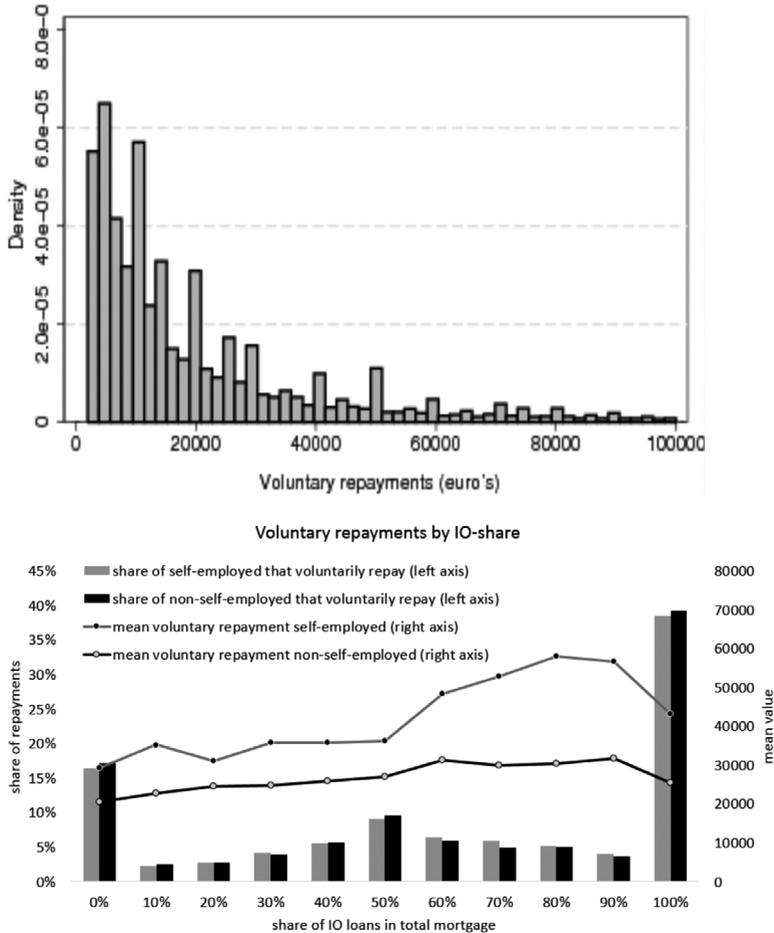
Voluntary repayments are not directly observed, but can be retrieved by taking the difference in the mortgage balance between the beginning of 2013 and of 2014, where we correct for contractual mortgage repayments.

Taking the yearly difference allows us to remove all seasonal components. However, given the limited number of waves in the LLD, we can calculate a proxy of the voluntary repayments for only one specific year. We should keep in mind that for the last two months of that period (starting from October 2013) the exemption from gift taxes was raised to 100,000 euro for home-related expenditures.

Considering the administrative costs of processing repayments, most lending institutions have set a lower limit. We therefore treat all voluntary repayments (calculated drops in outstanding debt above amortization) of less than 2,000 euro as 'zero', as we wish to capture the true underlying distribution (which we observe only for voluntary repayments above 2,000 euro).

As a result, we find that 13.74% of the borrowers in our sample made a voluntary repayment on their mortgage in 2013. The sum of these repayments is estimated to be 13.36 billion euro at the aggregate level, representing roughly 2% of the net mortgage debt. A histogram of the resulting (non-zero) voluntary repayments is provided in the left panel of Figure 2. The peaks indicate that, as expected, round numbers are more popular amounts to

Figure 2: Voluntary repayments distribution in 2013 (truncated at 100,000 euro), and voluntary repayments by IO share.



voluntarily repay. The right panel of the figure shows that voluntary repayments are not uniform across the population.

To illustrate, we show that the share of those repaying in 2013 differs, depending on the IO-share in the mortgage– with fully IO mortgages repaying more often. We also categorize down

Table 4: Descriptives IPO 2005, 2008 and 2011

Variable	2005			2008			2011		
	Mean	Std. dev	Median	Mean	Std. dev	Median	Mean	Std. dev	Median
Age	45.3	11.7	43	46.2	11.9	44	47.8	11.9	46
House value (€)	280,025	258,908	237,412	308,320	179,159	261,016	280,622	160,106	238,225
Gross debt (€)	163,032	169,507	135,500	194,445	174,385	163,600	206,674	175,184	176,000
Net savings (€)	44,292	227,898	18,808	39,755	285,174	18,642	38,750	270,909	18,171
Interest rate (%)	5.2	1.4	5.1	4.9	1.0	4.8	4.8	1.0	4.8
Observations	42,998			50,171			49,562		

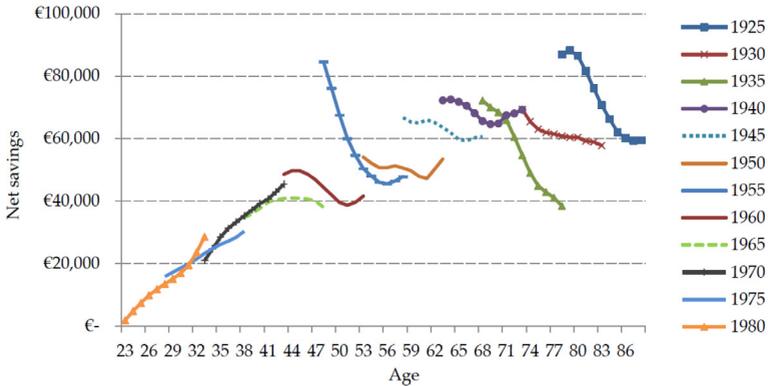
payments according to occupation. The share of repayments is not different when we look at the self-employed or at the non-self-employed, but the mean repayment is higher for the self-employed (who have larger debt) and increases with the IO-share.

3.2 Income Panel Study (IPO)

To analyze non-housing wealth, we use seven waves of the IPO dataset (2005–2011) gathered by the CBS. In total, the dataset consists of 1,852,323 observations containing information on 112,942 unique households. We select only the household heads that own a property financed by a mortgage. We estimate the mortgage interest rate by dividing the yearly mortgage interest payment by the gross mortgage debt. Subsequently, we remove observations for which the resulting interest rate is unrealistic (less than 1% or exceeding 10%). The selected sample consists of 341,118 observations on 63,791 unique borrowers.

The IPO dataset provides information on non-housing wealth that is missing in the LLD. Specifically, we are interested in net household savings, which we define to be the sum of all non-housing financial assets (savings and investment accounts

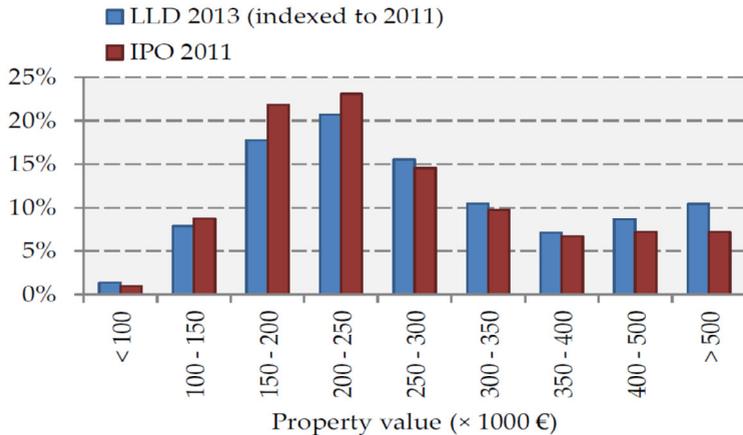
Figure 3: Net savings by birth cohort using nonparametric locally weighted regression (LOWESS) with a bandwidth of 0.8. Labels correspond to the middle year of each cohort.



not pledged to the mortgage, where shareholdings with substantial business interest are not considered) minus all outstanding debt balances other than the mortgage debt. Unfortunately, the LLD and IPO do not contain unique borrower identifiers by which the datasets could be matched. We aim to estimate a model for net savings based on variables that are observed in both datasets and use the resulting model to estimate net savings in the LLD. Descriptive statistics of all common variables and net savings appear in Table 4, for three of the seven waves. Especially noteworthy are the large standard deviation and relatively large difference between the mean and median of net savings. As will be discussed later, these signal that difficulties may arise when modeling net savings.

Figure 3 presents age and cohort patterns of the net savings, where we use five-year birth cohorts. Birth years 1923–1927 are for the oldest cohort and 1988–1992 for the youngest cohort, where the labels correspond to the middle year of each cohort. To

Figure 4: Distribution of the property value in both LLD and IPO

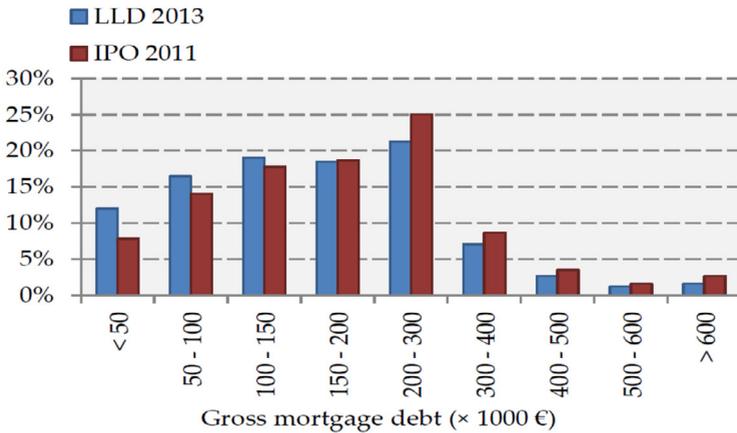


enhance the visual information, we fit a LOWESS curve (Cleveland, 1979) with a smoothing parameter of 0.8 for each cohort. We observe an increase in net savings over age for young cohorts and a decrease for older cohorts. Differences in average net savings between cohorts at the same age are indicated by vertical differences between the cohort curves.

