DEUTSCHE BUNDESBANK
EUROSYSTEM

Discussion Paper

Deutsche Bundesbank
No 20/2021

The impact of borrower-based instruments on household vulnerability in Germany

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Internet http://www.bundesbank.de

ISBN 978–3–95729–828–7

Non-technical summary

Research Question

Excessive household borrowing has been identified as an important determinant of financial crises. In this context, borrower-based macroprudential instruments have been proposed as a possible remedy. In Germany, two instruments have been available to macroprudential supervisors since 2017: a cap on the loan-to-value (LTV) ratio and an amortization requirement but none of them has been activated so far. While a number of ex post analyses using mostly aggregate cross-country data show that the activation of instruments dampens credit and price growth, analytical methods quantifying the effects of such instruments prior to activation are rare.

Contribution

Against this background, this paper proposes a simulation tool that allows the impact of activating borrower-based instruments to be evaluated ex ante, based on cross-sectional household data. We argue that our method is a useful approach when only infrequently collected cross-sectional data are available to the analyst, such as the microdata from the triennial German Panel on Household Finances (PHF). The simulation model is built around a set of behavioral equations that use variables such as employment status and wealth as inputs and determine individual households' behavior such as the decision to become a home-owner and the amount of new mortgage debt. In addition to exploiting the rich heterogeneity of the microdata, the model is also set up in a way that matches aggregate developments in the residential real estate market. The model thus ensures that results at the household level are consistent with developments at the macroeconomic level. Owing to this feature, the approach can be useful for detecting vulnerabilities in households' balance sheets and for quantifying the potential impact of borrower-based measures on these balance sheets in a coherent framework.

Results

An illustrative example of a hypothetical instrument activation shows that the introduction of an LTV cap on new mortgage loans in Germany could improve important indicators of household vulnerability. Importantly, we demonstrate that the activation of instruments would take a number of years to reduce the LTV in the stock of mortgages and thus to mitigate risks to lenders' balance sheets. Further, we show that an LTV cap could reduce not only the average LTV but also – as intended – the share of high-LTV loans (flows and stocks). The analysis also shows, however, that an LTV cap could lower mortgage growth. Thus, the paper highlights key trade-offs for policymakers.

Nichttechnische Zusammenfassung

Fragestellung

Übermäßige Kreditvergabe an private Haushalte gilt als eine zentrale Ursache von Finanzkrisen. Makroprudenzielle Instrumente, die an der Verschuldung der privaten Haushalte ansetzen, wurden mit dem Ziel entwickelt, dieses Risiko zu begrenzen. In Deutschland verfügen die makroprudenziellen Aufseher seit 2017 über zwei solche Instrumente: eine Obergrenze für das Verhältnis von Kreditvolumen zum Immobilienwert (Loan-to-Value Ratio) und eine Amortisationsanforderung. Keines der Instrumente wurde bisher aktiviert. Analysen auf Basis von internationalen, aggregierten Daten zeigen, dass nach einer Aktivierung solcher Instrumente das Kredit- und Preiswachstum im Immobilienbereich sinkt. Es gibt bislang jedoch nur wenige analytische Methoden, die die Wirkung von Instrumenten vor einer Aktivierung in einem bestimmten Land quantifizieren können.

Beitrag

Vor diesem Hintergrund präsentiert unser Papier eine Simulations-Methode, die es ermöglicht, die Wirkung von kreditnehmerbasierten makroprudenziellen Instrumenten im Voraus zu evaluieren, und zwar auf Basis von Querschnitts-Haushaltsdaten. Wir entwickeln einen innovativen Analyseansatz, der besonders hilfreich ist, wenn nur in größeren Zeitabständen erhobene Querschnittsdaten – wie die Mikrodaten der Studie „Private Haushalte und Ihre Finanzen“ (PHF) – zur Verfügung stehen. Der Kern des Simulations-Modells besteht aus Verhaltensgleichungen, die Variablen wie den Beschäftigungsstatus oder das Vermögen eines Haushalts als Ausgangsgrößen verwenden und daraus individuelles Verhalten ableiten, wie zum Beispiel die Entscheidung, Eigentümer einer Immobilie zu werden, und die Höhe eines dazu aufgenommenen Kredits. Das Modell nutzt dabei den Detailreichtum der Mikrodaten und bringt gleichzeitig die Entwicklungen auf der Haushaltsebene in Einklang mit den aggregierten Entwicklungen des Wohnimmobilienmarkts. Dank dieser Eigenschaft kann unser Ansatz finanzielle Verwundbarkeiten der privaten Haushalte aufdecken und die Wirkung von kreditnehmerbasierten Instrumenten für private Haushalte in einem konsistenten Ansatz quantifizieren.

Ergebnisse

Eine Beispielrechnung einer hypothetischen Instrumentenaktivierung zeigt, dass eine Obergrenze für das Verhältnis von Kreditvolumen zu Immobilienwert die Verwundbarkeit privater Haushalte in Deutschland senken könnte. Wichtig ist dabei, dass die Aktivierung erst nach einigen Jahren greifen würde und die Risiken auf Seiten der Kreditgeber zeitverzögert verringern würde, da nur das Neugeschäft betroffen ist. Darüber hinaus zeigen wir, dass die Obergrenze nicht nur das durchschnittliche Verhältnis von Kreditvolumen zu Immobilienwert senken könnte, sondern – so wie beabsichtigt – auch den Anteil von Krediten mit einem besonders hohen Verhältnis. Die Simulationsergebnisse weisen jedoch auch darauf hin, dass eine solche Obergrenze das Wachstum von Wohnimmobilienkrediten verringern könnte. Unser Papier verdeutlicht damit die zentralen Zielkonflikte der politischen Entscheidungsträger.

Deutsche Bundesbank Discussion Paper No 20/2021

The Impact of Borrower-Based Instruments on Household Vulnerability in Germany*

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This version: June 22, 2021

Abstract

Excessive household borrowing has been identified as an important determinant of financial crises. Borrower-based macroprudential instruments have been proposed as a possible remedy. In Germany, two instruments have been available to macroprudential supervisors since 2017: a cap on the loan-to-value (LTV) ratio and an amortization requirement, but none of them has been activated so far. Therefore, this paper presents a simulation tool that allows the impact of activating of borrower-based instruments to be evaluated ex ante. The simulation is based on microdata from the German Panel on Household Finances (PHF) and is at the same time calibrated to match aggregate developments in the residential real estate market. This micro-macro consistent simulation approach can be used to detect vulnerabilities in household balance sheets and perform an ex ante analysis of the activation and calibration of borrower-based macroprudential instruments. An illustrative example of a hypothetical activation shows that the introduction of a cap on the loan-to-value (LTV) ratio of new mortgage loans in Germany could improve important indicators of household vulnerability.

JEL classification: D14, G17, G21, G28, R21
Keywords: Household finance, mortgages, macroprudential policy, borrower-based instruments, financial stability

*We would like to thank Gaston Giordana, Michael Ziegelmeyer, one anonymous referee as well as participants in the ECB/BdP MPPG webinar and the Bundesbank research seminar for comments. Any errors are the sole responsibility of the authors. Disclaimer: The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Deutsche Bundesbank or the Eurosystem.

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1 Introduction

The nexus between household borrowing, house prices and financial stability has received a great deal of attention since the financial crisis. Excessive borrowing has been identified as an important determinant of financial crises in the past (Schularick and Taylor 2012), and it has been shown that financial crises following a credit boom have been much more harmful compared to other financial crises (IMF 2012). As a response, capital and liquidity-based regulatory measures have been introduced since 2007 to strengthen bank resilience. But many regulators have activated borrower-based macroprudential instruments as well. The aim of these instruments is to preemptively limit potential risks from lending booms. Four kinds of instruments are usually discussed: caps on the loan-to-value ratio (LTV), debt-to-income ratio (DTI), debt service-to-income ratio (DSTI) and an amortization requirement.

Although a variety of borrower-based macroprudential instruments have been activated in a wide range of countries in recent years, the costs, benefits and efficacy of the new policies are still under discussion. Literature on the ex post effects of these instruments is emerging and shows that these macroprudential interventions do indeed slow down growth in real estate prices, mortgage debt and, in some cases, consumption (McDonald 2015; Cerutti et al. 2017; Alam et al. 2019). These papers use cross-country data and average across economies with very different residential real estate markets. Thus, it is not clear to what extent the results can be used to reasonably predict the effect of borrower-based macroprudential instruments in a specific country at a certain point in time. More recently, the first microdata evidence on the effects of borrower-based instruments (mostly LTV limits) has begun to trickle in from various countries (Van Bekkum et al. 2019; Aastveit et al. 2020; Defusco et al. 2020; Tzur-Ilan 2020). These papers show that besides affecting prices and credit, the instruments can also substantially reduce the number of new mortgage borrowers. The strength of the effects, however, varies substantially across the individual countries under consideration making it hard to use these results for ex ante assessments in other countries.

Research on the ex ante impact assessment of the instruments has received somewhat less attention. This is surprising since an ex ante assessment of the effects of borrower-based macroprudential instruments is needed to guide the discussion about the costs and benefits of activating them. Moreover, an ex ante assessment is also necessary for the calibration of the instruments. Most of papers in this area use empirical methods to identify how many households would have been subject to a specific instrument in the past (Kelly et al. 2018; Albacete and Lindner 2017; Gross and Población 2017). The strength of these approaches is that they construct unobserved counterfactuals from realized data. However, they do not model households taking out new mortgages, even though these are the ones that would be affected by borrower-based instruments. Thus, these papers are silent on the effects of instruments in the household sector going forward.

This paper contributes to the growing body of literature on the ex ante evaluation of borrower-based macroprudential instruments by developing a new methodology to model households' balance sheets in a way that preserves the heterogeneity observed in the microdata but also constrains the model to match aggregates. The key feature of our approach is that it identifies potential new borrowers from current renter households, which can then be constrained by borrower-based instruments and simulated forward in time together with the existing home-owners. In this way, the methodology can be exploited for two main purposes. First, the simulation can be used to stress test the soundness of household balance sheets and reveal household vulnerabilities. By specifying paths for macro variables (e.g. higher interest rates or unemployment), we can assess changes in vulnerability indicators in different macroeconomic scenarios. Second, the approach is able to perform a micro-macro consistent ex ante evaluation of the efficacy of borrower-based macroprudential instruments.

The microsimulation is centered around households who engage in the property market, buy houses for their own use and finance these acquisitions with mortgage loans. The basic logic runs as follows: (i) in each period we identify households that buy houses, (ii) these new owners are assigned a house with a specific value and a mortgage contract to finance the house, (iii) the resulting wealth and debt dynamics for new *and* existing home-owners are then simulated for the following periods. The most important output of the simulation is the development of four indicators of household vulnerability referring to the stock of loans outstanding: the loan-to-value (LTV) ratio, the debt-to-income (DTI) ratio, the debt service-to-income (DSTI) ratio and a measure of household leverage (HHL).

For illustrative purposes, we apply the methodology to assess the effects of a hypothetical activation of an LTV on the financial vulnerability of households in Germany. An LTV cap and amortization requirement have formed part of the German macroprudential policy toolkit since 2017.[1] However, according to the German macroprudential authorities, there has been no need to activate borrower-based measures so far.[2] For ease of exposition, we refrain from modeling other borrower-based macroprudential instruments, which is easy to do, in principle. The German market is especially interesting since residential real estate prices have risen in an unprecedented manner since 2010, and there are significant overvaluations in urban areas (Deutsche Bundesbank 2019). The German case is also special because the ownership rate is one of the lowest in the world, and renters play a much more important role than in most other countries.

We calibrate the model to the particularities of the German residential real estate market using data from the German Panel on Household Finances (PHF) on the balance sheets of households.[3] In particular, our simulation matches the observed income, wealth

[1]The recommendation of the German Financial Stability Committee also included a DTI and a DSTI cap. However, the German legislator decided not to introduce these instruments. The legislator did not regard the other instruments as necessary and appropriate at that time.

[2]For a current assessment of developments in the domestic residential real estate market and the policy stance in Germany, see German Financial Stability Committee (2020).

[3]The PHF data are the national component of the European Household Finance and Consumption Survey (HFCS)

and ownership distribution of households. Owing to the nature of the microdata used, we can not only observe aggregate developments in the vulnerability indicators, but also track changes in their distributions.

To simulate hypothetical policy effects, we first run a baseline scenario with a defined path for macro variables like unemployment, interest rates and inflation where no borrower-based instruments are activated. After this, we simulate the hypothetical activation of the LTV cap and assess its effects on aggregate and distributional dynamics in the chosen macroeconomic scenario, assuming different household responses to the intervention. The chosen scenario should be regarded as illustrative and generally realistic but without capturing the most recent economic developments or simulating any particular policy action. In comparison to a baseline no-policy scenario, the simulation shows that indicators of household vulnerability could improve considerably after introduction of the cap. In particular, the LTV and DTI ratios of the stock of loans outstanding would be lower in the policy scenario. In the interests of brevity, we report only a limited set of results. However, given that we are ultimately working on microdata, it is easy to construct other metrics of interest.

Overall, the results of the simulation show that the methodology developed in this paper can be used to inform current discussions on the activation of borrower-based instruments and that activation of an LTV cap could reduce vulnerabilities in household balance sheets. Note furthermore that while we refer to the LTV cap as a regulatory measure, a voluntary tightening of LTV requirements by banks would have an equivalent effect on household vulnerability. Thus, our results can also be interpreted as implications of voluntary changes in bank lending standards.

The remainder of the paper is structured as follows. We start by describing the related literature and our contribution to this literature in Section 2. Section 3 summarizes the modeling procedure, while Section 4 gives a brief overview of the data and how we measure household income and assets. Details on the simulation process are then split up into two parts: the creation of new owner households is described in Section 5, and simulations of owner households (with debt) are presented in Section 6. The scenarios used for the simulation are presented in Section 7.1, while the results of the simulation are summarized in Section 7.2. In Section 8, we conduct several model validation exercises. Finally, Section 9 concludes.