Figure 4 compares the distribution of the property value as observed in both the 2011 wave of the IPO and the 2013 Q4 wave of the LLD, where the values are indexed to 2011 for the latter dataset. Reassuringly, the distributions are very similar. A comparison of the distribution of the gross mortgage debt appears in Figure 5.

Finally, both the LLD and IPO report the first two numbers of the postal code. This allows us to impute some variables based on postcode level in both the IPO and LLD, such as the debt-weighted share of IO mortgage per postcode, the average property value per postcode and the number of real estate transactions

Figure 5: Distribution of the gross mortgage debt in both LLD and IPO



per postcode. The former two are obtained from the LLD and the latter from the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM [Nederlandse Vereniging van Makelaars o.g. en Vastgoeddeskundigen]).

4. Methodology

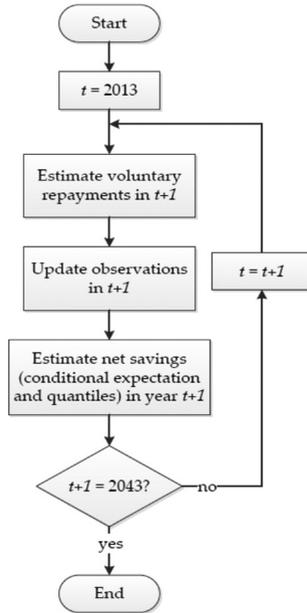
4.1 Microsimulation model of the Dutch mortgage portfolio

We differentiate between three components that jointly determine the net mortgage debt of each borrower: 1) the periodic mortgage repayments as contractually specified, 2) the capital accumulation on accounts pledged to the mortgage, and 3) voluntary repayments. The first two components are modeled deterministically, based on the structure of the mortgage and some assumptions, whereas the latter component is modeled stochastically. We focus therefore in the Appendix on the latter, while here we describe the simulation method only.

We start our simulation in 2014 using the borrowers from the LLD observed on December 31st 2013. To alleviate computational intensity, we select a random subsample of 50,000 borrowers. For these borrowers we simulate the mortgage debt and net savings for the upcoming 30 years, where 2043 is the last simulated year. Figure 6 provides a general overview of the simulation procedure per borrower.

The first step in the microsimulation is to simulate the voluntary repayments for the upcoming year (2014). Anticipating on the estimation results, this will be done according the Cragg log-normal hurdle presented in equation (6) in the Appendix. First, to simulate the participation decision, we draw a random value from the uniform distribution for each borrower. Only if this random variable is less than the predicted value from the probit model (Part I) will the borrower voluntarily repay. Next, to simulate the amount of the voluntary repayment, we use the predicted value from Part II of the log-normal hurdle, where repayment shocks are drawn from the normal distribution with zero mean

Figure 6: Flowchart of the microsimulation per borrower



and variance . Here, is the estimated variance of from equation (6). Finally, the exponential function is used to transform the repayment amount back to (predicted) levels.

Now that we have simulated the voluntary repayments in 2014, we can update all other debt-related variables (total net debt, debt-weighted share of IO loans, LTV, and so forth.). Here, we assume that the voluntary repayments are first used to repay the IO loans. If the borrower no longer has these loans, the repayments will be used to discharge mortgage loans for which capital is accumulated in a separate account (investment⁸/savings/life

8 Notice that repayment of an investment loan without penalties is typically prohibited, as this would be equivalent to withdrawing money from the investment fund.

Table 5: Estimation results for different models for voluntary repayments
(Tobit in levels, Tobit in logs and the Cragg log-normal hurdle)

	Probit (Part I)		Tobit (in levels)		Tobit (in logs)		Two-Part (Part II)
	Coef	ME	Coef	ME ($\Pr(y_i > 0 x_i)$)	Coef	ME ($\Pr(y_i > 0 x_i)$)	Coef
age/10	0.261*** (0.00687)	-0.00968*** (0.000241)	21 170*** (448.6)	-0.00357*** (0.000223)	1.000*** (0.0233)	-0.00801*** (0.000235)	0.447*** (0.0127)
(age/10) ²	-0.0317*** (0.000619)		-2354*** (4.06)		-0.118*** (0.00210)		-0.0423*** (0.00116)
share I-0	0.209*** (0.00337)	0.0452*** (0.000730)	14,061*** (219.8)	0.0442*** (0.000688)	0.741*** (0.0114)	0.0468*** (0.000718)	0.208*** (0.00607)
interest rate	1.125*** (0.135)	0.244*** (0.0292)	-44,469*** (8 777)	-0.140*** (0.0276)	1.225*** (0.456)	0.0774*** (0.0288)	-8.236*** (0.260)
underwater	-0.673*** (0.0142)	-0.00660*** (0.00116)	-53,579*** (912.2)	-0.00201* (0.00105)	-2.550*** (0.0480)	-0.00992*** (0.00112)	-0.912*** (0.0263)
age × underwater	0.0126*** (0.000332)		1,038*** (21.06)		0.0469*** (0.00111)		0.0146*** (0.000603)
NHG	-0.0985*** (0.00327)	-0.0214*** (0.000709)	-4,677*** (211.2)	-0.0147*** (0.000663)	-0.354*** (0.0110)	-0.0224*** (0.000696)	-0.0844*** (0.00593)
currentLTV / 10 ²	-0.123*** (0.00495)	-0.0267*** (0.00107)	4709*** (320.0)	0.0148*** (0.00101)	-0.102*** (0.0167)	-0.00642*** (0.00105)	0.914*** (0.00877)
Constant	-1.597*** (0.0205)		-122 037*** (1 343)		1.732*** (0.0698)		8.204*** (0.0375)
<i>N</i>	1,901,566		1,901,566		1,901,566		1,901,566
pseudo <i>R</i> ²	0.010		0.006		0.010		
Log-likelihood	-750,856		-3,712,000		-3,667 000		-2,881,000
∂ ²			65,986				1.048
<i>Two-Part model:</i>							
pseudo <i>R</i> ²							0.010
Log-likelihood							-3,632,000
<i>p-value LM tests:</i>							
heteroskedasticity	0.000						
normality	0.000						
Standard errors below coefficients *** p<0.01, ** p<0.05, * p<0.1							

Table 6: Three probability models (linear, logit and probit) for the participation decision to voluntarily repay (1 = voluntary repayment, 0 = no voluntary repayment).

	Linear Probability		Logit		Probit	
	Coef	ME	Coef	ME	Coef	ME
Age/10	0.0480*** -0.00143	-0.00964*** -0.000257	0.494*** -0.0131	-0.00994*** -0.000241	0.261*** -0.00687	-0.00968*** -0.000241
(Age/10) ²	-0.00610*** -0.000127		-0.0600*** -0.00118		-0.0317*** -0.000619	
Share I-0	0.0462*** -0.00073	0.0462*** -0.00073	0.387*** -0.00626	0.0454*** -0.000734	0.209*** -0.00337	0.0452*** -0.00073
Interest rate	0.234*** -0.029	0.234*** -0.029	2.143*** -0.246	0.251*** -0.0289	1.125*** -0.135	0.244*** -0.0292
Underwater	-0.119*** -0.00292	-0.00654*** -0.00114	-1.309*** -0.0275	-0.00603*** -0.00116	-0.673*** -0.0142	-0.00660*** -0.00116
Age × underwater	0.00222*** -0.0000694		0.0246*** -0.000632		0.0126*** -0.000332	
NHG	-0.0196*** -0.000688	-0.0196*** -0.000688	-0.182*** -0.00622	-0.0214*** -0.00073	-0.0985*** -0.00327	-0.0214*** -0.000709
Current LTV / 100	-0.0300*** -0.00109	-0.0300*** -0.00109	-0.237*** -0.00913	-0.0278*** -0.00107	-0.123*** -0.00495	-0.0267*** -0.00107
Constant	0.0534*** -0.00433		-2.796*** -0.0385		-1.597*** -0.0205	
N	1,901,566		1,901,566		1,901,566	
Pseudo R ²	0.01		0.01		0.01	
Log-likelihood	-760,934		-750,842		-750,856	
Standard errors below coefficients *** p<0.01, ** p<0.05, * p<0.1						

Table 7: Estimation results of a robust regression on net savings and three quantile regressions on the inverse hyperbolic sine transformation of net savings.

	Robust regression (in levels)	Quantile regression (IHS transformed)		
		q=0.25	q=0.5	q=0.75
age/10	526.08** -265.13	0.0947*** -0.00979	0.0750*** -0.00584	0.0802*** -0.00525
(age/10) ²	-324.6 -274.65	-0.0765*** -0.00983	-0.0571*** -0.00573	-0.0617*** -0.00566
gross mortgage debt/10 ³	13.979** -5.924	0.000562** -0.00025	0.000537*** -9.3E-05	0.000328*** -9.7E-05
property value/10 ³	-2.482 -5.806	-5.9E-05 -0.00032	-0.00016 -0.00016	-0.00016 -0.00011
interest rate	2698.6 -10458	0.526 -0.616	-0.396 -0.285	-1.083** -0.431
CPI	-4.262 -39.53	-0.00576 -0.00377	0.00157 -0.00242	0.00522*** -0.00194
GDP	25.181 -34.79	0.00337 -0.00385	-0.00102 -0.00253	-0.00265 -0.00236
# transactions per postcode/10 ²	-12.705** -26.85	0.00348*** -0.00079	0.00202*** -0.00049	0.00107*** -0.00041
l-0 share per postcode	-6310.179*** -4410	0.846*** -0.107	-0.203*** -0.0685	-0.500*** -0.0515
mean house price per postcode/10 ³	-0.835* -2.49	0.0000109** -4.7E-06	4.65E-06 -3.8E-06	-9.2E-07 -2.9E-06
Average gross mortgage debt/10 ²	-3.447*** -0.76	-0.000334*** -2.3E-05	-0.000165*** -1E-05	-0.0000919*** -1.1E-05
Average property value/10 ²	7.275*** -0.77	0.000351*** -3.4E-05	0.000413*** -1.7E-05	0.000444*** -1.2E-05
Average interest rate	107430*** -28208	11.40*** -1.029	9.564*** -0.431	9.054*** -0.718
Birth cohorts	Yes	Yes	Yes	Yes
Constant	-24043*** -74470	5.518*** -0.308	7.507*** -0.288	8.546*** -0.156
N	341,118	341,118	341,118	341,118
R2		0.0137	0.0343	0.0578
p-value Wald test for joint significance:				
Birth cohorts	0.927	0	0	0
Postcode variables	0.481	0	0	0
Standard errors in below coefficients; panel-robust bootstrap standard errors are reported for the robust regression *** p < 0.01, ** p < 0.05, * p < 0.1				

insurance). The voluntary repayments will only be used to repay amortizing mortgages (annuity/linear) in case the borrower has no other mortgage loans. The contractual mortgage repayment and capital accumulation are calculated as described above. Furthermore, we make a few assumptions on the change in property value, GDP and CPI. The basis scenario assumes constant house prices and a yearly 2% increase in both GDP and CPI. To test the sensitivity of the results to these assumptions, we experiment with yearly house price changes of 3% and -2%, and with GDP and CPI changes of 4% and -2%.