2 Related literature

The existing literature on the vulnerability of households and the effects of borrower-based macroprudential instruments has so far followed a number of approaches, some partly overlapping. One strand of the literature empirically analyzes the financial vulnerability of households with no particular focus on borrower-based instruments. Some

that is administered by the Eurosystem.

of these papers use a static approach by measuring the number of periods households can finance some (minimum) amount of consumption from their liquid assets in case they are affected by an adverse shock, e.g. unemployment or higher interest rates (Ampudia et al. 2016; Meriküll and Rõõm 2017; Giordana and Ziegelmeyer 2019). Others simulate households with existing mortgages forward in time and are thus partly dynamic, but they do not introduce new households or new borrowers into their simulation (Michelangeli and Pietrunti 2014; Bettocchi et al. 2018). These approaches are thus of limited use for an ex ante analysis of the effects of borrower-based instruments. The approach most closely related to our paper is Palligkinis (2017) who extends the model of Ampudia et al. (2016) to also include new mortgage borrowers. He generates new owners with the help of a reduced-form econometric model so that aggregate mortgage growth matches an exogenously determined rate. The main focus of his paper is on stress-testing the balance sheets of households under various macro-scenarios, but in his approach it is also possible to analyze the effects of an introduction of LTV limits. Note, however, that his analysis is ceteris paribus, and the introduction of LTV limits does not alter the exogenous rate of mortgage growth. Thus, the model is silent on the endogenous reaction of new mortgage lending to the introduction of LTV limits.

Another strand of the literature specifically focuses on the effects of the introduction of borrower-based instruments. These papers add hypothetical restrictions on borrowing – such as LTV or D(S)TI caps – to analyses on household vulnerability, but they implement these restrictions counterfactually on already realized mortgage contracts in the data. Kelly et al. (2018) and Albacete and Lindner (2017) analyze how many households would have been affected in the past if borrower-based instruments had been activated. To measure the effects of the instruments, the amount of initial debt taken out and the corresponding debt service are readjusted ex post such that the restrictions at the time of borrowing were fulfilled. More recently, Reichenbachas (2020) has shown how this framework can be extended in a way that allows the effects not just of tightening LTV limits, but also of loosening them to be analyzed. Gross and Población (2017) offer an extensive framework that allows the effects of activating LTV and DSTI caps on a subset of EU economies to be estimated dynamically over time. However, they identify the effect of the instruments not by adding new borrowers, but by excluding those existing borrowers from their simulation that have exceeded the (hypothetical) caps in the past. In an application of their framework to Slovakia, Jurča et al. (2020) also enhance the model of Gross and Población (2017) by adding endogenous loan granting. In their baseline scenario, the volume of new mortgage loans needs to match an exogenous aggregate lending forecast, but new loans react endogenously when borrower-based instruments are activated in a policy scenario. In contrast to our approach, Jurča et al. (2020) do not select new mortgage borrowers from the distribution of current renters, but recalculate the weights of current mortgage borrowers to generate new lending. The focus of their paper is more on the effects of borrower-based instruments on the balance sheets of banks, and less on the vulnerability of households.

Lastly, another example of an approach including new borrowers is the agent-based model by Baptista et al. (2016). This detailed simulation of the UK housing market differentiates between first-time buyers, home-owners, buy-to-let investors and renters, and allows the dynamic effects of an activation of borrower-based instruments to be assessed ex ante. Their model, however, is calibrated to a steady state economy and does not represent the housing market at a specific point in time. Therefore, it is challenging to use this approach to analyze the introduction of instruments in different macroeconomic scenarios.[4]

Our approach builds on the papers simulating existing owners forward in time, but extends the literature to include detailed modeling of new owner households. We select new owners from the distribution of current renter households and are able to simulate the complete distribution of households (owners and renters) forward in time. We consider this an especially relevant feature since interventions in real estate markets in the form of LTV or D(S)TI caps only affect new mortgage contracts. Because these interventions may take some time to become to show up in the data, it is critical to model both the evolution of existing debtors (owners) and the effect of the restriction on *new* owners.

Note, that there is also a related theoretical strand of literature on the effects of borrower-based instruments. Korinek and Simsek (2016) show that in a setting where excessive leverage leads to liquidity traps and interest rates are limited by the zero lower bound, macroprudential policies which reduce household leverage ex ante can make all households better off. In a related paper, Korinek and Sandri (2016) demonstrate that in advanced economies macroprudential policies that restrict borrowing are also needed to mitigate fire sales and asset price volatility. Other theoretical papers integrate borrower-based instruments into full-blown macro models at the expense of ignoring the distributional effects of potential credit restrictions (Gerali et al. 2010; Grodecka 2019). Heterogeneous agent models such as Iacoviello and Pavan (2013) model heterogeneity and macroeconomic effects jointly.[5]

3 Modeling procedure

We start with a single cross-section of households in t. In our application, this corresponds to the cross-sectional snapshot of the German household sector in the PHF 2017 survey. The model dynamics materialize by simulating households over time and, as in reality, transforming some renters into owners in every period.

[4]Moreover, the approach uses observed microdata for calibration purposes only and neglects the rich information structure of the data.

[5]Other heterogeneous agents models dealing with mortgage market issues (but without examining regulatory effects) are Garriga et al. (2009) and Chambers et al. (2008).

Generating new owners

Our modeling procedure builds on the insight that renters in period t are potential owners in period $t + 1$. Renters who are to be transformed into owners are identified using the predictions from a reduced-form model. In each simulation period we use an updated cross-section of renters as the pool of potential new owners (see below). If a household is assigned owner status, it takes out a mortgage and uses part of its liquid assets as a down payment. The challenge in this step is to generate a set of new owners characterized by a realistic joint distribution of assets, income, age, household size, etc. This is achieved by a combination of estimation and calibration as described in detail in Section 5. Once a household has become an owner, it is simulated according to the rules applied to the existing owner households.

Updating existing renters

Our model needs renters only for the purpose of generating new owners. Therefore, in each period we use the original cross-section of renters from the PHF data in t and carry the original pool of renters forward from period to period, but update important nominal variables (we do not simulate the "ageing" of renter households). By doing so, we implicitly assume that the structure of the pool of potential buyers remains constant over the simulation horizon. The assumption of constant renter characteristics seems appropriate, as their socioeconomic characteristics are likely to adjust only slowly. Renter households are on average younger, have fewer children and are more often single households compared to owner households. Simulating such households forward in time would – after some periods – result in a non-representative sample of renter households. However, in order to keep time-variant household characteristics of renters with nominal values (wages, financial assets and liabilities) "up to date" over the simulation horizon, we update them by scaling with appropriate scaling factors. Further details on the updating of renters are provided in Section 5.4.

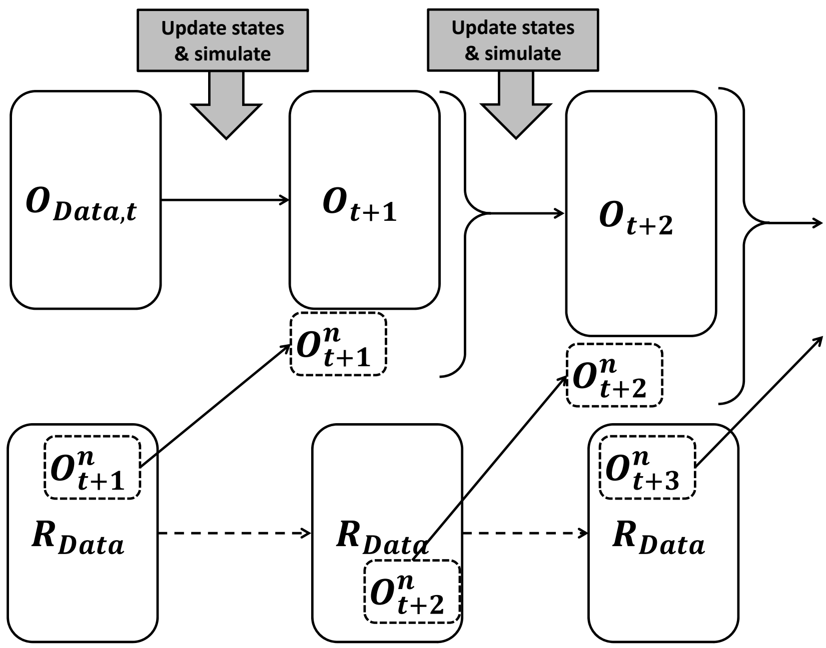
Simulation of existing owners

The simulation of owner households is rather standard. We carry owners – those already existing in the original data and those transformed from renters – forward in time by simulating their "ageing". Every period, we update each household member's income which we then aggregate to compute household labor income. Capital income is scaled by using the corresponding index from the national accounts. Non-labor (other) income is updated based on the general price level. Debt is paid down by applying the modalities of the credit contract. If the interest fixation period expires, households are assigned a new contract with a new interest rate and fixation period. Asset values are updated using market prices or inflation. Section 6 describes the simulation procedure for existing owners in more detail.

The overall modeling procedure is summarized in a simplified manner in Figure 1. Owner households are denoted with O and renters with R. The first cross-section of owners and renters on the left of the graph is taken from the original data and therefore labeled with the subscript $Data$. Starting from the left, we update the relevant state variables of the original owner households $O_{Data,t}$ and carry them forward into the next period. We denote them now as O_{t+1}. At the same time we extract a set of households O^n_{t+1} from the original set of renters R_{Data} and transform them into new owners in period $t+1$ ("n" for new owner). As for owners, the state variables of these households are updated.

From period $t+1$ onwards, the "old" owners O_{t+1} and the new owners O^n_{t+1} are treated identically. In period $t+1$ we again identify households from the pool of renters R_{Data} and transform them into new owners O^n_{t+2}. Note that while for owner households the "ageing" process is simulated from period t to period $t+1$ (solid line), the pool of renters consists of the same households as in period t and we have only updated their relevant state variables (dotted line). As becoming an owner is partly stochastic, we will not always transform the same renters into owners. This is illustrated by the different location of the box with the broken line (the new owners) in the set of renters. The process is then repeated for all future periods. In early simulation periods, the economy will therefore be dominated by the original data. In the more distant future, the model economy will consist mostly of artificially generated owner households.

Figure 1: Model set-up



Notes: O denotes Owner; R is a renter which can become owner next period.

Household decisions

All household choices, like the "decision" to become an owner, how much to invest in a new house and how much to consume/save, are determined by reduced-form behavioral equations estimated using PHF data. These equations will be explained in more detail in the following sections. To avoid a deterministic simulation, all estimated behavioral reduced-form equations are shocked with random terms taken from the estimations.

The reduced-form equations used for modeling household behavior take the household-level updated state variables as inputs. Given the nature of the approach, aggregated individual decisions will typically not match observed outcomes or aggregate outcomes required in scenarios (e.g. growth of aggregate mortgages). Nor will individual household decisions generated on the basis of the updated state variables match observed values or the values required in scenario analyses (e.g. average LTVs). Micro-macro consistency is enforced via a calibration procedure in which we scale the results from the reduced-form equations such that we meet the calibration targets at the micro and macro level.

Calibration

The calibration procedure is motivated by the models' range of applications: stress tests and calibration exercises for macroprudential instruments. For these purposes, the model must be able to replicate a micro-macro consistent economy. At the same time, the model must also be able to take previously calibrated parameters as given and endogenously produce outcomes following policy changes, e.g. a cap on LTVs. This combination is achieved using the following approach.

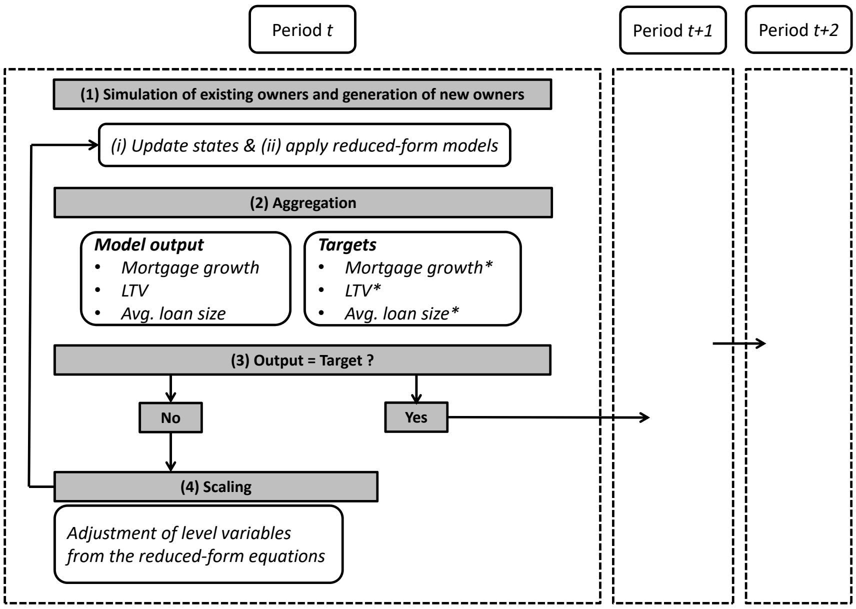
We start with the observed PHF data collected in 2017 and calibrate the model such that it replicates observed outcomes for selected variables up to the most recent point in time (see below). This ensures that for further analyses the microdata are "up to date". We then develop macro-scenarios (for future periods) for the same variables and require the model to match them. These scenarios can come from various sources, e.g. from standard forecasting models, but they can also represent a specific scenario of interest to policymakers, e.g. a boom in mortgage lending. At the end of the procedure, aggregated household decisions match the target variables.[6] Figure 2 visualizes the procedure.

These scenarios should be interpreted as the baseline without an activated macroprudential instrument.[7] For the policy scenarios in which an instrument is activated, we keep the calibrated parameters from above constant and restrict household decisions by applying exogenous regulatory constraints, e.g. a cap on the maximum LTV. The model outcomes are now endogenous: relevant variables such as aggregate mortgage growth or the average LTV of new owner households, including its distribution, are determined jointly by the calibrated parameters and the restriction.

[6] This approach also allows "what if" scenarios to be modeled: what happens to the distribution of the DTI ratio if aggregate credit growth accelerates and recently issued loans are characterized by an increasing LTV?

[7] No macroprudential instrument has been activated so far in Germany.

Figure 2: Calibration strategy



As calibration targets we choose three variables: (i) the evolution of aggregate mortgage debt (stock), (ii) the average mortgage loan size (flow) and (iii) the average LTV per new owner household (flow). We consider these variables particularly relevant to the situation in Germany. To match these targets, we adjust (i) the number of new owners, (ii) the average house price and (iii) the size of the down payment made by the new owners. The adjustment is done by scaling the household-level variables that are the outcome of the reduced-form equations (see next sections).

Other variables fed exogenously into the model fall in two categories. Individual or household-level inputs, such as life-cycle labor income profiles, unemployment or retirement replacement rates and labor force participation rates, are estimated from the microdata. Macroeconomic data such as interest rates, growth rates of wages or asset prices, are taken from the sources generating the scenarios above. Unlike above, these variables are taken as inputs only and are not targets for calibration.