Recursively estimating the voluntary repayments and updating the values of the variables until 2043 completes the simulation.

5. Results

5.1 Estimation results

5.1.1 *Voluntary repayments*

The first two columns in Table 5 show the estimated coefficients and associated ME of the probit model on the decision to voluntarily repay. Partly due to the large sample size, all coefficients and ME are statistically significant at the 1% level. Unfortunately, as indicated by the low value of the pseudo R^2 , the model fits rather poorly. Much of the variance in the choice to voluntarily repay is still not explained by the regressors; this implies that in the simulation much of the results will be driven by the random draws of the unexplained part. Also, for the same reason, we do not discuss the economic interpretation of the results, and use the model only as the scoring device needed in the simulation method. The LM tests strongly reject the hypothesis of homoskedasticity and normally distributed error terms. Again, the rejection might be attributed to the large sample size. To investigate the scale of this problem, we compare the ME of the probit model with the ME resulting from a linear probability and logit regression. If the assumptions on the error term are wrong, the ME should differ substantially— as the underlying distributional assumptions differ across the models. The estimation results for the three probability models are presented in Table 6. The estimated ME are very similar for all three models, thereby providing an incentive to assume that the probit model is correctly specified, even though the heteroskedasticity and normality tests are rejected.

The third and fourth columns in Table 5 present the estimation results of the Tobit model, where the dependent variable is the

level of voluntary repayment. If the Tobit model is correctly specified, the probit and Tobit models should yield similar estimates of the ME. However, we observe that the ME of the interest rate and the current LTV are different in both sign and magnitude. When transforming the data using the natural logarithm, we find that the distribution is almost symmetrical (skewness=0.37), with negligible non-normal kurtosis of 2.75. The estimated Tobit model of voluntary repayments in logs also appears in Table 5. As can be seen, the estimated ME now resemble much more closely the ME of the probit model (all estimates have the same sign, but the magnitude of the ME of the interest rate and the current LTV is still different). Also, the Tobit model in logs fits the data considerably better in terms of both pseudo and log-likelihood (although the is still very low).

Finally, the last column of reg-level presents the estimation results of Part II of the Cragg log-normal hurdle. We find that the estimated Cragg log-normal hurdle yields the same pseudo as the Tobit in logs, but has a larger log-likelihood. We thus choose to model the voluntary repayments using the Cragg log-normal hurdle. Additionally, to allow for variation in coefficients between mortgages with different shares of IO loans, we fit a Cragg log-normal hurdle for all six IO categories, as defined in *subsub:descriptives* separately. By doing so, we also allow the variance of the error terms in both parts of the Cragg log-normal hurdle to be different for all IO categories (i.e. we partly allow for heteroskedasticity).

5.1.2 Net household savings

The first column in Table 7 presents the estimation results of the robust regression on net savings, using panel-robust bootstrap

standard errors. Not all variables are statistically significant, but we choose not to exclude any of the regressors from the model.

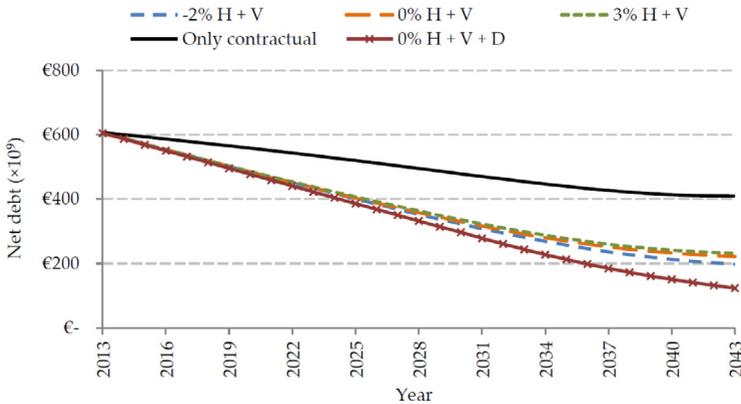
We want to use every variable that the IPO and LLD have in common in order to estimate net savings in the LLD. Remarkably, the birth cohorts (and postcode variables) are jointly insignificant, which contradicts the visual information from Figure 3.

The estimation results of the three quantile regressions also appear in Table 7, where the dependent variable is the inverse hyperbolic sine (IHS) transformation of net savings. Recall that we do not present bootstrap errors for this regression, due to the computational intensity. As a result, the cohort and postcode variables incorrectly appear to be jointly significant (a robust regression on net savings without bootstrap standard errors yields jointly significant cohort effects at a 1% significance level as well). In spite of the large number of regressors included in the model, the quantile regressions still fit rather poorly, as indicated by the low values.

5.2 Simulation results

In this discussion of the simulation results, we first focus on how much of the current mortgage debt will be redeemed in the upcoming 30 years. Figure 7 presents the simulation results of the aggregate net mortgage debt for different scenarios. The upper line represents the scenario in which borrowers make no voluntary repayments, which provides a quick check on whether we have modeled the contractual repayments correctly. In this scenario, roughly 33% of the current mortgage debt will be redeemed in 2043. Indeed, the remaining 67% comes from all 10 loans (58%), investment loans (7%) and loans classified as "other" (2%), for which we assumed no capital is accumulated for the moment. Later we relax this assumption. If we treat the

Figure 7: Simulation of the aggregate net mortgage debt for currently existing mortgages in the Netherlands. Different scenarios are considered (H = house price change; V = voluntary repayments; D = mortgage is repaid at death (85 years old)).



latter two types similar to the way we treat savings mortgages, we find that 42% will be redeemed in 2043 (rather than 33%; not presented in the figure).

The three dashed lines in Figure 7 allow for voluntary repayments, where different house price scenarios are considered. We observe that voluntary repayments contribute substantially to the redemption of the mortgage debt; almost half of the redeemed mortgage debt in 2043 comes from voluntary repayments. As can be seen, this result is not very sensitive to different house price assumptions. Additionally, the marked line shows that another hundred billion euro will be redeemed when mortality is taken into account. Older borrowers, however, typically have substantial home equity. Consequently, only 0.7% of these borrowers are underwater upon reaching the age of 85, where we assume constant house prices. Hence, the losses incurred by the lending institutions are probably very limited. Nonetheless, it is likely that

Figure 8: Simulation of the average LTV of the mortgages currently existing in the Netherlands, where different scenarios are considered (H = house price change; V = voluntary repayments).

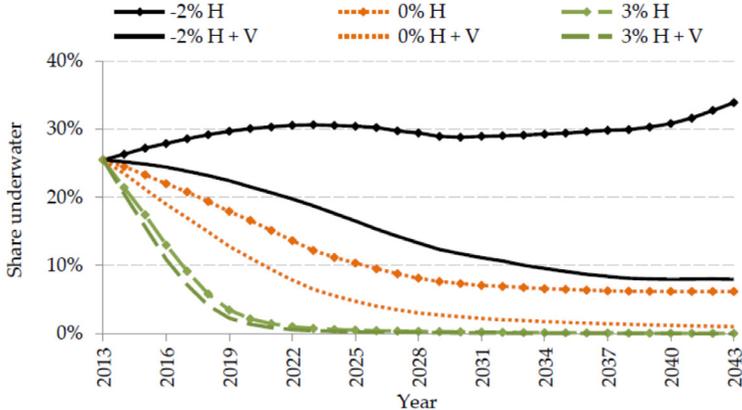


about a third of currently outstanding debt will not be repaid in the upcoming 30 years, thus aggravating the funding gap problem of banks described above. The development of the average LTV is presented in Figure 8, where different house price scenarios are considered. We also highlight at the bottom of the figure that the self-employed start with a higher LTV ratio. It takes this group longer to reduce the LTV below given thresholds (almost ten years longer to reduce it below 60%, for instance), but their repayment behavior is such that they will also (in most scenarios) finally end up with a similar level of indebtedness as the whole sample.

Figure 9 shows the evolution of the share of underwater mortgages. Mortgages currently underwater are typically amortizing mortgages (at least partially), such that the share of negative equity mortgages will decrease even when considering constant house prices. In the most optimistic scenario we find that almost all mortgages currently existing will be above water in 2022. In that same year, only 6% will be underwater when house prices remain constant and voluntary repayments are allowed. Only if house prices decrease by 2% annually and voluntary repayments are not considered do we observe an increase in both average LTV and the underwater share. Both figures again show that the contribution of voluntary repayments is substantial.