4 Data

The microdata used in this paper are taken from the German Panel on Household Finances (PHF), a household panel survey conducted by the Research Centre of the Deutsche Bundesbank. The PHF is the German component of the Household Finance and Consumption Survey (HFCS), a harmonized multi-country survey carried out in 18 euro area countries, as well as in Poland and Hungary.[8] The PHF features representative and detailed information on, amongst others, income, demographic characteristics, and the different forms of household wealth and debt, which makes it ideal for studyig the dynamics of asset formation and household indebtedness. Three waves of PHF data are currently available (for the years 2010/11, 2014 and 2017), and between 3,500 and 5,000 households were interviewed for each wave.[9] For the simulations we use the third and most recent wave from 2017.[10] This is also the cross-section that we use to initialize the model.

Household income

Household income is grouped into labor income, capital income and other income. Capital income includes income from own businesses, financial assets and renting out property. Other income consists of government and private transfers. Labor income is determined for each household member separately and then aggregated to compute household labor income. Individual labor income is determined by four factors: employment status, the position in the life-cycle income profile, a permanent income shock shifting the life-cycle income trajectory, and finally the growth of aggregate wages. Shocks to income, unemployment rates and the life-cycle profile are education-specific. Agents are grouped into three educational categories.[11]

Household balance sheet

On the assets side, we distinguish between real and financial assets. Real assets are real estate property and other real assets like cars or other tangibles. Financial assets include stocks, bonds, deposits and other nominal assets. On the liabilities side, we restrict ourselves to the sum of mortgages (secured by the household's main residence or any other real estate), consumer debt and net worth as the residual.[12] This concept is commonly used in the literature (Gross and Población 2017; Ampudia et al. 2016). Table 1 displays the stylized household balance sheet.

Timing and notation

The model is set up at an annual frequency. Households enter the model at the age of 20, retire at the age of 65, and live until the maximum model age of 90 (J). For household-level variables, we use the age of the household head and for labor market variables the

[8] More detailed information can be found at `https://www.ecb.europa.eu/stats/ecb_surveys/hfcs/html/index.en.html`

[9] For more information on the PHF data, see `https://www.bundesbank.de/en/bundesbank/research/panel-on-household-finances`

[10] We use all five imputations. Averages and aggregates are obtained by using household weights.

[11] The three categories are (i) only elementary education, (ii) vocational degree and (iii) tertiary education.

[12] In the data some households hold mortgages on other than owner-occupied real estate. They report as renters so we treat these households as potential buyers.

Table 1: Household balance sheet

Assets		Liabilities	
Real estate	A^h	Net worth	NW
Other real assets	A^{or}		
Deposits	A^d		
Stocks	A^s	Mortgage debt	D^M
Bonds	A^b		
Other nominal assets	A^{on}	Consumer debt	D^C

age of each person. Variables will be indexed by j for age, t for time, i for household, and p for person. Aggregate variables will carry a superscript Agg and variables indicating new owners (flow) a superscript n.

5 New owners

This section describes in more detail our modeling procedure for new owners, i.e. households changing their status from renters to owners. Our goal is to develop a modeling procedure that is sophisticated enough to realistically map the household's income and balance sheet without being overloaded. To this end, we focus on a typical renter household without real estate assets.

We refrain from modeling special cases such as (i) households moving up the property ladder, (ii) renter households acquiring real estate property that they do not use as their main residence or (iii) buy-to-let (BTL) investors. The first two types are rather rare in Germany and are thus of minor relevance for the housing market.[13] BTL investors account for about 10% of households in Germany. They are characterized by significantly higher income and wealth – and therefore lower credit risks – compared to households owning only self-occupied property.[14] Against this background, explicitly capturing BTL investment decisions in the model would probably not improve the model's performance with respect to the ex ante assessment of borrower-based instruments, but it would significantly increase the model's complexity. Instead of explicitly modeling BTL investors, we capture them implicitly in our simulations as they are included in our dataset used for estimation and calibration, specifically, when simulating existing owners (see Section 6).

[13] According to calculations based on the PHF 2017 data, renter households owning real estate property (e.g. rented properties or commercial real estate) represent less than 2% of the German household sector. Further, moving up the property ladder appears to be less common in Germany due to the relatively high transaction costs involved in acquiring of property (e.g. the real estate transfer tax and the tax on speculative gains). Moreover, households in Germany typically become first-time buyers at the age of 30-40 years and thus in a life phase where the most living space is needed due to family formation. This implies that a sufficiently large property is acquired at once.

[14] The median income of BTL investors is about 55,000 euro according to PHF 2017 data, whereas the median income of households with only self-occupied properties is about 42,000 euro.

Finally, to verify the validity of this relatively simple modeling approach, we inspected the model's performance by benchmarking the simulation outcome against various debt characteristics of the indebted households with the observed data. Overall, the results confirm that the model performs well (see Section 8 and Section A.2).[15]

5.1 Identifying new owners

Estimation

New owners are determined by a combination of estimation and calibration. The estimation part is performed using the PHF data and estimating a logit regression that assigns each renter household a probability of becoming an owner household (more details on the estimation procedure can be found in Technical Appendix A.3). This can be regarded as a simple reduced-form representation of a structural model. In such models, households typically make their decisions based on their preferences and the value of state variables, such as income, assets, age, household size, relative price of owning versus renting (e.g. (Iacoviello and Pavan 2013)).

The PHF focuses on the interview year and provides only a limited amount of information on these state variables at the time of house purchase. Thus, we resort to a simple set-up using only a few state variables which are available at the time of purchase: age, labor market experience (as a proxy for income, which we do not observe retrospectively) and own funds used for the purchase.[16] To control for household composition, we also add dummy variables for the number of adults and children in the household at the time of house purchase. The estimated equation which we later use for the simulations takes the following form:

$$\begin{aligned} P(Ownership) = \quad & \beta_1 + \beta_2 \times Age + \beta_3 \times Exp + \beta_4 \times Exp^2 \\ & + \beta_5 \times D.Adults = 2 + \beta_6 \times D.Kids = 1 \\ & + \beta_7 \times ln(OwnFunds) + \epsilon^{Prob} \end{aligned} \tag{1}$$

with coefficients $\beta_1 = -4.887$, $\beta_2 = -0.057$, $\beta_3 = 0.214$, $\beta_4 = -0.005$, $\beta_5 = 0.912$, $\beta_6 = 0.696$, $\beta_7 = 0.824$. All coefficients are significant at conventional levels. The result of the estimation shows that the probability of becoming an owner household is significantly related to the age of the household head, the labor market experience of the household head, the number of individuals in the household and the own funds. Other economically relevant variables available in the PHF data at the time of house purchase did not turn out to be significantly related to the probability of becoming an owner. For the stochastic part of the simulation, we add a shock ϵ^{Prob} drawn from the

[15] Further validation exercises included a comparison between the data and the simulation outcome with respect to the portfolio composition as well as the level and distributions of real and liquid assets. For brevity, the results are not presented in this paper, but can be provided upon request.

[16] For non-owners, we use the sum of their financial assets (deposits, stocks, bonds, etc.) as the value of their own funds.

standard logistic distribution. Note that by choosing this approach, we cannot model other important motives for becoming a home-owner, such as household formation.

As an alternative to the estimation approach, it is also possible in principle to use the panel structure of the PHF data and identify those households that change ownership status between waves. Empirical transition matrices, then, could be another option for generating new owners for our simulation.[17] When estimating such transition matrices, it becomes clear, however, that the number of households in the data that change status is too small to generate reliable predictions for the simulation. Qualitative results from the analysis of empirical transition matrices confirm our insights from the estimation: Household income, financial assets and higher education are found to increase the probability of renters becoming owners (and to decrease the probability of owners becoming renters). The age of the household head, by contrast, decreases the probability of becoming an owner household.[18] Households consisting of only one person are less likely to become owners compared to multi-person households.[19]

Calibration

The calibration part takes the estimated equation from above as given and adds an additional dummy variable for household heads with a medium level of education. The final equation, then, is $P(Ownership) = P(Ownership)^{Equation(1)} + \beta_8 \times D.Educ_{medium}$ with the first term on the right-hand side denoting Equation (1). The value for β_8 is calibrated by matching the share of households with a medium level of education (46%) in the first cohort (flow) of new owners.[20] This yields a value of $\beta_8 = 1.58$. This calibration step is necessary because the coefficient for education in the estimated equation is not significant, but without such a correction, we overestimate the share of tertiary education in the sample of new owners.

Note that the estimated equation only provides information about relative purchasing probabilities of individual households. To calibrate the absolute number of new owners, we start with the simulation of the purchasing probabilities based on Equation (1). We exclude unemployed households from the pool of potential buyers.[21]

In the next step, we estimate the cross-sectional age distribution of new owner households from the PHF data (Figure 3(a)). This distribution represents the flow of new owners in each year, which we approximate by combining all mortgages in the PHF sam-

[17]Two potential alternatives are available to model new owners. First, we could use households that switched from renters to owners between two waves. Second, we could use only households that became owners in the last year of the sample to approximate new owners. However, because of the small sample size for both options, neither procedure seems to be sufficiently robust.

[18]This is likely to be a nonlinear process but the small number of observations renders meaningful analysis impossible.

[19]More detailed results are available from the authors upon request.

[20]The calibration target is the average share of new owners with a medium level of education in the flow of new owners; the latter we approximate with mortgages issued between 2012 and 2017 (see also Section 8).

[21]We cannot estimate this effect directly because information about the labor market status at the time of purchase is unavailable in the data.

ple issued in the last five years (which is still a rather small sample). To pin down the sum of weights of new owners, we introduce a time-varying scaling factor γ_t which corresponds to the absolute number of new owners in a given period. γ_t will be determined using a calibration procedure as described in Section 5.2. The number of new owners is given by

$$\sum_{j=20}^{J} \omega_{j,t}^{n} \quad = \quad \sum_{i=1}^{I} \omega_{i,j=20,t=1} + \gamma_t \sum_{j=21}^{J} \lambda_j \tag{2}$$

where $\omega_{j,t}^{n}$ denotes the number (weight) of new owner households of age j in period t (stock) and λ_j is the age-specific share of the per-period new owners (flow, Figure 3(a)). The term on the left is the sum of new owner households. The first term on the right is the number of 20-year-old households that start their life with a house (exogenous, from the original data). The second term is the sum of all households which will become owners in period t. New owners are represented by an age and time-specific vector $\omega_{j,t}^{n} = \gamma_t \lambda_j$ which is distributed as shown in Figure 3(a). To identify the individual households transformed into new owners, for each age group we rank all households by their simulated purchasing probabilities from Equation (1). We then compute the cumulative sum (weights) of all sorted households by age and use the value for $\omega_{j,t}^{n}$ to identify for each period the marginal buyer (by matching the target value for $\omega_{j,t}^{n}$).

Absent further correction, though, the number of owners will permanently grow (or stay constant) over the life-cycle and over time in the economy. To correct for this upward bias in ownership, we follow the literature (Li et al. 2016) and assume that owners without mortgage debt receive every period a preference (moving) shock which can be thought of as e.g. the desire to live in smaller houses or the desire to move into the vicinity of children and grandchildren. We assume that this affects only households beyond the age of 52, which is the age with the maximum number of owners. We calibrate the absolute number of households which have to receive the shock by targeting the number of owners aged 90 (maximum age) and distribute this required number of owners linearly over the respective age groups. The calibrated number of households which lose their ownership status corresponds to about 80% of the generated new owners from the baseline period.[22]

The time-invariant number of households which receive the preference (moving) shock and lose ownership status is denoted by $\omega_{j|j>52}^{out}$. It is computed as

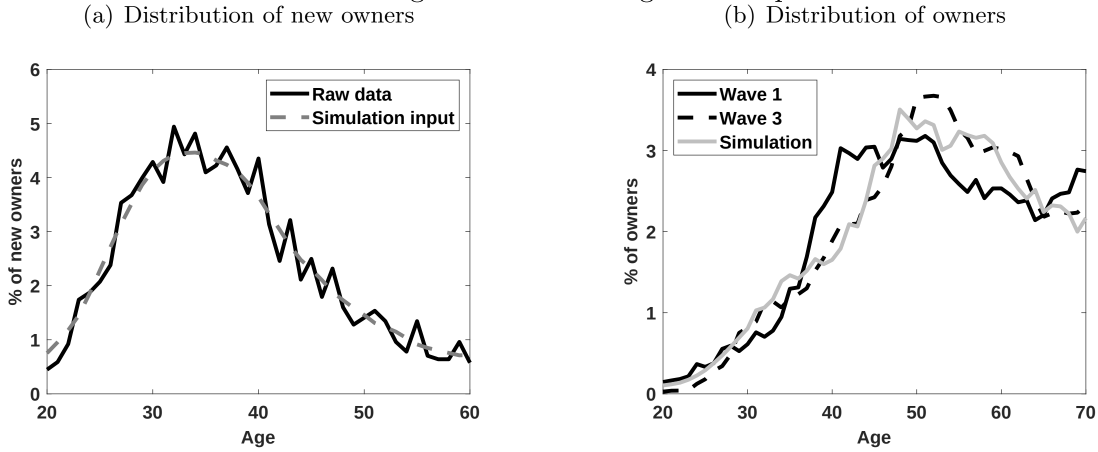
$$\omega_{j|j>52}^{out} = \frac{\sum_{i=1}^{I} \omega_{i,j=52} - \sum_{i=1}^{I} \omega_{i,j=J}}{J-52} \tag{3}$$

Combining inflows of new owners and outflows from ownership gives the law of motion for the ownership profile which is described by the following equation:

$$\omega_{j+1} = \omega_j + \omega_j^{n} - \omega_{j|j>52}^{out} \tag{4}$$

[22]In theory and in fully structural GE models, these households would become renters and potentially purchase a house again later. We avoid this approach as it is at odds with our assumption of a roughly constant pool of renters over time. Further, transforming such owners into renters would not change the model's predictions substantially as these households would become owners again only with a very small probability (see Figure 3(a)).

Figure 3: Calibrating ownership



Notes: Source: Own calculations based on PHF data. Panel (a) shows the cross-sectional age distribution of the flow of new owner households estimated from the PHF data. Simulation input is based on a local polynomial smoothing. Panel (b) shows the ownership rates depending on age. "Data" is based on a 5-year moving average calculation.

with the notation from above and $\omega^{out}_{j|j>52}$ denoting the number of households receiving the exogenous moving shocks.