We now consider the mortgage characteristics at maturity, as most borrowers thereafter become no longer eligible for tax-deductibility. To say something about the associated risk in terms of LGD, we present in Figure 10 the median home equity of all mortgages with the same maturity year. Moreover, Figure 11 reveals that most mortgages mature around 2037, confirming what we expected from Figure 7. We find that the median home equity at maturity is positive for all years and in all scenarios, where only in the most pessimistic scenario does the median home equity

Figure 9: Simulation of the share of underwater mortgages among the mortgages currently existing in the Netherlands, again considering different scenarios (H = house price change; V = voluntary repayments).



approach/draw close to zero in 2037. When house prices remain constant, and voluntary repayments are allowed (which we consider to be the most realistic assumption), we find that only 3% of the mortgages that mature in 2037 are underwater.

It might be interesting to focus for the moment only on the mortgages that are currently underwater, as presented in Figure 12. Figure 13 depicts how almost all of these mortgages originated around 2008, as a result of the bursting of the housing bubble. For the mortgages that mature around this period, we observe a mean home equity that is once again positive in almost all scenarios. Only in the most pessimistic scenario is median home equity negative, but close to zero. This is again explained by the fact that mortgages that are currently underwater typically contractually amortize (at least to some extent), such that most of them are again above water at maturity.

Figure 10: Median home equity per maturity year of the mortgages currently existing in the Netherlands. Different scenarios are considered in the simulation (H = house price change; V = voluntary repayments).

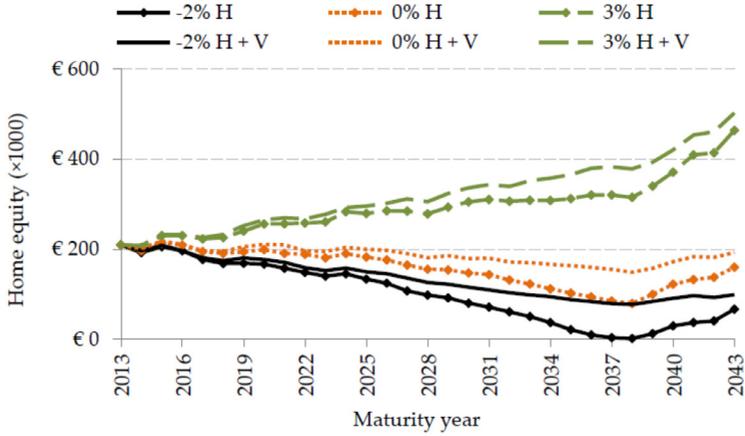


Figure 11: Number of borrowers in the simulation per maturity year of the corresponding mortgage.

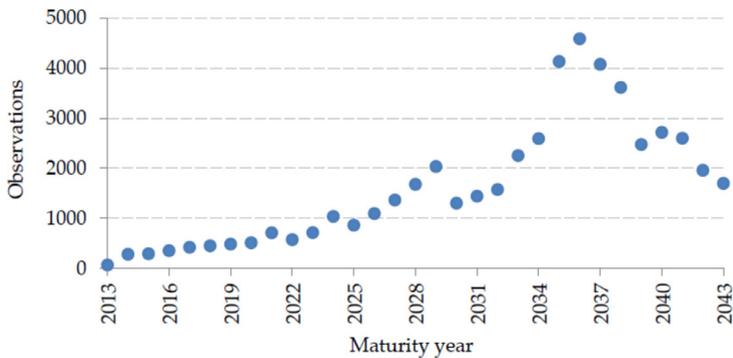


Figure 12: Median home equity per maturity year of the mortgages that are underwater in 2013. Different scenarios are considered (H = house price change; V = voluntary repayments).

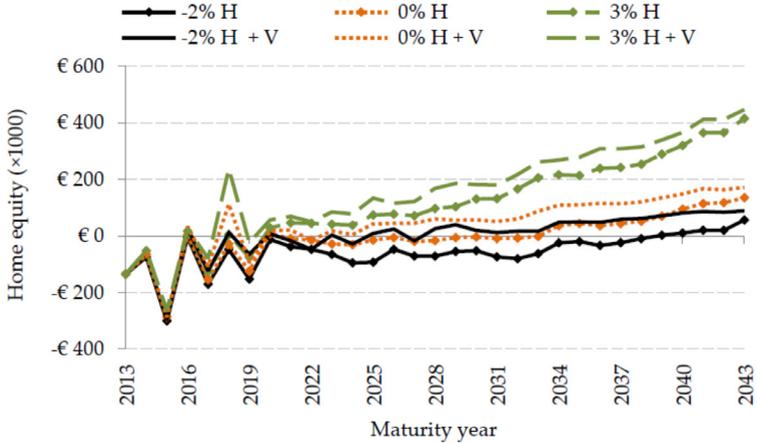
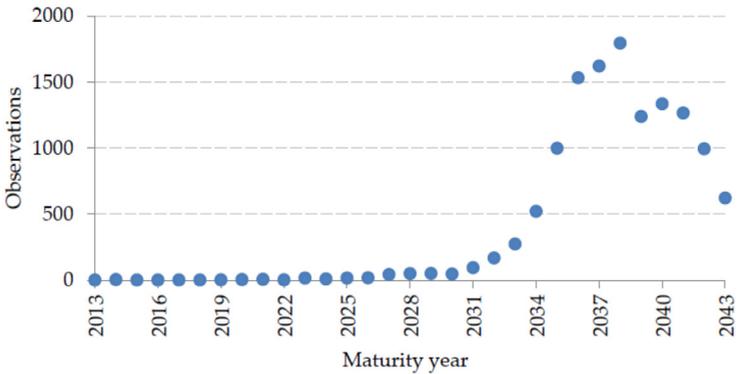


Figure 13: Number of borrowers in the simulation that are underwater in 2013 per maturity year of the corresponding mortgage.



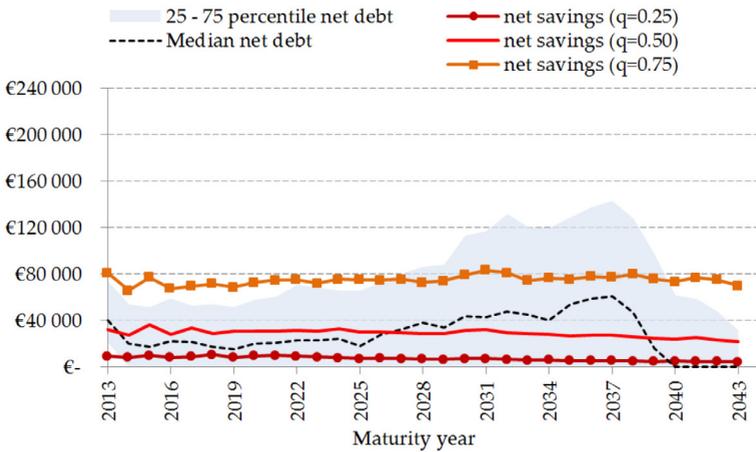
The final step in our analysis of the simulated data incorporates the distribution of net savings. Here we are interested in whether households have saved enough at maturity to fully repay their mortgage. Figure 14 presents the distribution of both net mortgage debt and net savings per maturity year of the whole sample and of the self-employed. We consider only the scenario where house prices remain constant, as neither net savings nor net mortgage debt appear to be very sensitive to house price changes in our model results. Interpreting the figure is rather difficult. We do not directly observe net savings of each borrower, but only have estimations of the conditional expectation and quantiles. The quantiles of net savings presented in the figure represent the average of all conditional quantiles of the borrowers corresponding to a specific maturity year, which is not necessarily the same as the quantile of the distribution. Furthermore, the difference between median net savings and median net debt is not necessarily equal to the median of this difference. The figure does, however, provide the general impression that most borrowers will not have saved enough to enable them to repay debt at maturity—especially for those mortgages that are set to mature in the period between 2030 and 2038. The figure also suggests that the heterogeneity in the debt distribution across the self-employed is much larger than that of the whole sample.

Figure 15 presents the sensitivity of the distribution of net savings to different assumptions on the annual change in CPI and GDP. Especially the right tail of the distribution of net savings appears to be rather sensitive to different assumptions about CPI and GDP, whereas other parts of the distribution do not.

Figure 16 presents the average mortgage debt and the average conditional expectation of net savings per maturity year. From this figure we indeed observe that households will not, on average,

Figure 14: Distribution of net mortgage debt and net savings per maturity year. The quantiles of net savings represent the average of all estimated conditional quantiles of the borrowers with corresponding maturity year. Voluntary repayments are considered, house prices are assumed to remain constant and both GDP and CPI increase by 2% annually.

Whole sample:



Self-employed:

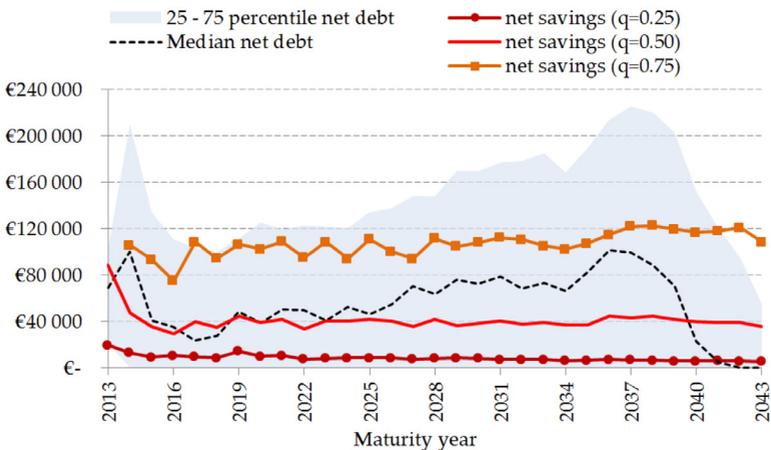
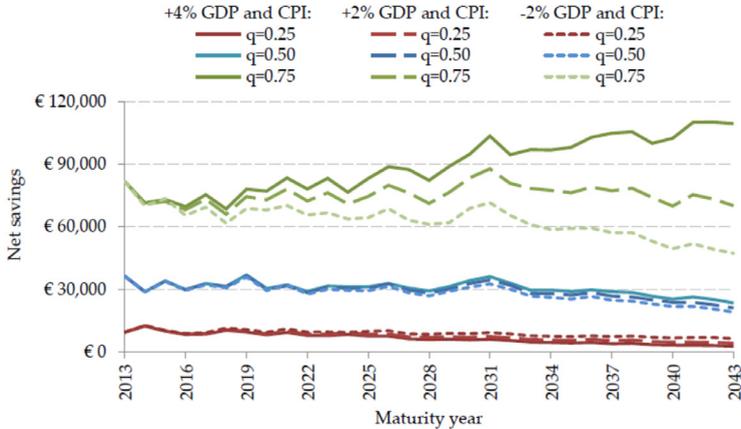


Figure 15: Sensitivity analysis of the distribution of net savings, where different CPI and GDP scenarios are considered in the simulation. The quantiles represent the average of all estimated conditional quantiles of the borrowers with corresponding maturity year.