Note that the shape of the ownership profile (stocks) from the model and from the data are close to each other (Figure 3(b)). This suggests that the approach works well in practice.[23]

5.2 Determining the amount of debt of new owners

Estimation

The size of the mortgage loan for new owners is computed as the difference between the price of the purchased property, including transaction costs, and the down payment. The price of the property is modeled as a function of household age and own funds of the household at the time of purchase as well as dummy variables for the number of adults in the household and the household head's education.[24] The dependent variable is the price of the house when purchased, adjusted by the consumer price index. Only the age of the household head, the amount of own funds and two dummy variables are significantly related to the house price. The house price equation is

$$\begin{aligned} Price = \quad & \beta_1 + \beta_2 \times Age + \beta_3 \times Age^2 + \beta_4 \times *D.Adults = 1 \\ & + \beta_5 \times *D.Educ_{high} + \beta_6 \times OwnFunds + \epsilon^{Price} \end{aligned} \tag{5}$$

[23] If the model used a grossly misspecified distribution of new owners, the shape of the age distribution would not match the observed data. A simple linear rescaling of the distribution of new owners would then translate into a misspecified age profile of ownership in general. For instance, putting too much weight on very young households would yield a very steep age-ownership profile.

[24] More details can also be found in Technical Appendix A.3.

with $\beta_2 = 5,535.8$, $\beta_3 = -58.4$, $\beta_4 = 31,808.7$, $\beta_5 = 37,800.0$ and $\beta_6 = 1,074.1$. All coefficients are significant at conventional levels. Because the constant is not significant, we drop it when simulating the model. Similar to the equation determining the probability of becoming an owner, ϵ^{Price} is a stochastic term that is added to the price of the house. The error term is calibrated with the standard error of the estimated error term. Because of the stochastic component, the resulting house prices might be unrealistically low or high. To keep them within reasonable bounds, we set the minimum house value at 60,000 euro (corresponding to the 1st percentile of the house price distribution) and the maximum house value at the maximum observed in the sample (1,200,000 euro).

Calibration

We start the calibration of the average mortgage loan size by setting the value of the property ($A^h_{i,t}$) using the satellite model estimated in Equation (5). Expressed in a single equation, $A^h_{i,t} = \phi_t f(X_i, A^f_{i,t})$, with ϕ_t being the time-variant scaling factor to be calibrated, $A^f_{i,t}$ the total financial assets, and X_i the other household characteristics (e.g. education). We then deduct the additional transaction costs for purchasing the property (real estate transaction tax, broker fees, etc.) from the household's liquid assets, as these costs are typically paid out of pocket. Transaction costs η are assumed to be proportional to the value of the house and set to 10%.[25] If households do not have sufficient liquid assets to pay the transaction costs, they cannot purchase a house. Households use a share δ_t of their remaining liquid financial assets as a down payment. The fraction is identical across households. Putting all these pieces together, new debt for household i is given by

$$D^{M,n}_{i,t} = A^h_{i,t} - \delta_t(A^\ell_{i,t} - \eta A^h_{i,t}) \tag{6}$$

$$D^{M,n}_{i,t} = (1 + \delta_t \eta) A^h_{i,t} - \delta_t A^\ell_{i,t} \tag{7}$$

$$A^h_{i,t} = \phi_t f(X_i, A^f_{i,t}) \tag{8}$$

Using these definitions, the average size of the mortgage loan per new owner (calibration target) is given by

$$\overline{D^{M,n}_t} = \frac{\sum_{i=1}^{I_t} D^{M,n}_{i,t} \omega^n_{i,t}}{\sum_i^{I_t} \omega^n_{i,t}} \tag{9}$$

where I_t is the period-specific number of households which become new owners. Note that the number of new households becoming owners (I_t) is time-dependent and is a function of γ_t, i.e. $I_t = I(\gamma_t)$. γ_t is one of the three calibration parameters. Adjusting the number of households as a way of altering the aggregate volume (growth rate) of mortgages in the economy (for a given average new loan size). To match this target, we do not simply scale a fixed number of households (at a given average loan size and with given characteristics) by an appropriate factor. We rather adjust the marginal buyer

[25]Transaction costs vary in Germany across federal states, but 10% is a reasonable country-wide average.

household by adjusting I_t. We thereby alter the characteristics and thus the "quality" of new owners. This means that by increasing (decreasing) the number of owners, we go down (up) the ladder of the probability of purchasing a house. Given the inputs in the estimated equation, this implies that households with less (more) own funds and less (more) labor market experience will also become owners.

Much like the case of the price equation, households may be assigned unrealistically high values of debt. To keep the model realistic, we assume that households with very high values for the ratio of new debt to current household income (above 7, corresponding to the 90th percentile) are not allowed to purchase a house. Finally, the LTV ratio of newly issued loans is given by

$$
\begin{aligned}
LTV_{i,t}^{n} &= \frac{D_{i,t}^{M,n}}{A_{i,t}^{h}} && (10)\\
&= \frac{A_{i,t}^{h} - \delta_t (A_{i,t}^{\ell} - \eta A_{i,t}^{h})}{A_{i,t}^{h}} && (11)\\
&= (1 + \delta_t \eta) - \frac{\delta_t A_{i,t}^{\ell}}{\phi_t f(X_i, A_{i,t}^{f})} && (12)\\
\overline{LTV_t^{n}} &= \frac{\sum_i^{I_t} LTV_{i,t}^{n} \omega_{i,t}^{n}}{\sum_i^{I_t} \omega_{i,t}^{n}} && (13)
\end{aligned}
$$

Because all parameters have an effect on all targets, the calibration is done in one step. As targets are time-varying, the vector of parameters $\{\gamma_t, \delta_t, \phi_t\}$ is also time-varying.[26]

Having pinned down the price of a property, and taking the amount of own funds available for a down payment as given, debt and thus the debt-to-income ratio for newly issued loans adjust as a residual. Note also that by setting the average LTV of the new loan we affect the liquid asset position of the new owner. A household's liquid asset position after purchasing a property (combined with its savings behavior) determines its ability to buffer labor income shocks later. The aggregate growth rate of mortgage debt is then given by

$$
g_t^{M,Agg} = \frac{D_t^{M,Agg}}{D_{t-1}^{M,Agg}} - 1. \qquad (14)
$$

5.3 Determining interest rates, interest rate fixation periods, and loan maturities

Households selected to become new owners are assigned a contract with a fixation period, a corresponding interest rate and a redemption rate on a random basis. The loan maturity is endogenously determined, with the interest and redemption rates serving as inputs. Note that after the interest rate fixation period expires, the interest rate may change, so that the ex ante and ex post loan maturity will typically not be the same. The fixation

[26] These parameters are shown in Figure 5 and discussed later in more detail.

period is especially important as typical German credit contracts come with fixed interest rates.[27]

The distribution of interest rate fixation periods and the corresponding interest rate is taken from the official Bundesbank interest rate statistics. When assigning the interest rate, we use the data from the interest rate statistics ($i_{base,t}$) and add a markup which is an increasing function of the distance of the individual LTV ($LTV_{i,t}$) from the average LTV in that period ($L\bar{T}V_t$).[28] The final interest rate assigned to the household is then

$$i_{i,t} = i_{base,t} + RiskPrem_t \quad (15)$$

$$RiskPrem_t = 0.83 \times (LTV_{i,t} - L\bar{T}V_t) \quad (16)$$

where the slope of the risk premium function translates into a risk premium of about 8 basis points for an increase in the LTV of 0.1 (0.1 × 0.83). The slope is estimated using data from a commercial provider. Redemption rates and their distribution are also taken from a commercial data provider.[29] Because of the stochastic nature of the simulation, the ratio of debt service to income can get very high (e.g. if households draw a high redemption and high interest rate). To prevent this, we exclude households with a loan service-to-income (LSTI) ratio of more than 50% from buying a house.

5.4 Updating state variables of renters

Renters in our model are needed as a source of potential new buyers. Therefore, we also need to keep their state variables up do date. We proceed as follows. Nominal values – like wages or financial assets and liabilities – are scaled with scaling factors following Ampudia et al. (2016) to account for changes in prices. The value of other real assets, nominal assets and consumer debt are scaled with the CPI. The value of real estate is updated using the residential property index of the Deutsche Bundesbank (same as for owners). Stocks and bonds are updated using the corresponding German indices. Deposits are updated using aggregate deposit growth. Wages are updated based on an index of compensation per employee. Other income is updated with the CPI. Payments on consumer debt are also updated with the CPI. The interest rate charged on these loans is updated with the change in the corresponding aggregate indices of the Bundesbank. We also simulate and adjust the employment status and wage level (see section 6.1 below). By contrast, socioeconomic characteristics like education, household size, etc. are kept constant. The latter assumption seems appropriate, as such features are likely to adjust only slowly.

[27] This differs from a number of countries with predominantly floating interest rate arrangements (European Central Bank 2009). While this feature of the German market has been relatively stable over time, an appropriate policy (scenario) analysis should allow for modeling changes in the market structure. As Danish experience shows, such a transition can take place within a relatively short period of time (Kuchler 2015).

[28] We do not model the interest rate level as a function of the LTV, as the level is taken from the official statistics.

[29] EUROPACE; data can be downloaded from report.europace.de/ebix-etb/europace-ebix

6 Existing owners

The next subsections describe the updating procedure for existing owners in more detail.

6.1 Updating household income

Each person's p labor market status can take on four values: employed, short-term or long-term unemployed, and retired. For each person in a household i, we simulate the labor market status using a Markov process for which the transition probabilities depend on the agent's education and ownership status. If working, the labor income of a person changes due to an exogenous life-cycle component (θ_j), due to the permanent income shock ($\tau_{p,t}$), and due to wage growth at the macroeconomic level (W_t). The first two depend on a person's education; W_t is identical across agents. Net labor income $Y^{\ell}_{p,t,j}$ is then

$$Y^{\ell}_{p,t,j} = Y^{\ell}_{p,t-1,j-1} \frac{\theta_j}{\theta_{j-1}} \frac{W_t}{W_{t-1}} \tau_{p,t} \tag{17}$$

If a person becomes unemployed, unemployment benefits are a fraction (RR^{job}) of their last labor income. To calibrate the unemployment replacement rates, we rely on data from the OECD. The OECD provides unemployment replacement rates for short and long-term (more than one year) unemployment as well as by income group, marital status, and number of children (see Table 3).[30] When a person returns to the labor market, its labor income is set to their last observed wage level (when employed) and adjusted for aggregate wage growth.[31] From this point in time, it will again follow the process described above. For agents entering the model as unemployed, we use their estimated shadow wages as labor income if they become active in the labor market during the simulation (see Technical Appendix A.4 on the estimation of the shadow wage). As long as the originally unemployed agents stay unemployed, we scale their unemployment benefits (from the data) by aggregate wage growth. If those agents become unemployed again, we treat them as a "standard" case, with their last wage as a base for computing unemployment benefits.

Agents are forced to retire at the exogenous age of 65.[32] For the pension replacement rate we use 57.8%, the value reported by OECD (2013) for the median earner.[33] To match the observed life-cycle profile of labor market participation, we assume that agents enter early retirement with an exogenous probability calibrated to match cross-sectional age and education-specific labor force participation rates (Figure 4(b)). To calibrate the

[30] A more detailed table used in the simulation is shown in the Technical Appendix (Table A.4).

[31] The person does not return to the life-cycle profile.

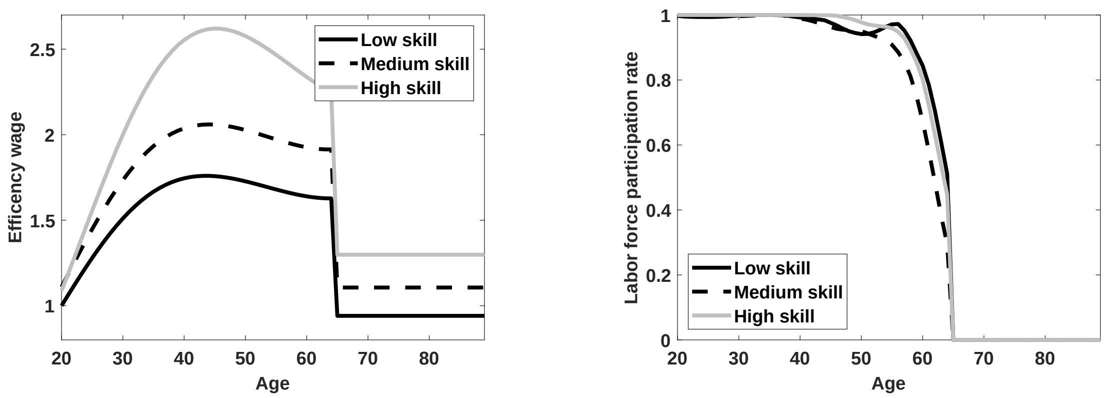
[32] In the simulation we also assume that agents who reached the retirement age of 65 will retire in the next period. Further, in the initial data we force agents older than 65 with a job to retire. Not doing so leads to a built-in bias in the population distribution.

[33] The German pension system's redistributive component is very small. Net replacement rates are between 55 and 58 percent thus rather income-insensitive.

life-cycle growth in labor income and the permanent shocks, we rely on the estimates from Le Blanc and Georgarakos (2013). The profiles are estimated using the German socioeconomic panel (GSOEP) and shown in Figure 4(a).

Figure 4: Calibrating income and labor force participation

(a) Deterministic life-cycle wage profiles (b) Labor force participation rates



Notes: Source: Le Blanc and Georgarakos (2013) for the life-cycle profiles (efficiency wage) and own calculations based on PHF data. Efficiency wage profile standardized to 1 for low-skill workers.

All possible combinations of labor market states and income realizations are shown in Table 2. RR stands for "Replacement Rate", which is a function of household-specific socioeconomic characteristics (X_i). The tilde over the age index j indicates that the value (wage) is taken from the last date on which the agent was employed. Household income is then the sum of household labor income, capital income and other household income:

$$Y^h_{i,t,j} = \sum_{p=1}^{P} Y^\ell_{p,t,j} + Y^o_{i,t,j} + Y^c_{i,t,j} \tag{18}$$

$$Y^o_{i,t,j} = Y^o_{i,t-1,j-1} \frac{P^C_t}{P^C_{t-1}} \tag{19}$$

$$Y^c_{i,t,j} = Y^c_{i,t-1,j-1} \frac{GM_t}{GM_{t-1}} \tag{20}$$

Other income $Y^o_{i,t,j}$ is kept constant in real terms and updated with the consumer price index P^C_t. Capital income is updated with an index of gross operating surplus and mixed income (denoted GM) from the national accounts.