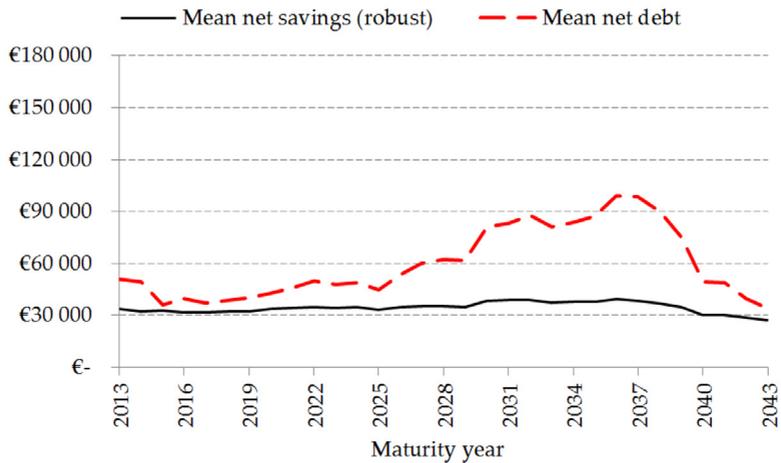


have saved enough to repay the mortgage at maturity in all years. Mortgages that mature in the period between 2030 and 2038 will fall short by roughly 60,000 euro on average (100,000 euro for the self-employed). They will then have saved about 30,000 euro (60,000 euro for the self-employed). This figure shows that the self-employed are potentially more exposed to housing market risk, relative to the whole population.

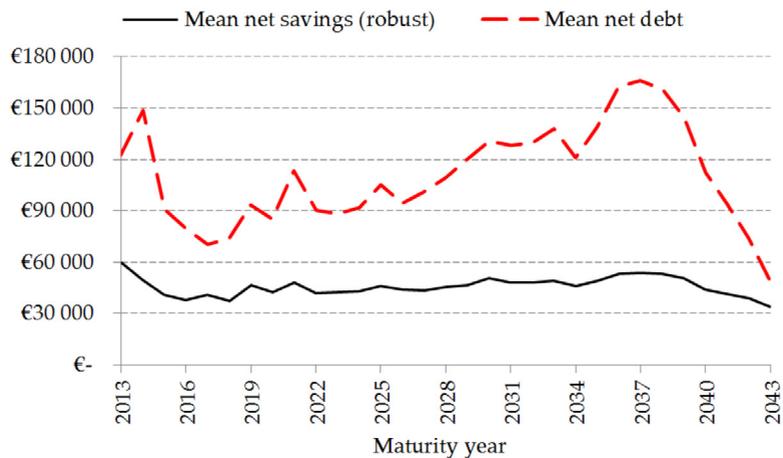
This is even more evident in Figure 17, where we look at outstanding debt at the age when the mortgage interest deduction expires (here computed as 30 years after origination). Only about 25% of the sample will be younger than 65 at maturity. In the figure, we also plot two lines representing the cumulative distribution of the share of the population whose mortgage matures by that age. The outstanding debt of the self-employed

Figure 16: Average net debt and average net savings per maturity year. Here, average net savings are calculated by taking the average of the conditional expectations of all borrowers having a specific maturity year. House prices are considered to remain constant, and both GDP and CPI increase by 2% annually.

Whole sample:



Self-employed:



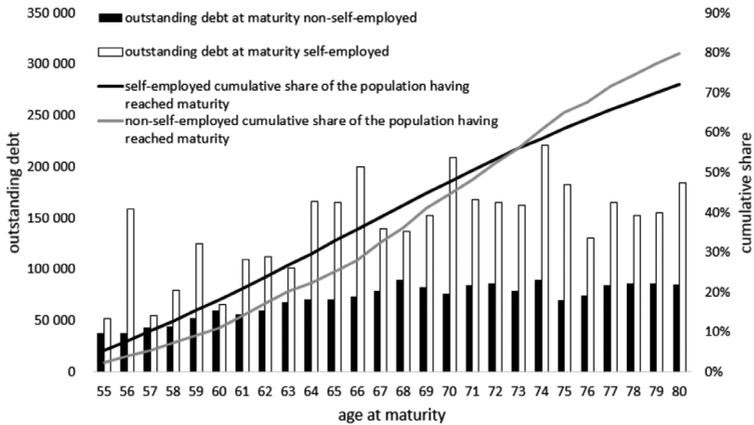
between the ages of 65 and 70 (very likely future retirement ages) is higher for those who were self-employed at origination— while their corresponding savings are not (not shown in this figure). The figure shows that the outstanding debt of the self-employed is about twice as large—averaging sometimes between 150,000 – 200,000 euro.

A back-of-the-envelope computation suggests that, with an interest rate of 3%, the mortgage costs of those prolonging their loans after maturity would amount to monthly payments between 375 and 500 euro, if the self-employed could buy or keep an IO perpetuity (so he or she would continue to pay the interest rate only until death). However, not all IO loans were sold as perpetuities. Given the old age of most respondents around maturity, it is plausible that banks would offer, after maturity, an annuity to be redeemed shortly, in say ten years, for the residual part of the debt. If this happens, the monthly payments of the self-employed would increase to about 1500–2000 euro.⁹ For the non-self-employed, with an average outstanding debt of about 75,000 euro (comprising the majority of the sample here), the monthly costs of a perpetuity or of a ten-year annuity vary between 190–740 euro a month.

These computations show that the future financial burden of retirees with outstanding IO debt not only will vary according to both their characteristics (with the self-employed being more indebted), and to institutions (mortgage interest deduction expiring), but also will depend on the behavior of banks. If banks were to once again offer IO perpetuities, then the monthly costs of all households would easily be covered by the current social secu-

⁹ This is assuming that private savings are not used to repay debt and assuming that the mortgage interest deduction is no longer available.

Figure 17: Outstanding mortgage debt at maturity by age of the mortgagor.



rity benefit. If this would not be the case— say, that banks were to offer a ten-year annuity mortgage— then the financial burden might become difficult for households to bear. In the worst case depicted here, a self-employed household with an outstanding debt of 200,000 euro that shifts from an IO loan before maturity to a ten-year annuity afterwards would experience an increase in monthly costs in the range of 500 to 2000 euro, with an interest rate equal to 3%.

5.3 Investment loans

In the computations above, we have not discussed the evolution of investment loans (thereby assuming, in effect, that nothing was saved for these loans). Also, since it is fiscally unattractive and costly to redeem these products before maturity, we assumed that no voluntary repayments are observed on these products. Our assumptions might not prove to be overly restrictive, however, due to several reasons connected to the very nature of invest-

Table 8: Combination of investment loans with IO loans

	20% investment	40% investment	60% investment	80% investment	100% investment
no IO component	3%	4%	7%	11%	100%
20% IO	3%	4%	3%	89%	
40% IO	9%	7%	90%		
60% IO	12%	85%			
80% IO	73%				
Explanatory note: The diagonal cells indicate no amortization. The residual category is non-investment and non-IO loan.					

ment loans. Typically for these loans, low premiums are paid in the saving/investment account (BEW), as periodic payments are set assuming a fixed expected return (typically 8%). A cursory look at the stock market reveals that this mean expected return of 8% was not achieved in the last decade. In addition, investment loans represent only about 5-7% of outstanding debt; thus, also at the macro level the BEWs represent a relatively small amount of cumulative capital.

In the data we further observe that investment loans are in many cases only a portion of the household mortgage. This does not mean, however, that the residual part will provide any amortization. Table 8 shows that investment loans are very often combined with IO loans. For instance, 90% of households with an investment component of 60% of total mortgage have a residual share of their mortgage (40%) in IO loans and no other amortization. This means that limited amortization is present in the mortgage of those who own an investment loan.

6. Summary & conclusions

This study shows what part of the current mortgage debt has already been repaid in the Netherlands and what part is likely to be repaid before maturity, even if this debt is partly in IO mortgages or investment loans. Using a novel dataset containing rich information on individual loan characteristics, we have shed light on two variables that are not observed in official statistics: the accumulated assets pledged to the mortgage, and voluntary repayments. We find that 58% of the current net mortgage debt comes from IO loans— which are, however, often combined with amortizing loans. This is the case also for different subgroups (e.g. both for the wage-employed and the self-employed). Borrowers having a full IO mortgage are typically older borrowers having substantial home equity, such that the risks regarding these mortgages are limited. Starters almost never have a full IO mortgage.

The microsimulation model in this study simulates mortgage debt 30 years into the future. Our results indicate that, in spite of the large share of IO loans, only about one-third of the current mortgage debt will be redeemed via voluntary repayments. If mortality is taken into account, then many more IO loans will also be redeemed; as most IO loans are with older borrowers, however, mortality will reduce current debt only further than 30 years in the future.