Calibration of the unemployment process is done in three steps. In an initial step, we calibrate a Markov matrix to match the unemployment rate and unemployment duration from the data. For the level we use PHF data; for the duration of the unemployment spells we rely on Bremus and Kuzin (2014). The level of unemployment is separately computed by education and ownership status. Owners typically have a lower unemployment rate, conditional on education. Because the duration of unemployment status is not contained in the PHF data, we determine the status of each unemployed person using an auxiliary

Table 2: Labor market states and income

State $t-1$	State t	Labor income
Employed	Employed	$Y^{\ell}_{p,t,j} = Y^{\ell}_{p,t-1,j-1} \frac{\theta_j}{\theta_{j-1}} \frac{W_t}{W_{t-1}} \tau_{p,t}$
Employed	Unemployed	$Y^{\ell}_{p,t,j} = Y^{\ell}_{p,t-1,j-1} \times RR^{job}(X_i)$
Unemployed	Unemployed	$Y^{\ell}_{p,t,j} = Y^{\ell}_{p,t-1,j-1} \frac{W_t}{W_{t-1}}$
Unemployed	Employed	$Y^{\ell}_{p,t,j} = Y^{\ell}_{p,t-\tilde{j},j-\tilde{j}} \times \frac{W_t}{Wt-\tilde{j}}$
(Un)Employed	Retired	$Y^{\ell}_{p,t,j} = Y^{\ell}_{p,t-\tilde{j},j-\tilde{j}} \times RR^{ret}$
Retired	Retired	$Y^{\ell}_{p,t,j} = Y^{\ell}_{p,t-1,j-1} \times \frac{W_t}{W_{t-1}}$

Table 3: Unemployment replacement rates in %

		Short term	Long term
Children	0	64.5	34.7
	1	71.0	41.9
	2	77.5	49.1
Income	Low	76.6	53.3
	Medium	70.1	41.6
	High	66.3	30.9
Marital status	Single	66.2	36.6
	Married	75.8	47.2

model. In a second step, we calibrate a transition matrix such that the economy moves to a target unemployment rate in the next period. Finally, we calibrate a transition matrix which applies after the economy has reached its target unemployment rate. These steps are described in more detail in the Technical Appendix (see A.6 and A.7).[34]

6.2 Consumption and accumulation of assets

Households use their net household income to consume, repay debt and accumulate liquid financial assets. When deciding about consumption they have a minimum consumption constraint which is set to the subsistence payment of 400 euro per capita (per month) times the household equivalence scale from the OECD.[35] If the sum of minimum consumption and debt payment is lower than available resources (cash on hand), households consume their minimum consumption. Leftovers are used for servicing debt. This mimics a reduced regular payment that is often negotiated between the borrower and the lender if households are finding it difficult to service debt.

For the unconstrained (optimal) consumption choice, the literature typically assumes

[34] As an additional option, one could first determine the new steady state transition matrix and then apply it to all future periods. In that case, the transition time to the new steady state unemployment rate would be endogenous and unconstrained.

[35] We use the following function: $EquivScale = 1 + (Adults - 1) * 0.5 + Kids * 0.3$.

that households make use of rule of thumb decision systems.[36] Other financial assets, such as pension claims, are considered illiquid and unavailable.[37] The household portfolio allocation algorithm is simple: keep the share of each asset within the portfolio constant (based on the monetary values of the portfolio).[38] Households either keep consumption constant (Ampudia et al. 2016), consume a fixed fraction of their income (Gross and Población 2017; Żochowski and Zajączkowski 2006) or choose their consumption such that they meet a target level of liquid wealth (Baptista et al. 2016).[39] In this paper, we follow the spirit of the latter and let households determine their optimal holdings of liquid assets for the next period as a function of expected income for the next period.[40] The optimal stock of liquid financial assets in the next period and consumption are

$$A^*_{i,j+1} = \kappa_0 \mathbb{E}[Y_{i,j+1}]^{\kappa_1} \tag{21}$$

$$C_{i,j} = -A^*_{i,j+1} + A_{i,j} * (1 + r_t) + Y_{i,j} - Rep_{i,j} \tag{22}$$

with standard notation and κ_0 and κ_1 to be determined. Next-period expected labor income is computed for each household member separately using the transition probabilities and the rules described in Subsection 6.1. Because the equation is written in levels, we perform an adjustment to account for trend growth. This adjustment ensures that the nonlinear relationship between income and optimal asset holdings is only a cross-sectional phenomenon.[41]

We determine the parameters κ_0 and κ_1 using a calibration procedure. The first calibration target is the ratio of liquid assets to household net income. The second target is the elasticity of liquid assets with respect to current net household income. Because we are interested in the behavior of indebted agents, we use only households with outstanding mortgages for the calibration. To obtain the values for our targets, we use our single cross-section and compute a) the average liquid asset-income ratio and b) run a regression of log-liquid assets on log-income (and a constant).[42] We initialize the algorithm with a guess for κ_0 and κ_1 and simulate the model forward for three periods.[43] We then

[36] Cocco et al. (2005) show that household decisions based on simple rule of thumb are reasonably close to decisions based on complex structural models with perfectly rational agents.

[37] Such assets would only matter in the case of bankruptcy when they need to be liquidated.

[38] The share can be kept constant only for given prices. After the price shock has materialized, the portfolio shares will change.

[39] The latter approach is akin to "buffer stock" saving behavior in the spirit of Carroll (1997). Fully rational, forward looking, and utility-maximising agents implicitly target a (household specific) ratio of liquid assets to (permanent) income. Empirical evidence supporting this hypothesis can be found in Gourinchas and Parker (2002) or Cagetti (2003). Outcomes from models using different assumptions (but all featuring uncertainty and risk-averse agents) are typically indistinguishable, empirically speaking, from the behavior implied by the buffer-stock model (Carroll 2004). Furthermore, a number of papers show that while agents deviating from optimal model-implied (fully rational) behavior typically incur welfare losses, these losses are typically not large (Winter et al. 2012; Cocco et al. 2005).

[40] Another interpretation is that households are myopic or boundedly rational.

[41] Technically, we adjust the "input" into the households' decision rule for the trend growth factor of income G_{t+1} such that the ratio of $A_{t+1}/E[Y_{t+1}]$ stays constant, i.e. $A^*_{i,t+1} = G_{t+1}\kappa_0 E[Y_{i,t+1}/G_{t+1}]^{\kappa_1}$. Without adjustment, the trend growth in income would push up the savings rate for all households.

[42] We use the inverse hyperbolic sine transformation because some households may have zero assets.

[43] The choice of three periods is motivated by the need to have at least a few cross-sections to validate the model

compute the asset-income ratio and the regression coefficient (elasticity) for each of the three cross-sections of the simulated data and average over them. The final parameters are obtained by iterating over the two parameters and minimizing the distance between the targets from data and the realizations from the simulation. The calibrated values are $\kappa_0 = 0.059$ and $\kappa_1 = 1.25$. Note that $\kappa_1 > 1$ implies that the savings rate (asset-income ratio) is an increasing function of the income level (from a cross-sectional perspective, see above and footnote 41) as evidenced by prior research (Späth and Schmidt (2018), Carroll et al. (2014)).

If current household income is not sufficient to cover debt repayments and optimal consumption, the household will tap into its liquid assets in the first instance. If liquid assets are not sufficient to cover all outflows, the household will reduce its consumption but keep paying for its debt. If the minimum consumption constraint is binding, we set consumption to that minimum amount and adjust debt repayment down while the household keeps paying interest on its debt. This decision structure is shown in Table 4.

If households take up employment again, they may resume paying the original regular installments in case they could do so, i.e. if repaying the original unrestricted monthly installment does not violate the "no borrowing constraint" (while consumption could still be below its optimal value).

Table 4: Consumption, repayment, assets

Consumption	Repayment	Saving	Assets
$C^*_{i,t-1}$	$Rep^*_{i,t-1}$	$Y^h_{i,t-1} - C^*_{i,t-1} - Rep^*_{i,t-1} \gtrless 0$	$A_{i,t} \gtrless 0$
$C^{res}_{i,t-1} < C^*_{i,t-1}$	$Rep^*_{i,t-1}$	$Y^h_{i,t-1} - C^{res}_{i,t-1} - Rep^*_{i,t-1} < 0$	$A_{i,t} = 0$
$C^{min}_{i,t-1} < C^{res}_{i,t-1}$	$\max Rep^{res}_{i,t-1}, 0$	$Y^h_{i,t-1} - C^{res}_{i,t-1} - Rep^{res}_{i,t-1} < 0$	$A_{i,t} = 0$

Notes: *Rep* refers to total debt repayment, i.e. the sum of Rep^M and Rep^C. A_t refers to total liquid assets for the next period.

6.3 Updating debt

For updating the household's debt position we apply the following updating equations:

$$D^M_{i,t} = D^M_{i,t-1} \times (1 + i^M_{i,t-1}) - Rep^M_{i,t-1} \quad (23)$$

$$D^C_{i,t} = D^C_{i,t-1} \times (1 + i^C_{i,t-1}) - Rep^C_{i,t-1} \quad (24)$$

where $i^M_{i,t-1}$ and $i^C_{i,t-1}$ are the interest rates applied to the respective type of debt and *Rep* is the regular stream of repayments (annuity). These equations are applied as long as the amount of debt is positive. If the repayment amount is higher than the outstanding amount of debt (including interest) we restrict the repayment to that amount.

and the restriction that the model is – as such – not built to perform simulations over a longer horizon. However, the above statistics also prove stable when simulating the model forward by more than three periods.

For consumer debt we assume that the interest rate is updated every period, while for mortgage debt we only adjust the interest rate if the interest rate fixation period has expired. Formally,

$$\begin{aligned}
i^C_{i,t} &= i^C_{i,t-1} + (i^{C,agg}_t - i^{C,agg}_{t-1}) && (25)\\
i^M_{i,t} &= i^M_{i,t-1} \quad \text{if fixation has not expired} && (26)\\
&= i^{M,agg}_{m,t} + RiskPrem_t \quad \text{if fixation has expired} && (27)
\end{aligned}$$

where $RiskPrem_t$ is modeled as for new mortgages as described in Subsection 5.3. The subscript m in $i^{M,agg}_{m,t}$ indicates that the household-specific mortgage rate – if the interest rate fixation period expires – will be replaced by an interest rate drawn from the empirical distribution observed in the data.[44] We do this because households have the option to re-negotiate and sign a new contract. This comes with a new interest rate (see above) and a different regular payment Rep^M. Note that the interest rate on consumer debt also stays household-specific and hence preserves the (unobserved) risk premium as the interest rate is updated with the *change* in the corresponding aggregate interest rate.

For determining the repayment (redemption rate), we leave the ratio of debt service to income (DSTI) at its level at loan origination. Without such adjustment, the DSTI ratios over the life-cycle would drop considerably due to increasing nominal wages (at constant interest rates). This is at odds with the observation in the data with roughly constant DSTI ratios for indebted agents along the life-cycle.[45] Moreover, assuming constant DSTI ratio is also consistent with a relatively frequent usage of the partial prepayment option (*Sondertilgung*) to increase redemptions after a positive income shock.[46]

6.4 Updating assets

A household's asset position can change because of exogenous price movements and because of endogenous (dis)saving decisions as described in Subsection 6.2. For the latter, after the realization of the income shocks, the consumption decision, and the payments on outstanding debt, households may have to allocate some free cash flow to financial assets. Alternatively, if income is not high enough, they might be forced to tap into their liquid assets to sustain (minimum) consumption and keep paying for their debt.

Households are assumed to actively manage only their liquid assets (stocks, bonds, deposits). This applies to positive and negative savings. Households without positive financial assets in the data, but positive net savings allocate their savings according to the sample averages. Households with net borrowing (e.g. because of unemployment) also apply the rule described above.

[44] We do not model the potential third margin of adjustment – lowering the outstanding amount by using liquid assets.

[45] Based on a cross-sectional analysis.

[46] The probability of exercising the partial prepayment option is about 40% (Barasinska et al. 2019).

6.5 Measuring households' solvency risk

In this framework we do not formally model (the probability of) default. When households are experiencing financial difficulties, we keep them in the sample and simulate them forward by updating their income, repayment and assets according to the rules described above (see Subsections 6.1, 6.3 and 6.4 above).

As a risk metric we compute the leverage of each household in each period and report the time series at the economy-wide level. Household leverage is the ratio of total debt over the value of assets that can be recovered – applying a discount function to account for the house price change during stress:

$$HHL_{i,t} = \frac{D^M_{i,t} + D^C_{i,t}}{A^{or} + A^h_{i,t} \times Disc_t + A^{\ell}_{i,t} + A^{on}} \tag{28}$$

We assume that while other real assets can be sold at market values, residential real estate may need to be sold at a discount. The discount ($Disc_t$) is modeled following Barasinska et al. (2019) and depends on the macroeconomic environment. Selling in a recession will yield lower prices than in a boom. The functional form of the discount function is

$$\begin{aligned} Disc_t &= 1 - min(0, -max(-0.5, -0.25 + 2.5\Delta P)) \qquad (29) \\ \Delta P &= P^H_t / P^H_{t-1} - 1 \end{aligned}$$

This function assumes that in an environment with annual price declines of 10% or more, the discount will be 50%. With stagnating prices, the discount is 25%. In a booming market with prices increases of 10% or more, the property sold will fetch the going market price. The calibration matches the empirical observation of 78% for the average recovery value of defaulted German properties, as reported by Ingermann et al. (2016).

7 Illustrative application of the model

7.1 Scenarios

This section introduces the macroeconomic scenarios. It is important to note that while these scenarios are generally realistic, they not reflect the recent economic environment (or its outlook) shaped by the coronavirus pandemic. We use one baseline scenario (which does not include any macroprudential policy) and two selected policy scenarios which simulate different versions of an LTV cap being activated. The reference point for all our comparisons is the baseline scenario, which has also been used for model calibration (see subsection in Section 3). Macroeconomic scenario variables (e.g. inflation, unemployment), however, do not differ between the baseline scenario and the policy scenarios.