This study relates mortgage debt to non-housing wealth, showing that most households with a residual debt will not save enough to fully repay the mortgage at maturity. Particularly those mortgages originating around the bursting of the housing bubble will have substantial remaining debt (approximately 60,000 euro on average; about 100,000 euro for the self-employed), which

will not be fully compensated by household financial wealth (30,000 euro on average; 60,000 euro for the self-employed). Examining these figures by age, we show that households that are about to retire could face a substantial increase in monthly costs— depending on whether the bank will offer again an IO perpetuity or will demand a quicker repayment— as interest payments after mortgage maturity will no longer be tax-deductible. Specific groups, such as the self-employed and owners of investment loans, could then be confronted with larger financial problems. For instance, the mean self-employed individual with no financial wealth, who shifts from a fully IO mortgage before maturity to a ten-year annuity afterward, will face an increase in monthly costs that is as high as the current social security benefit. Nevertheless, almost all borrowers will have positive home equity at maturity, which will limit the risks associated with the banking sector.

References

- Almeida, H., M. Campello and C. Liu (2006). The Financial Accelerator: Evidence from International Housing Markets. *Review of Finance* 10(3), 321–352.
- Bernanke, B., M. Gertler and S. Gilchrist (1996). The Financial Accelerator and the Flight to Quality. *Review of Economics and Statistics* 48(1), 1–15.
- Bostic, R., S. Gabriel and G. Painter (2009). Housing Wealth, Financial Wealth, and Consumption: New Evidence From Micro Data. *Regional Science and Urban Economics* 39(1), 79–89.
- Bovenberg, A.L. and B. Jacobs (2008). *Human capital and optimal positive taxation of capital income*, Netspar DP 12/2008–056.
- Cameron, A.C. and P.K. Trivedi (2005). *Microeconometrics: Methods and Applications*. New York, NY: Cambridge University Press.
- Campbell, J.Y. and J.F. Cocco (2007). How Do House Prices Affect Consumption? Evidence From Micro Data. *Journal of Monetary Economics* 54(3), 591–621.
- Carson, R.T. and Y. Sun (2007). The Tobit Model with a Non-Zero Threshold. *The Econometrics Journal* 10(3), 488–502.
- CBS (2014a). Documentatierapport Inkomenspanel Onderzoek (IPO) 2011. Voorburg: Centraal Bureau voor de Statistiek.
- CBS (2014b). Documentatierapport Selectie Inkomenspanelonderzoek. Centraal Bureau voor de Statistiek.
- Cleveland, W.S. (1979). Robust Locally Weighted Regression and Smoothing Scatterplots. *Journal of the American Statistical Association* 74(368), 829–836.
- CPB (2014). *CPB Financial Stability Report 2014*. CPB Communication 2014, CPB Netherlands Bureau for Economic Policy Analysis.
- Cragg, J.G. (1971). Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods. *Econometrica* 39(5), 829–844.
- Dillingh, R., H. Prast, M. Rossi and C.U. Brancati (2015). *The Psychology and Economics of Reverse Mortgage Attitudes. Evidence from the Netherlands*, Netspar Design Paper 38.
- DNB (2014). *Overview of Financial Stability – Spring 2014*. Amsterdam: Dutch Central Bank.
- D’Orazio, M., M. Di Zio and M. Scanu (2006). *Statistical Matching: Theory and Practice*. Chichester: Wiley.
- Heckman, J. (1976). The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models. *Annals of Economic and Social Measurement* 5(4), 475–492.
- Jansen, J., M. Bijlsma, M. Kruidhof and C. Pattipeilohy (2013). Funding Problems in the Mortgage Market. DNB Occasional Studies 11(1).
- Kiyotaki, N. and J. Morre (1997). Credit Cycles. *Journal of Political Economy* 105(2), 211–248.

- Koenker, R. (2005). *Quantile Regression*. New York, NY: Cambridge University Press.
- Lorenzoni, G. (2008). Inefficient Credit Booms. *Review of Economic Studies* 75(3), 809–833.
- Mastrogiacomo, M. and R. van der Molen (2015). Dutch mortgages in the DNB loan level data. DNB Occasional Studies 4.
- Mian, A. and A. Sufi (2015). *House of Debt: How They (and You) Caused the Great Recession, and How We Can Prevent It from Happening Again*, University of Chicago Press.
- Rässler, S. (2002). *Statistical Matching: A Frequentist Theory, Practical Applications and Alternative Bayesian Approaches*. New York, NY: Springer.
- Sun, W., R.K. Triest and A. Webb (2007). Optimal Retirement Asset Decumulation Strategies: The Impact of Housing Wealth (January 20, 2007). FRB of Boston Public Policy Discussion Paper No. 07-2.
- Tobin, J. (1958). Estimation of Relationships for Limited Dependent Variables. *Econometrica* 26(1), 24 – 36.
- Verardi, V. and C. Croux (2009). Robust Regression in Stata. *The Stata Journal* 9(3), 439–453.
- Verbruggen J., R. van der Molen, S. Jonk, J. Kakes and W. Heeringa (2015). Effecten van een Verdere Verlaging van de LTV-limiet, DNB Occasional Study (2).
- Wooldridge, J.M. (2010). *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

Appendix

Voluntary repayments

Let y_i denote the voluntary repayments for borrower $i = 1, 2, \dots, N$. We have that y_i takes on the value zero with positive probability, but is a continuous random variable over strictly positive values. Variables with this specific characteristic are typically modeled using corner solution response models (see Wooldridge (2010) for an introduction to corner response models). We will compare a number of different model specifications, where comparison is based on, among other things, the log-likelihood and pseudo R^2 . We use the squared correlation between fitted values and actual observations as a measure for the pseudo R^2 , as they are directly comparable across classes of models. First, we consider a standard Tobit model (Tobin, 1958):

$$y_i^* = \mathbf{x}'_i \boldsymbol{\beta} + \varepsilon_i, i = 1, 2, \dots, N, \quad (2)$$

In our specification we use the following $k = 8$ explanatory variables: age, age squared, current LTV, debt-weighted share of IO loans, mortgage interest rate, a dummy indicating the borrower has NHG, a dummy indicating the mortgage is underwater and an interaction term between age and the underwater dummy. Now, instead of observing the latent variable y_i^* , we observe

$$y_i = \begin{cases} y_i^* & \text{if } y_i^* \geq L \\ 0 & \text{if } y_i^* < L, \end{cases} \quad (3)$$

where we argued (see Section 2) setting $L = 2000$. Maximum likelihood estimation of the standard Tobit model with zero censoring point is explained in standard econometric textbooks (e.g. Cameron and Trivedi (2005)). However, here we are dealing with a non-zero threshold. We estimate $\boldsymbol{\beta}$ by running a standard Tobit on $y_i^* = \max(0, y_i^* - L)$, which has zero censoring point, and then adjust the estimated intercept by L . We further define the participation equation

$$w_i = \begin{cases} 1 & \text{if } y_i > 0 \\ 0 & \text{if } y_i = 0, \end{cases} \quad (4)$$

such that the conditional probability of a voluntary repayment is given by

$$\begin{aligned} \Pr(w_i = 1 | \mathbf{x}_i) &= \Pr(y_i^* \geq L | \mathbf{x}_i) \\ &= \Pr(\mathbf{x}'_i \boldsymbol{\beta} + \varepsilon_i \geq L) \\ &= \Pr\left(\frac{\varepsilon_i}{\sigma} \geq \frac{L - \mathbf{x}'_i \boldsymbol{\beta}}{\sigma}\right) \\ &= \Phi\left(\frac{\mathbf{x}'_i \boldsymbol{\beta} - L}{\sigma}\right), \end{aligned}$$

where the last step follows since the distribution of ε_i is symmetric around zero. Hence, if (2) and (3) are true, then w_i follows a probit model. By running a probit model on w_i , we can test for heteroskedasticity and normality in the error term of the latent equation (2). The probit and Tobit should yield similar parameter estimates, as they are based on the same latent model. Notice, however, that σ and $\boldsymbol{\beta}$ are not uniquely identified in a probit model (for identifiability, it is assumed

that $\sigma = 1$). Instead, we get an estimate of the $(k + 1) \times 1$ vector $\boldsymbol{\gamma} = (\gamma_1, \dots, \gamma_{k+1})' = ((\beta_1 - L)/\sigma, \beta_2/\sigma, \beta_3/\sigma, \dots, \beta_{k+1}/\sigma)$. Some manipulations of the Tobit estimates are therefore necessary to make them comparable with the probit estimates. As $\sigma > 0$, we would at least expect that Tobit and probit estimates have the same sign. One could also compare the marginal effects (ME) of a change in regressor on $\Pr(y_i > 0 | \mathbf{x}_i)$ with the ME from the probit model. Let x_{ij} denote the j th component of \mathbf{x}_i . Now, the ME of change in regressor x_{ij} on $\Pr(y_i > 0 | \mathbf{x}_i)$ is given by

$$\frac{\partial \Pr(y_i > 0 | \mathbf{x}_i)}{\partial x_{ij}} = \frac{\beta_j}{\sigma} \phi\left(\frac{\mathbf{x}'_i \boldsymbol{\beta} - L}{\sigma}\right), \quad (5)$$

for $j = 2, \dots, k + 1$. Also, the ME for the probit model are given by

$$\frac{\partial \Pr(y_i > 0 | \mathbf{x}_i)}{\partial x_{ij}} = \gamma_j \phi(\mathbf{x}'_i \boldsymbol{\gamma}),$$

which is the same as (5) (notice that the ME for $j = 1$ is not considered, as x_{i1} is a constant). Altogether, the estimated ME resulting from the Tobit estimates should be similar to the ME from the probit model if the Tobit model is correctly specified. We observed that the distribution of the voluntary repayments was highly right-skewed with considerable non-normal kurtosis. It might work better to take the natural logarithm. Now, instead of (2) and (3) we introduce a log-normal variant of the standard Tobit model by specifying

$$y_i^* = \exp(\mathbf{x}'_i \boldsymbol{\beta} + \varepsilon_i), \varepsilon_i | \mathbf{x}_i \sim NID(0, \sigma^2),$$

where we should note that β , ε_i and σ^2 are redefined and not the same as in (2). Moreover, we observe

$$y_i = \begin{cases} y_i^* & \text{if } \ln(y_i^*) \geq \ln(L) \\ 0 & \text{if } \ln(y_i^*) < \ln(L). \end{cases}$$