The baseline scenario assumes that the good economic conditions continue between 2019 and 2022. The following period (2023-25) is assumed to be a recession including a

Table 5: Key scenario variables (%)

		good conditions prevail				*recession period*		
	2018	2019	2020	2021	2022	2023	2024	2025
Unemployment rate (ILO)	3.4	3.1	3.1	3.0	3.0	5.6	7.5	8.4
CPI inflation	1.8	1.4	1.5	1.6	1.7	1.0	0.6	0.2
Wage growth	2.8	3.1	2.1	2.6	2.5	-0.6	-2.9	1.1
Residential real estate price growth (yoy)	8.2	6.5	4.8	4.0	3.8	-13.2	-14.3	0.0
Interest rate on mortgage loans	1.9	1.5	1.5	1.5	1.5	1.5	1.5	1.5
Stock of mortgage loans growth (yoy)								
Baseline (exogenous)	4.6	5.0	4.8	4.6	4.5	3.6	2.8	2.6
Policy “Baseline & Reg.” (endog.)			1.3	1.2	1.1	0.7	0.3	0.2
Policy “Max. Leverage” (endog.)			1.7	1.7	1.6	1.4	1.0	0.9
Avg. size of mortgage loans growth (yoy)								
Baseline (exogenous)	4.7	4.7	4.7	4.7	4.7	-14.1	-13.3	-0.8
Policy “Baseline & Reg.” (endog.)			7.0	4.5	9.1	-17.6	-11.5	-2.4
Policy “Max. Leverage” (endog.)			-3.5	4.1	4.6	-11.0	-14.7	-0.8

sharp rise in unemployment and a substantial decrease in real estate prices. The values of the scenario variables for the first part of the scenario are mostly taken from the 2019 German Joint Economic Forecast (*Gemeinschaftsdiagnose*, GD).[47] The values for the recession period are based on the adverse macrofinancial scenario for the 2018 EU-wide banking sector stress test[48], albeit quantitatively adjusted to generate a more severe recession.

According to the baseline scenario, unemployment is further reduced in the years 2019-22 to a very low level and real estate prices continue to grow, albeit at a flatter rate. During the following recession period, wage growth first turns negative, before recovering at the end of the scenario in 2025. Real estate prices decrease by around 25% in the first two years of the recession, but their growth rate also reverts to 0% in the final year. See Table 5 for an overview of the development of key scenario variables. For the growth rates of the average mortgage loan size and the growth rate of aggregate mortgage debt in the different scenarios, see also Figure 5. Figure 5(c) also shows the values of the calibrated model parameters. The value of the average house and thus loan size increases initially (ϕ). The share of own funds used as a down payment (δ) declines slowly over time. When the recession hits, the average mortgage size drops sharply, the share of own funds declines and the number of new owners (γ) increases slightly. This constellation reflects the combination of a relatively small decline in the aggregate mortgage growth rate and a sharp drop in the average mortgage loan size.

Scenario variables that are also calibration targets (average loan size, growth rate of

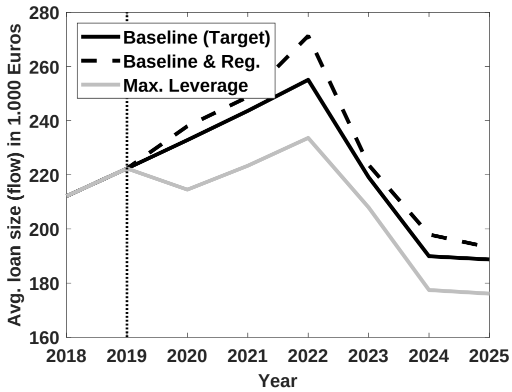
[47]See `http://gemeinschaftsdiagnose.de/wp-content/uploads/2019/10/GD_H19_Langfassung_online.pdf`

[48]See `https://www.esrb.europa.eu/mppa/stress/shared/pdf/esrb.20180131_EBA_stress_test_scenario__macrofinancial.en.pdf`

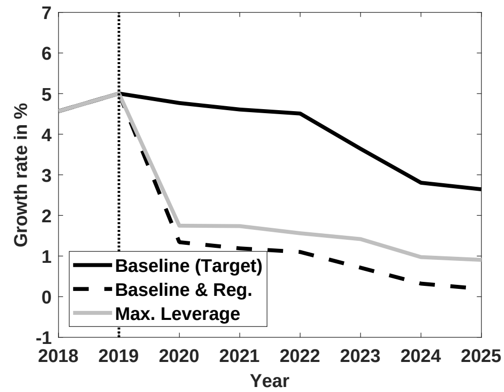
the stock of aggregate mortgage loans and the LTV of new loans) are depicted in Figures 5(a), 5(b) and 7(c). To the left of the vertical dotted line, the data points are realizations. The scenarios are shown to the right of the line. Note that for the calibration targets, the observed data and the targets are identical and therefore cannot be distinguished from each other.

Figure 5: Calibration targets

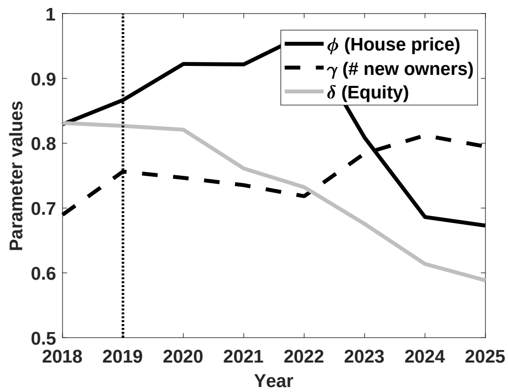
(a) Average mortgage loan size



(b) Growth rate of aggregate mortgage debt



(c) Calibrated values of model parameters



Notes: Source: Own simulations. Vertical line marks the begining of scenario data. Calibration targets and calibrated values (result) denoted by "Baseline (Target)" in the legend as they perfectly overlap.

Regarding our endogenous calibration targets, we assume that in the baseline scenario the average loan size continues growing by approximately the rates observed in the most recent past (about 5% per year), but drops in parallel with the decrease of real estate prices in the recession period (Figure 5(a)). Aggregate mortgage debt (Figure 5(b)) continues to grow by around 5% per year until the downturn, when the growth rate is reduced to 3%. Finally, we assume that the LTV ratio of new mortgages rises to around 80% and stabilizes at that level (Figure 7(c)).

While macroprudential policy is absent in the baseline scenario, both policy scenarios include an LTV cap at 90% that is activated in 2020 and kept constant until the end of the scenario horizon. We make two polar assumptions about the household response to the LTV cap that are the basis for the policy scenarios. In the first case, labeled "Baseline & Reg." ("Reg." stands for regulation), we assume that all households above an LTV of 90% are declined a mortgage contract (black broken line). The policy thus acts on the extensive margin. In the second case, we assume that households adjust their behavior. Restricted households will reduce the value (size) of their property and borrow an amount such that they comply exactly with the regulatory constraint. We label this scenario "Max. Leverage"(gray solid line).

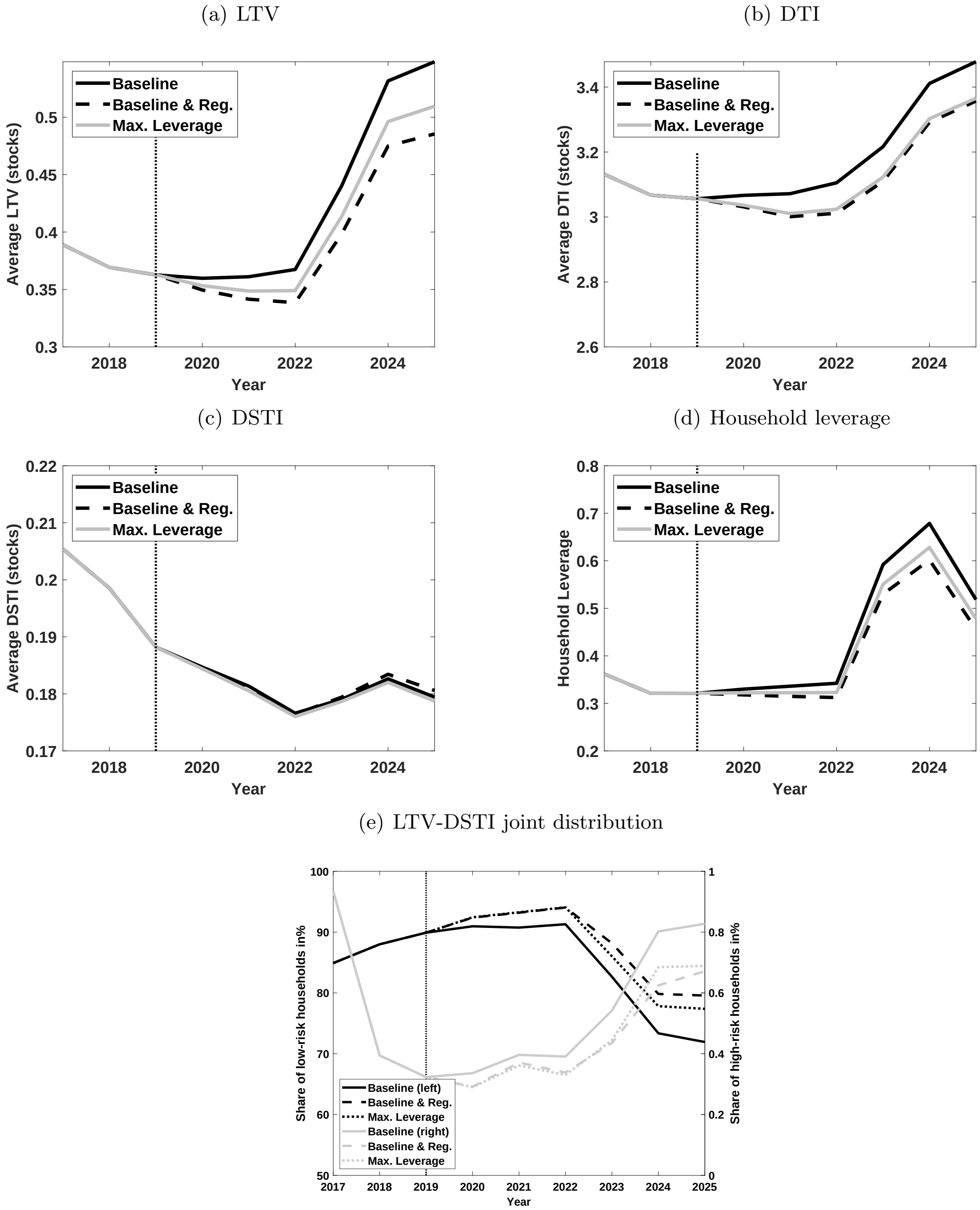
7.2 Results

In this section we present the results in terms of the key indicators of household vulnerability (Figure 6). These indicators are the average LTV, DTI, DSTI of the stock of loans outstanding as well as the household leverage (HHL) indicator. New loans originated in the simulated period become an ever more important share of the total stock of loans over time. The baseline is a no-policy scenario in which the economy moves along the pre-specified, exogenous path (achieved by calibration) and no borrower-based policy is active. We will use this no-policy scenario to benchmark the results for the two alternative scenarios described above. It is important to keep in mind that the difference between the no-policy scenario and the policy scenario in each case is the relevant metric for interpreting policy effectiveness. Absolute levels (e.g. average LTV) depend on the assumptions (scenarios) and should not be seen as forecasts (or proxies for policy effectiveness).

Figure 6 shows the development of the average LTV of the stock of loans in panel (a). In all scenarios the LTV increases substantially after 2022 when house prices start to decline in our scenario. In case all households above an LTV of 90% are declined a mortgage, the average LTV is significantly lower over the whole simulation horizon. The "Maximum Leverage" scenario does not exclude households with high LTV ratios completely from obtaining a mortgage, which means that the development of the aggregate LTV in this scenario is lower compared to the baseline scenario, but not as low as in the "Baseline & Reg." scenario. Importantly, policies substantially dampen the increase in average LTVs.

The DTI of the stock of loans depicted in panel (b) also increases after 2022 in all three scenarios as household income decreases due to the recession. The level in 2025 is again lower in the "Baseline & Reg." and "Maximum Leverage" scenarios compared to the baseline since the LTV restriction reduces the flow of new debt. Panel (c) shows the average DSTI of the stock of mortgage loans, which declined strongly between 2010 and 2019 due to the low interest rate environment that reduced households' debt servicing costs. The DSTI continues to decline in all three scenarios until 2022 and then increases slightly in the following two years before falling again. The level of the DSTI does not differ substantially between the three scenarios. As we do not assume any increase in interest rates, the low interest rate environment keeps the DSTI low in all scenarios. Due to this effect, the DSTI ratio in the current situation is probably a less reliable

Figure 6: Key vulnerability indicators: stocks



(a) LTV

(b) DTI

(c) DSTI

(d) Household leverage

(e) LTV-DSTI joint distribution

Notes: Source: Own simulations. Vertical line marks the beginning of scenario data.

indicator of household vulnerability than the DTI ratio, which is not affected by low interest rates. We notice that the calibrated DSTI for new lending is low in general (as it is in the data) but can (in scenario or robustness analyses) be calibrated to higher values (e.g. by increasing the average repayment rate). This would increase its sensitivity to shocks. The household leverage indicator (HHL) presented in panel (d) is more or less flat in all three scenarios until 2022 as total household debt increases at the same pace as asset values. HHL then reacts very strongly to the fall in house prices, since the price substantially lowers not only the value of the households' real assets $A^h_{i,t}$, but also the discount factor $Disc_t$. When the market recovers in 2025, the discount factor returns to an average value, causing average household leverage to decline again in all scenarios. In the baseline scenario, though, the overall increase in HHL is strongest. In both policy scenarios, household indebtedness is reduced, which means that the increase in average HHL is lower when house prices fall after 2022.

The final key risk indicator is the joint distribution of LTV and DSTI (Figure 6(e)). For reasons of simplicity, we group households into "high risk" and "low risk" categories. The former (latter) are households with an LTV greater (lower) than 90% and a DSTI above (below) 40%. The results show that – as intended – the LTV cap helps containing the drop in "low-risk" households in terms of the joint distributions of DSTI and LTV (which cannot be seen if only the average DSTI is considered; see above). The figure once again reveals that the positive impact takes some years to materialize.[49]

The model's key transmission channel is that it excludes some households from purchasing a home or restricts their leverage, and the key variables of interest are the vulnerability indicators concerning the stock of loans outstanding. But as a by-product of our simulation, we can also analyze how the LTV cap translates into changes in average DTIs and DSTIs for newly issued loans. This is shown in Figure 7. Panels (a) and (b) show that the two policy scenarios reduce DTI and DSTI flows compared to the baseline no-policy scenario.[50] The LTV flow depicted in panel (c) is set exogenously for the baseline scenario and identical to the calibration target. For the two policy scenarios, the LTV flow is endogenous and below the calibration target. This again shows that household vulnerability is reduced in the policy scenarios. However, as one would expect, the average LTV flow is substantially lower in the "Baseline & Reg." scenario compared to the "Maximum Leverage" scenario.

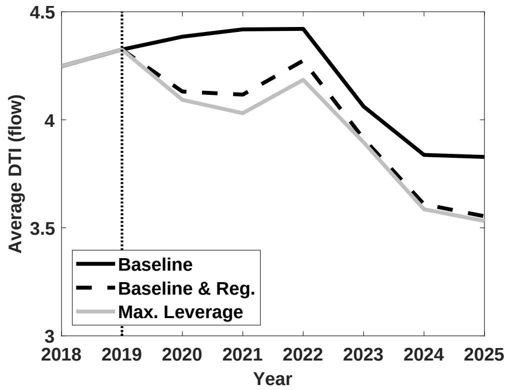
The average mortgage loan size and the growth rate of aggregate debt depicted in Figure 5 (see above) are calibration targets in the baseline scenario as well. In the policy scenarios, however, they also become endogenous. As one would expect, the average mortgage loan size shown in panel (a) is always smaller in the "Maximum Leverage" scenario compared to the baseline since households are restricted. In the "Baseline & Reg." scenario, though, mortgage loan size is slightly above the baseline, which is counterintuitive but can be explained by a composition effect: the group of new borrowers is smaller compared to both the baseline and the "Maximum Leverage" scenario and

[49]The effect on the distribution of risk metrics (e.g. LTV, DTI, etc.) individually is as expected. Regulation has a greater impact at high values of LTV, whereas the lower end of the LTV distribution is far less affected. Results are available upon request.

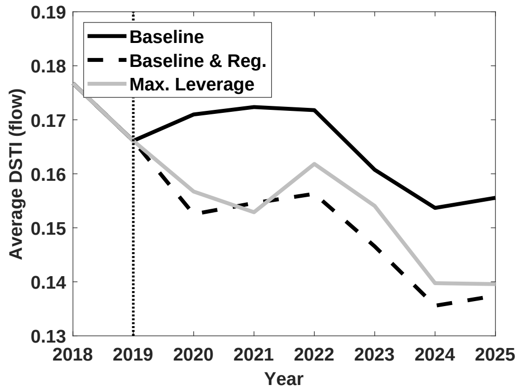
[50]The average DTI flow in the "Maximum Leverage" scenario is lower than in the "Baseline & Reg." scenario at some points in time due to a composition effect: the group of new debtors is smaller in the "Baseline & Reg." scenario as some buyers are denied a loan. The group of new debtors in the "Maximum Leverage" scenario, though, is identical to the baseline scenario.

Figure 7: Key vulnerability indicators: flows

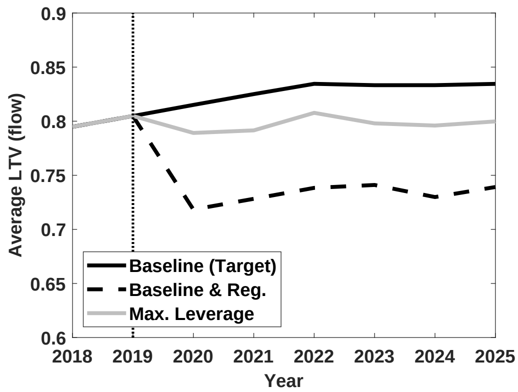
(a) DTI flow



(b) DSTI flow



(c) LTV flow



Notes: Source: Own simulations. Vertical line marks the beginning of scenario data. Calibration targets and calibrated values (result) denoted by "Baseline (Target)" in the legend as they perfectly overlap.

the households dropping out request smaller loan amounts on average those with lower LTVs. This shows that high LTVs need not necessarily go hand in hand with large loan sizes. Panel (b) shows the development of the growth rate of aggregate mortgage debt in the three scenarios. In line with intuition, the growth rate is substantially smaller in both policy scenarios compared to the baseline and smaller in the "Baseline & Reg." scenario than the "Maximum Leverage" scenario. Panel (c) shows the time series of the calibrated parameters. The parameter ϕ, which scales the value of the property, increases on the back of higher house prices. The number of new owners γ that makes the average mortgage loan size and the aggregate growth of mortgages mutually consistent increases on balance. The ratio of liquid assets used for down payments δ decreases over time. This can most likely be explained by a high growth rate of liquid assets (including deposits) for renter households. If these prospective owners were to see their funds available to finance the down payment experience lower growth rates, the model would "force" those households to increase the share of financial assets used for down payments.[51]

[51] Note that this issue is, however, not innocuous as with the current calibration, households also have a relatively

8 Model validation

In this section we compare selected variables from the model with realized data from the PHF. To this end, we use the first wave of the PHF (collected 2010/2011) as an input and calibrate the model as described above. As inputs and targets for calibration, we use the observed realizations of the same variables as used in the simulation up to 2017 (third wave).[52] Each observation in our simulation is a combination of the original data plus new owners added in the course of the simulation. When comparing the "predicted" third wave with its realization, it is important to keep in mind that the result depends on the representativity of the inputs, on the model's ability to replicate past observed behavior, and on its ability to capture potential structural change. The first issue is important because for calibrating e.g. LTVs, average mortgage sizes and redemption rates, we use data that are probably not representative. If the inputs are differ from the true realizations fed into the data, we will fail to match the third wave's corresponding statistics, no matter how well the model works in general. Likewise, the last issue is important as the application of simple reduced-form equations (even with perfect inputs) will not be able to produce decent results. With this caveats in mind, our validation exercise takes on four perspectives.

First, we compare the distribution of relevant indicators such as LTV, DSTI and LTI for newly issued loans from the data with the model-implied outcomes in Figure 8. Note that the data on new owners are approximated by combining all mortgages issued between 2007-2011 to achieve a sufficient sample size, which is still small. Further, some inputs, such as household income can be only extrapolated with aggregate growth rates. Our procedure performs reasonably well for DSTI and LTI, but overestimates the LTV at the lower end of the distribution. Values around the 90th percentile of the respective distributions are also in line with the data, but there are differences across risk metrics.[53] This is important as the regulatory interventions are likely to take place around these values.

Second, we use the first wave of the PHF as an input and simulate the model up to 2017 (i.e. eight years of simulation). Then we compare several model-implied values (averages and distributions) for LTVs, DTIs, and DSTIs and the joint LTV-DSTI distribution for indebted households with the data from the third wave. Results are shown in Table 9 for the average values, in Table 6 for selected percentiles, and in Table 7 for the joint distribution of LTV and DSTI.

The model underestimates LTV and DTI and somewhat overestimates DSTI. Looking at the distributions, we can confirm that our modeling approach does a decent job of matching the dynamics of the real data. The dynamics of the joint distribution also point into the right direction: the model correctly predicts the increase in the share of

high buffer of liquid assets post purchase.

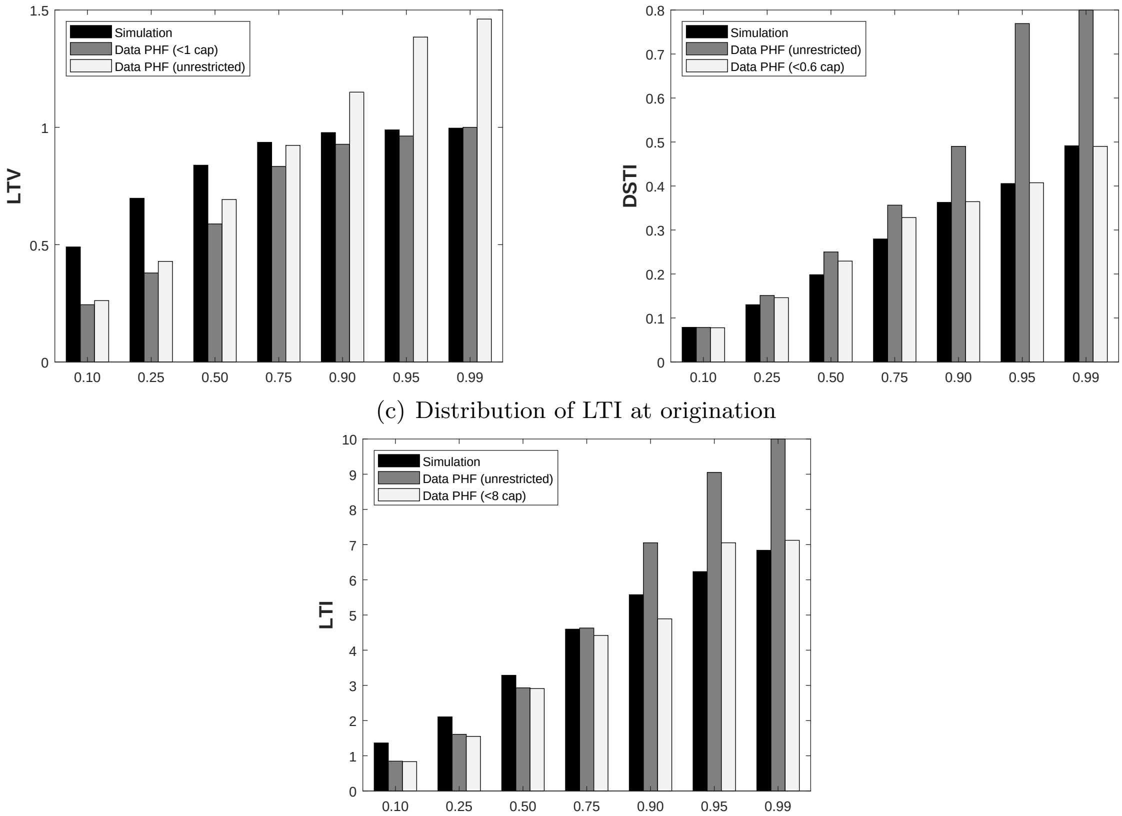
[52]Because no policy intervention took place, we perform this exercise in the baseline scenario.

[53]Note that there is a non-trivial number of households with LTV and DSTI values above 1, and the 99% LTI percentile is around 18. These numbers seem unrealistic.

Figure 8: Distribution of risk indicators at origination, simulation and PHF data

(a) Distribution of LTV at origination

(b) Distribution of DSTI at origination



(c) Distribution of LTI at origination

Notes: Sources: Own simulations, PHF. PHF data smoothed with a 5-year moving average. As no information on consumer debt is available at the time of purchase, we use LTI as a proxy for DTI. Statistics computed for new owners ("at origination") with debt.

low-risk households (upper left-hand corner) and the reduction in high-risk households (lower right-hand corner). While the other two quadrants are slightly off, the model qualitatively correctly predicts a decreasing share of households with a high DSTI.

Third, we benchmark the simulated cross-sectional age profiles for selected variables against their empirical counterparts in the third wave (Figures 9 and 10). When interpreting the results, it is important to note that the cross-sectional profiles were not an explicit calibration target. Against this background, our model seems to perform sufficiently well for an empirical application. For some statistics, such as the distribution of liquid assets or debt, the model struggles to match the data for older age groups. By contrast, the LTV exhibits implausible high values for very young households. This is due to a combination of two factors. First, when computing averages *by age*, the relatively small number of observations for very young and old households (see figure on distribution of owners with debt) may produce less robust statistics due to outliers. Second, the relatively parsimonious modeling assumptions neglect a number of relevant factors, such as life-cycle savings motives or liquidity constraints. For instance, the DSTI for households seems to be too low in general, but especially so for young households.

Table 6: Comparison of stocks: model vs. data for indebted households

	LTV			DTI			DSTI		
	p25	p50	p75	p25	p50	p75	p25	p50	p75
PHF 2010	0.17	0.35	0.60	0.94	2.10	3.72	0.15	0.23	0.36
PHF 2017	0.13	0.31	0.50	1.01	2.11	3.59	0.12	0.20	0.29
Simulation 2017	0.13	0.30	0.56	0.86	1.96	3.60	0.11	0.19	0.31

Table 7: Comparison of stocks: model vs. data for indebted households (joint distribution)

		LTV$<$0.9	LTV$\geq$0.9
DSTI$<$ 0.4	PHF 2010	76.0%	4.2%
	PHF 2017	83.5%	2.3%
	Simulation 2017	84.9%	4.9%
DSTI$\geq$ 0.4	PHF 2010	16.1%	3.7%
	PHF 2017	13.8%	0.4%
	Simulation 2017	9.3%	0.9%

Notes: Numbers refer to owner households with outstanding mortgages.

The “problem” with young households is that our reduced-form model prefers households with high levels of assets, which reduce the need for high levels of debt and thus debt service. In the data, by contrast, the average debt of young owners is relatively high (not shown). This suggests that very young households that are able to obtain a mortgage are “special” (e.g. can post additional collateral/guarantees or have a personal relationship with the lender) and cannot be expected to be modeled in a realistic manner with this simple approach.

Finally, using the same logic as above, we examine the model's performance when slicing the data across the income distribution. We do this by dividing the population of indebted households into terciles and computing average values for the usual risk metrics. We find that the model in general is able to preserve the observed ranking across the income distribution (Table 8). If the model under or overestimates the average level of a certain variable, it does so for all income levels, consistent with the general upward or downward trend documented in Table 9.

Section A.2 of the Technical Appendix presents an extensive robustness check. We find that modeling the process of generating new owners is the most important ingredient. We also show, however, that some seemingly less relevant aspects (from a broader perspective) can have a significant impact on selected model statistics. For instance, while modeling life-cycle wage profiles does not seem to play an outstanding role in general, ignoring this element does cause household (labor) income to be overestimated at

Table 8: Comparison of stocks by income: model vs. data for indebted households

	DTI			DSTI			LTV		
	Income tercile			Income tercile			Income tercile		
	1	2	3	1	2	3	1	2	3
PHF 2010	3.60	2.59	2.44	0.31	0.26	0.23	0.44	0.43	0.37
PHF 2017	3.87	2.73	2.41	0.30	0.27	0.24	0.34	0.34	0.29
Simulation 2017	4.27	2.69	2.42	0.25	0.20	0.17	0.44	0.40	0.32

higher ages.

Table 9: Comparison of stocks: model vs. data for indebted households (mean values)

	LTV	DTI	DSTI
PHF 2010	0.42	2.9	0.27
PHF 2017	0.39	3.1	0.21
Simulation 2017	0.36	2.66	0.23

Notes: The numbers are not identical to the ones using the full sample because of the adjustment of the household structure.

9 Conclusion

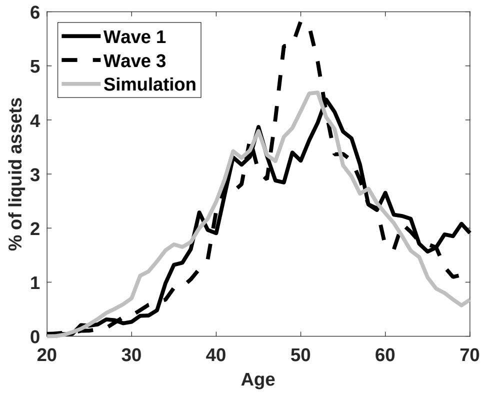
Excessive borrowing by households and high leverage are often singled out as important causes of financial crises. Once a crisis has materialized, overindebtedness is identified as the main cause for slow recoveries and protracted recessions (IMF 2012). The typical policy response to such developments are borrower-based instruments. Against this background, it is important to understand what the effects of such measures could be ex ante and what the effects have been ex post. Our paper contributes to the former.