Notice that $\ln(0)$ is not defined, such that all censored observations are lost when transforming to log-normal data. Among others, Carson and Sun (2007) show that consistent estimates are obtained by setting all censored observations to the minimum non-censored value of $\ln y_i$.¹

The Tobit model has some restrictive implication, e.g. the ME of x_{ij} on $\Pr(y_i > 0 | \mathbf{x}_i)$ and $E(y_i | \mathbf{x}_i, y_i > 0)$ always have the same sign. By relaxing these assumptions, we might obtain a better fit. Thus, we consider the Cragg log-normal hurdle (Cragg, 1971), or Two-Part model, which allows separate mechanisms to determine the participation decision ($w_i = 0$ or $w_i = 1$) and the amount decision (magnitude of y_i when $y_i > 0$). Here we express y_i as follows:

$$y_i = w_i \cdot y_i^* = I(\mathbf{x}'_i \boldsymbol{\lambda} + v_i > L) \exp(\mathbf{x}'_i \boldsymbol{\delta} + u_i), \quad (6)$$

Where $I(\cdot)$ is the indicator function, $v_i | \mathbf{x}_i \sim NID(0, 1)$ and $u_i | \mathbf{x}_i \sim NID(0, \sigma^2)$, and where we assume v_i and u_i are independent. As can be seen, the same regressors are used in both parts, as there are no obvious exclusion restrictions.

¹ Actually, when using a canned statistical package like STATA, we need to set the censored observations to an amount slightly smaller than the minimum non-censored value of $\ln y_i$ (i.e. $\ln(L) - 1.10^{-6}$). Otherwise, the minimum non-censored value will be treated as a censored value as well.

Estimation is done in two parts. First, we run a probit regression on w_i to estimate λ (Part I). Second, we estimate δ and σ^2 by running an OLS regression on $\ln y_i$ using only the observations for which $y_i > 0$ (Part II).

The assumption that v_i and u_i are independent might be rather strong. The Heckman selection model (Heckman, 1976) relaxes this independence assumption. However, identification of such a model can be fragile without a valid exclusion restriction (i.e. a variable that affects the selection equation but not the main equation). It is hard to find such a variable in practice.

Moreover, for practical reasons we also choose not to consider a Heckman model; a Cragg log-normal hurdle is much easier to implement in the simulation.

Non-housing wealth

Let y_{it} denote the net savings for borrower i at time t . The distribution of net savings is highly right-skewed and can have both extreme positive and negative values. Using the natural logarithm to normalize the distribution of the data does not help, as log-transformations for non-positive observations are not defined. Keeping this in mind, let us consider the following panel model:

$$y_{it} = \mathbf{x}'_{it}\boldsymbol{\beta} + c_i + u_{it}, i = 1, \dots, N; t = 1, \dots, T. \quad (7)$$

where c_i is an unobserved individual effect, u_{it} is an error term and \mathbf{x}_{it} is a $(k + 1) \times 1$ vector including k regressors and a constant. Here, we assume the observations are independent across individuals, but not necessarily across time. Regarding the error term, we only make the assumption that

$E(u_{it}|\mathbf{x}_{it}, c_i) = 0$. Hence, for reasons discussed above, we do not make the usual assumptions that u_{it} is i.i.d. and normally distributed. Moreover, we assume $E(c_i|\mathbf{x}_i) = 0$, where $\mathbf{x}_i = (\mathbf{x}_{i1}', \dots, \mathbf{x}_{iT}')'$. If we make the fixed effect assumption instead, i.e. $E(c_i|\mathbf{x}_i) \neq 0$, we cannot estimate c_i for the individuals in the LLD (estimation of the individual-specific effect requires that net savings are observed in at least one time period for that specific individual). Instead, we try to imitate fixed effects by including a number of time-invariant regressors in \mathbf{x}_{ij} . In total, we use the following $k = 28$ regressors: age, age squared, gross mortgage debt, property value, mortgage interest rate, nominal consumer price index (CPI), nominal gross domestic product (GDP), three variables on postcode-level (number of real estate transactions, average debt-weighted share of interest-only mortgage and average property value), three time-invariant variables constructed by averaging time-varying variables over time (average gross mortgage debt, average property value and average interest rate) and fifteen cohort dummies.

Now, let $v_{it} = c_i + u_{it}$ such that (7) can be rewritten as $y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + v_{it}$. The assumptions on u_{it} and c_i imply that $E(v_{it}|\mathbf{x}_{ij}) = 0$, such that the conditional expectation of y_{it} is given by $E(y_{it}|\mathbf{x}_{it}) = \mathbf{x}_{it}'\boldsymbol{\beta}$. $E(v_{it}|\mathbf{x}_{ij}) = 0$ is sufficient to prove that $\boldsymbol{\beta}$ can be consistently estimated using Pooled OLS. However, simple OLS regression is highly sensitive to the presence of outliers in the data and might be inefficient under highly non-normal errors. To deal with this, several robust regressions have been proposed in the literature, yielding a more resistant estimate of $\boldsymbol{\beta}$. The general idea is that most influential observations in the simple OLS regression (associated with Cook's distances larger than one) are dropped, after which the remaining observations with large

absolute residuals are down-weighted. The exact down-weighting procedure for the specific robust regression we use in this study is extensively described in Verardi and Croux (2009). Now, let the estimate of β resulting from the robust regression be denoted by $\hat{\beta}$. To obtain panel-robust standard errors we apply the bootstrap method. Specifically, $B = 50$ pseudo-samples of $N_b = 10000$ borrowers are constructed by drawing with replacement over i and using all observed time periods for that borrower. For each pseudo-sample, we perform a robust regression of y_{it} on \mathbf{x}_{it} , yielding B estimates of β denoted by $\hat{\beta}_b, b = 1, \dots, B$. Now, let $\bar{\beta} = \frac{1}{B} \sum_{b=1}^B \hat{\beta}_b$, such that the panel bootstrap estimate of the variance matrix of $\hat{\beta}$ is given by

$$\hat{\mathbf{V}}_{boot}(\hat{\beta}) = \frac{1}{B-1} \sum_{b=1}^B (\hat{\beta}_b - \bar{\beta})(\hat{\beta}_b - \bar{\beta})'$$

Next, quantile regression (QR) is used to provide a more complete picture of the conditional distribution of y_{it} . In contrast to OLS regression, QR is robust against outliers and is equivariant to monotone transformations. This last property is important here, as we need to transform the data in order to achieve convergence in the quantile regression. Specifically, we apply the inverse hyperbolic sine (IHS) transformation to y_{it} :

$$y_{it}^{\bullet} = \sinh^{-1}(y_{it}) = \ln \left(y_{it} + \sqrt{y_{it}^2 + 1} \right),$$

where the hyperbolic sine function is used to transform the data back:

$$y_{it} = \sinh(y_{it}^{\bullet}) = \frac{1}{2} (e^{y_{it}^{\bullet}} - e^{-y_{it}^{\bullet}}).$$

Now, let $q \in (0,1)$ and denote the q th conditional quantile of the distribution of y_{it}^* by $Q_q(y_{it}^*|\mathbf{x}_{it})$, where we assume $Q_q(y_{it}^*|\mathbf{x}_{it})$ is linear in \mathbf{x}_{it} , i.e. $Q_q(y_{it}^*|\mathbf{x}_{it}) = \mathbf{x}_{it}'\boldsymbol{\beta}_q$. The subscript in $\boldsymbol{\beta}_q$ indicates that the parameters are different for different points in the conditional distribution. In particular, we estimate $\boldsymbol{\beta}_q$ for $q = 0.25, 0.50, 0.75$. Estimation of $\boldsymbol{\beta}_q$ is done by minimizing the following objective function:

$$Q_N(\boldsymbol{\beta}_q) = \sum_{i:y_{it}^* \geq \mathbf{x}_{it}'\boldsymbol{\beta}_q} q |y_{it}^* - \mathbf{x}_{it}'\boldsymbol{\beta}_q| + \sum_{i:y_{it}^* < \mathbf{x}_{it}'\boldsymbol{\beta}_q} (1 - q) |y_{it}^* - \mathbf{x}_{it}'\boldsymbol{\beta}_q|.$$

This objective function is not differentiable, but fortunately linear programming methods can be used to solve the minimization problem (see Koenker, 2005). After obtaining an estimate for $Q_q(y_{it}^*|\mathbf{x}_{it})$, we simply transform this estimate using the hyperbolic sine function to get an estimate for $Q_q(y_{it}|\mathbf{x}_{it})$. Again, the bootstrap method should be used to obtain panel-robust standard errors, which adds considerably to the computational intensity (we show these results in Table 7). Since the quantile regressions alone already take more than a day to run, we choose not to report panel-robust standard errors.

OVERZICHT UITGAVEN IN DE DESIGN PAPER SERIE

- 1 Naar een nieuw pensioencontract (2011)
Lans Bovenberg en Casper van Ewijk
- 2 Langlevenrisico in collectieve pensioencontracten (2011)
Anja De Waegenaere, Alexander Paulis en Job Stigter
- 3 Bouwstenen voor nieuwe pensioencontracten en uitdagingen voor het toezicht daarop (2011)
Theo Nijman en Lans Bovenberg
- 4 European supervision of pension funds: purpose, scope and design (2011)
Niels Kortleve, Wilfried Mulder and Antoon Pelsser
- 5 Regulating pensions: Why the European Union matters (2011)
Ton van den Brink, Hans van Meerten and Sybe de Vries
- 6 The design of European supervision of pension funds (2012)
Dirk Broeders, Niels Kortleve, Antoon Pelsser and Jan-Willem Wijckmans
- 7 Hoe gevoelig is de uittredeleeftijd voor veranderingen in het pensioenstelsel? (2012)
Didier Fouarge, Andries de Grip en Raymond Montizaan
- 8 De inkomensverdeling en levensverwachting van ouderen (2012)
MARIKE KNOEF, ROB ALESSIE en ADRIAAN KALWIJ
- 9 Marktconsistente waardering van zachte pensioenrechten (2012)
Theo Nijman en Bas Werker
- 10 De RAM in het nieuwe pensioenakkoord (2012)
Frank de Jong en Peter Schotman
- 11 The longevity risk of the Dutch Actuarial Association's projection model (2012)
Frederik Peters, Wilma Nusselder and Johan Mackenbach
- 12 Het koppelen van pensioenleeftijd en pensioenaanspraken aan de levensverwachting (2012)
Anja De Waegenaere, Bertrand Melenberg en Tim Boonen
- 13 Impliciete en expliciete leeftijdsdifferentiatie in pensioencontracten (2013)
Roel Mehlkopf, Jan Bonenkamp, Casper van Ewijk, Harry ter Rele en Ed Westerhout
- 14 Hoofdlijnen Pensioenakkoord, juridisch begrepen (2013)
Mark Heemskerk, Bas de Jong en René Maatman
- 15 Different people, different choices: The influence of visual stimuli in communication on pension choice (2013)
Elisabeth Brügggen, Ingrid Rohde and Mijke van den Broeke
- 16 Herverdeling door pensioenregelingen (2013)
Jan Bonenkamp, Wilma Nusselder, Johan Mackenbach, Frederik Peters en Harry ter Rele
- 17 Guarantees and habit formation in pension schemes: A critical analysis of the floor-leverage rule (2013)
Frank de Jong and Yang Zhou

- 18 The holistic balance sheet as a building block in pension fund supervision (2013)
Erwin Fransen, Niels Kortleve, Hans Schumacher, Hans Staring and Jan-Willem Wijckmans
- 19 Collective pension schemes and individual choice (2013)
Jules van Binsbergen, Dirk Broeders, Myrthe de Jong and Ralph Koijen
- 20 Building a distribution builder: Design considerations for financial investment and pension decisions (2013)
Bas Donkers, Carlos Lourenço, Daniel Goldstein and Benedict Dellaert
- 21 Escalerende garantietoezeggingen: een alternatief voor het StAr RAM-contract (2013)
Servaas van Bilsen, Roger Laeven en Theo Nijman
- 22 A reporting standard for defined contribution pension plans (2013)
Kees de Vaan, Daniele Fano, Heralto Mens and Giovanna Nicodano
- 23 Op naar actieve pensioenconsumenten: Inhoudelijke kenmerken en randvoorwaarden van effectieve pensioencommunicatie (2013)
Niels Kortleve, Guido Verbaal en Charlotte Kuiper
- 24 Naar een nieuw deelnemergericht UPO (2013)
Charlotte Kuiper, Arthur van Soest en Cees Dert
- 25 Measuring retirement savings adequacy; developing a multi-pillar approach in the Netherlands (2013)
Marika Knoef, Jim Been, Rob Alessie, Koen Caminada, Kees Goudswaard, and Adriaan Kalwij
- 26 Illiquiditeit voor pensioenfondsen en verzekeraars: Rendement versus risico (2014)
Joost Driessen
- 27 De doorsneesystematiek in aanvullende pensioenregelingen: effecten, alternatieven en transitiepaden (2014)
Jan Bonenkamp, Ryanne Cox en Marcel Lever
- 28 EIOPA: bevoegdheden en rechtsbescherming (2014)
Ivor Witte
- 29 Een institutionele beleggersblik op de Nederlandse woningmarkt (2013)
Dirk Brounen en Ronald Mahieu
- 30 Verzekeraar en het reële pensioencontract (2014)
Jolanda van den Brink, Erik Lutjens en Ivor Witte
- 31 Pensioen, consumptiebehoeften en ouderenzorg (2014)
Marika Knoef, Arjen Hussem, Arjan Soede en Jochem de Bresser
- 32 Habit formation: implications for pension plans (2014)
Frank de Jong and Yang Zhou
- 33 Het Algemeen pensioenfonds en de taakafbakening (2014)
Ivor Witte
- 34 Intergenerational Risk Trading (2014)
Jiajia Cui and Eduard Ponds
- 35 Beëindiging van de doorsneesystematiek: juridisch navigeren naar alternatieven (2015)
Dick Boeijen, Mark Heemskerck en René Maatman
- 36 Purchasing an annuity: now or later? The role of interest rates (2015)
Thijs Markwat, Roderick Molenaar and Juan Carlos Rodriguez
- 37 Entrepreneurs without wealth? An overview of their portfolio using different data sources for the Netherlands (2015)
Mauro Mastrogiacomo, Yue Li and Rik Dillingh

- 38 The psychology and economics of reverse mortgage attitudes. Evidence from the Netherlands (2015)
Rik Dillingh, Henriëtte Prast, Mariacristina Rossi and Cesira Urzi Brancati
- 39 Keuzevrijheid in de uittreedleeftijd (2015)
Arthur van Soest
- 40 Afschaffing doorsneesystematiek: verkenning van varianten (2015)
Jan Bonenkamp en Marcel Lever
- 41 Nederlandse pensioenopbouw in internationaal perspectief (2015)
MARIKE KNOEF, Kees Goudswaard, Jim Been en Koen Caminada
- 42 Intergenerationele risicodeling in collectieve en individuele pensioencontracten (2015)
Jan Bonenkamp, Peter Broer en Ed Westerhout
- 43 Inflation Experiences of Retirees (2015)
Adriaan Kalwij, Rob Alessie, Jonathan Gardner and Ashik Anwar Ali
- 44 Financial fairness and conditional indexation (2015)
Torsten Kleinow and Hans Schumacher
- 45 Lessons from the Swedish occupational pension system (2015)
Lans Bovenberg, RYANNE COX and Stefan Lundberg
- 46 Heldere en harde pensioenrechten onder een PPR (2016)
Mark Heemskerk, René Maatman en Bas Werker
- 47 Segmentation of pension plan participants: Identifying dimensions of heterogeneity (2016)
Wiebke Eberhardt, Elisabeth Brügggen, Thomas Post and Chantal Hoet
- 48 How do people spend their time before and after retirement? (2016)
Johannes Binswanger
- 49 Naar een nieuwe aanpak voor risicoprofielmeting voor deelnemers in pensioenregelingen (2016)
Benedict Dellaert, Bas Donkers, Marc Turlings, Tom Steenkamp en Ed Vermeulen
- 50 Individueel defined contribution in de uitkeringsfase (2016)
Tom Steenkamp
- 51 Wat vinden en verwachten Nederlanders van het pensioen? (2016)
Arthur van Soest
- 52 Do life expectancy projections need to account for the impact of smoking? (2016)
Frederik Peters, Johan Mackenbach en Wilma Nusselder
- 53 Effecten van gelaagdheid in pensioendocumenten: een gebruikersstudie (2016)
Louise Nell, Leo Lentz en Henk Pander Maat
- 54 Term Structures with Converging Forward Rates (2016)
Michel Vellekoop and Jan de Kort
- 55 Participation and choice in funded pension plans (2016)
Manuel García-Huitrón and Eduard Ponds
- 56 Interest rate models for pension and insurance regulation (2016)
Dirk Broeders, Frank de Jong and Peter Schotman
- 57 An evaluation of the nFTK (2016)
Lei Shu, Bertrand Melenberg and Hans Schumacher
- 58 Pensioenen en inkomensongelijkheid onder ouderen in Europa (2016)
Koen Caminada, Kees Goudswaard, Jim Been en Marike Knoef
- 59 Towards a practical and scientifically sound tool for measuring time and risk preferences in pension savings decisions (2016)
Jan Potters, Arno Riedl and Paul Smeets

- 60 Save more or retire later?
Retirement planning heterogeneity
and perceptions of savings
adequacy and income constraints
(2016)
Ron van Schie, Benedict Dellaert
and Bas Donkers
- 61 Uitstroom van oudere werknemers
bij overheid en onderwijs. Selectie
uit de poort (2016)
Frank Cörvers en Janneke Wilschut
- 62 Pension risk preferences. A
personalized elicitation method
and its impact on asset allocation
(2016)
Gosse Alserda, Benedict Dellaert,
Laurens Swinkels and Fieke van der
Lecq
- 63 Market-consistent valuation
of pension liabilities (2016)
Antoon Pelsser, Ahmad Salahnejhad
and Ramon van den Akker
- 64 Will we repay our debts before
retirement? Or did we already, but
nobody noticed? (2016)
Mauro Mastrogiacomio

Will we repay our debts before retirement?

In this study, researcher Mauro Mastrogiacomo presents an analysis of the future housing debt position of specific groups of Dutch mortgage owners, such as starters and self-employed, around the time of their future retirement. Various assets such as the role of voluntary repayments and the value of saving accounts are taken into consideration. The projections show that individual mortgages, even if not completely redeemed, are in general not problematic for the borrowers' financial position around retirement. If the interest-only part of debt is treated as a perpetuity, costs remain low. If not, however, they might become a financial burden, especially to the self-employed. Also these debts are substantial at macro-economic level. In the most favorable simulations 1/3 of the mortgage debt existing at the beginning of 2014 will not be repaid in the next three decades, possibly exacerbating the banks funding-gap problem.

This is a publication of:

Netspar

P.O. Box 90153

5000 LE Tilburg

the Netherlands

Phone 013 466 2109

E-mail info@netspar.nl

www.netspar.nl

November 2016