We develop a microsimulation model which quantifies the impact of a hypothetical activation of loan-to-value (LTV) caps on relevant metrics of household resilience and on household borrowing. One important element of our modeling approach is micro-macro consistency, which is needed for robust policy advice. We find that the activation of a cap on the Loan-to-Value ratio (LTV) could have a sizeable effect on the growth rate of mortgages upon activation but could also reduce relevant risk metrics. However, a significant reduction of the risk measures concerning the stock of loans outstanding – e.g. the current LTV or DTI – can only be achieved if the restriction is active for several years. This delay in transmission needs to be taken into account when decisions about activation of instruments are taken.

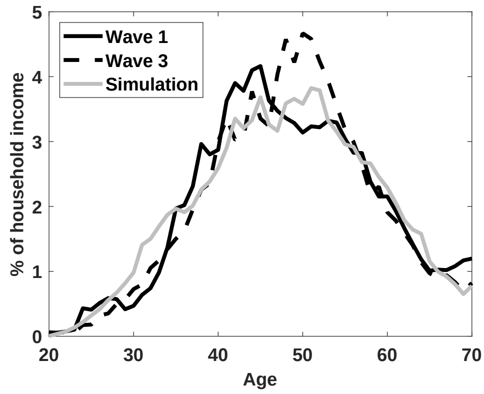
Our approach is simple, straightforward and transparent. It can easily be extended to cover other instruments (e.g. DTI, DSTI or amortization restrictions) or include other

Figure 9: Cross-sectional distributions, simulation and PHF data

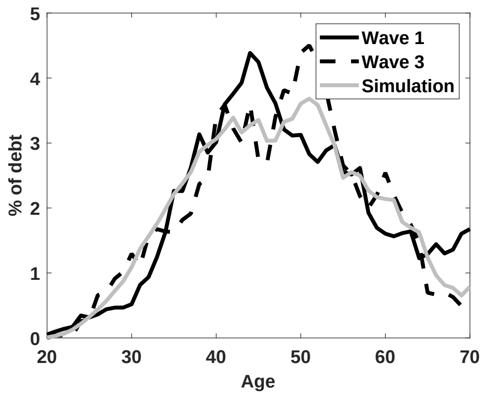
(a) LTV of indebted owners



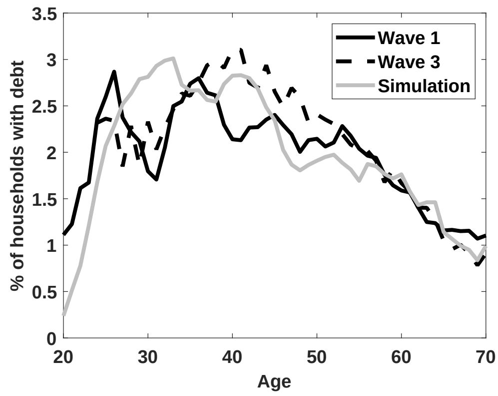
(b) Household income



(c) Debt



(d) Indebted households

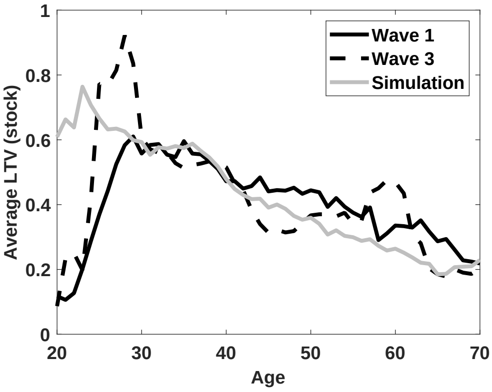


Notes: Sources: Own simulations, PHF.

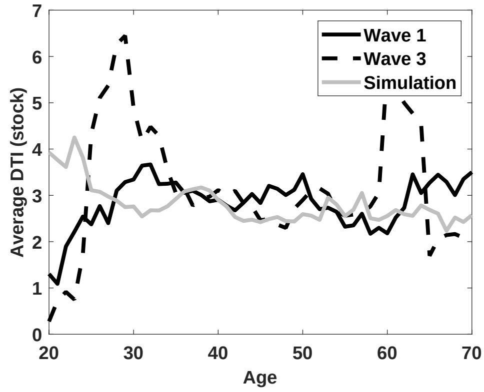
behavioral responses by households, e.g. unsecured borrowing to circumvent an LTV (consumer credit). However, the paper also has several shortcomings, flagging further areas of improvement. First, the paper takes macroeconomic scenarios as given and does not explicitly model general equilibrium feedback effects. Such feedback effects are, however, needed to analyze the total effects of regulatory restrictions in a meaningful way. Second, household behavior is based on estimated rule of thumb decision rules. While this a reasonable start, extending the model to cover more rational households, e.g. in the form of expectations-based optimizing behaviour, should be the next step. Both extensions are on our research agenda.

Figure 10: Cross-sectional distributions, simulation and PHF data

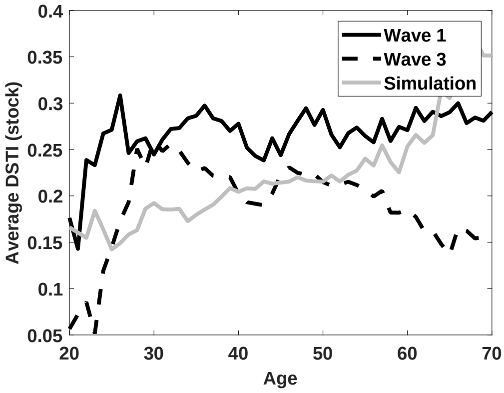
(a) LTV of indebted owners



(b) DTI of indebted owners



(c) DSTI of indebted owners



Notes: Sources: Own simulations, PHF.

A Technical Appendix

A.1 Key elements

In this subsection we provide a brief overview of the model elements. We group them into key elements and less important, minor elements. This judgement is based on the (expected) overall quantitative impact. For specific analyses, however, the minor elements may also have a substantial impact (see also Section A.2 for a robustness check).

Key elements

Introduction of new owners and "purchasing" decision: the probability of becoming a new owner is predicted by an estimated logit model, and the model could be misspecified. Incorrect coefficients would then lead to the relative cross-sectional importance of factors being wrong (e.g. role of family size could be too strong). A cross-check using the rather small panel component from consecutive waves shows that the results are qualitatively okay (see main text). Also, the reduced-form estimation of the value of the new real estate (including the amount of debt) could suffer from relative distortion (see above). Unlike relative distortion, distortion in levels (debt, ownership rate) is unlikely as they are calibrated to the "correct" levels.
Consumption/saving decision: the dynamic equations determining saving/consumption and thus the stock of liquid assets are based on economic theory, but are implemented via ad hoc reduced-form equations. If misspecified/miscalibrated, metrics involving liquid assets could be biased.
Calibration of the number of new owners: the distribution of new owners is based on realized data and could thus change over time (e.g. the number of older households becoming owners could increase). While this can be adjusted ad hoc (based on assumptions, expert judgement, etc.), a misspecified distribution will especially affect risk metrics relying on income because income dynamics vary mostly with age.
Household response to borrower-based instruments: in principle, various reactions to the introduction of borrower-based macroprudential instruments are conceivable: households could (i) decide not to borrow at all, (ii) save now and borrow at a later point in time, (iii) buy a cheaper home and borrow less, (iv) borrow money from friends or family. In the baseline simulation we have chosen to exclude households that do not fulfil the restrictions for borrowing and becoming owners, mainly for reasons of simplicity. In reality, a mix of all possible reactions will occur.

Minor elements

Modeling unemployment: the model currently has three unemployment states with corresponding replacement rates. For the model "to work", the number of states could be reduced to two states (employed and unemployed). Labor income could also be modeled as a continuous process, which then needs to introduce the right degree of persistence (agents should not jump randomly across states). However, it would then not be possible to model unemployment as a discrete state.

Modeling education: currently the model has three educational groups. For the model "to work" this heterogeneity is not needed as one could rely on a representative worker. However, labor income profiles (and unemployment rates) typically depend on the education level. This specification brings the model closer to reality at relatively low cost.

Risk sensitivity of interest rates of mortgages: this element introduces a realistic risk premium as a function of LTV. This feature would become more powerful if it were embedded in a more realistic modeling environment, one in which the household's LTV becomes an endogenous object which households can actively decide upon in an optimizing framework (e.g. potentially together with a DSTI).

Distinction between three types of liquid assets: this distinction is easy to implement and introduces some realistic heterogeneity across the income distribution. However, it is only likely to become very important in a situation where high-income households (for which stocks are a more important store of liquid wealth) are highly leveraged and the stock market crashes.

Early retirement: this element is intended to simulate exogenous reductions in income due to early retirement, e.g. due to higher unemployment risk (higher for older workers) or health shocks. It is a part of the "package" modeling the labor market. However, early retirement behaviour is partly endogenous (voluntary). This means that the households which the model forces into early retirement and therefore potentially into financial difficulties may not retire in reality.

Modeling the life-cycle component of income: this is an element of the model (as in reality) which needs some years of simulation to impact substantially on simulated wages (for the stock of owners). However, during those years wage income may change by several percentage points, which has an impact on income-based risk metrics but also on savings/assets.

A.2 Robustness checks

This section discusses of the role played by different modeling elements. By grouping them together and switching them on/off one by one. Then we compare the results produced by the different model versions and discuss the implications of the different assumptions for stock and flows, noting that the effect materializes mostly via changes affecting new owners. "Stocks" means that the figure refers to the stock of indebted households, whereas "flow" means that the number refers to new owners. The metrics used in this section are identical to the ones used in the main section of the paper. We run six different models and compare the results to the baseline version (V1). Whenever possible, we use data from the first and third waves as additional benchmarks. We therefore use realized outcomes but also expert judgement to assess the results. The legend in the figures is identical across figures but data for waves one and three are "empty" (not shown) for figures depicting flows (as no data are available for flows). Finally, it is important to note that results are produced without re-calibrating the model (i.e. we use the standard calibration).

In models two and three (blue) we switch off the maximum LSTI/LTI limits (V2) and, in addition, increase the variance of house prices and scrap the minimum and maximum house price (V3). In the fourth version (V4, green) we switch off the model predicting the probability of becoming an owner and assign random probabilities. The rest of the procedure is as in the main body of the paper: households are ranked by their score and are assigned a house and a contract. In version V5 (green) we additionally assume that all age groups are equally likely to become owners. In version six (V6, yellow) we assume that wages do not grow over the life-cycle. In model seven (V7, black) we combine all previous models. Table A.1 provides a compact overview.

Table A.1: Overview model variants for robustness checks

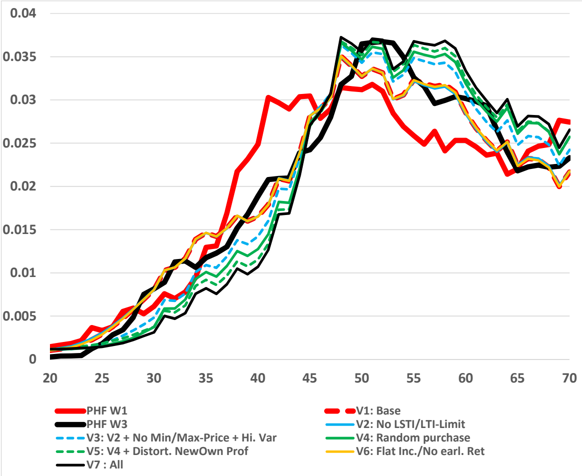
Model version	Change
V1	Baseline
V2	No LSTI/LTI limits
V3	V2 + high variance of house prices, no minimum or maximum house prices
V4	V1 + stochastic selection of new owners
V5	V4 + uniform distribution of new owners across age
V6	V1 + flat income profile and no early retirement
V7	V2 + V4 + V6

When looking at stocks, we observe that less realistic ways of modeling the process of becoming a new owner (green) and lifting the limits on maximum/minimum mortgage size/LTI have a strong (downward) effect on ownership, especially for younger households (Figure A.1 a and b). The result is that the distribution of debt in the population is likewise skewed toward the elderly. On aggregate, this results in the mortgage growth rate being underestimated (Figure c). In line with the result above, average mortgages and the DTI for younger households seem to be too high, compared to the profile from the baseline version and the data (Figure A.1 e and f). By contrast, the modeling assumption about the income process matters mostly for older households (income is overestimated due to the absence of early retirement and the non-decline in the income profile; consequently, DTI is underestimated). To sum up, the modeling of the purchasing process seems to be crucial and important for getting life-cycle profiles right.

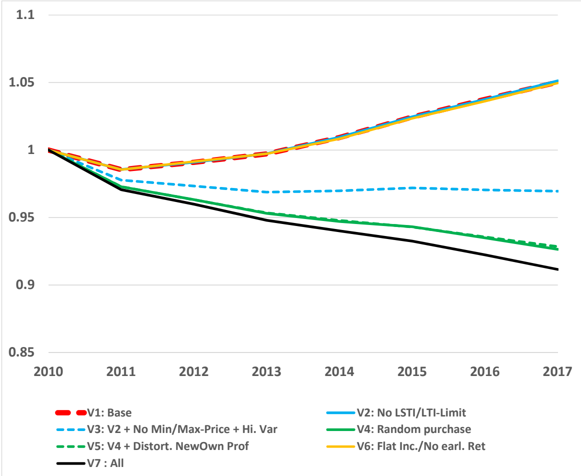
For the flows, virtually all deviations from the baseline approach push the DTI up, consistent with the lower incomes of new owners. Income decreases, as the selection process calibrated for the baseline model "prefers" households with high income and own funds. The new random process brings in more low-income and low-wealth households (green and black depict models implementing this random purchasing process). The DTI increases across the distribution. The direction of the deviation in the flow LTV is not consistent across models. In models with a random purchasing process, the LTV goes up (partly because low-wealth people are now more likely to buy). However, if we also eliminate maximum LTI/LSTI limit and the minimum/maximum price restriction, the LTV decreases on average. This is probably because unreasonably high prices can push the flow LTV from an average value of approx. 0.8 up to a maximum value of 1, but extremely low prices (which are also are more frequent due to the higher variance) can push the LTV down much more, hence the downward bias. There is no obvious difference between model variants across the life-cycle.

Figure A.1: Robustness checks - stock variables (1)

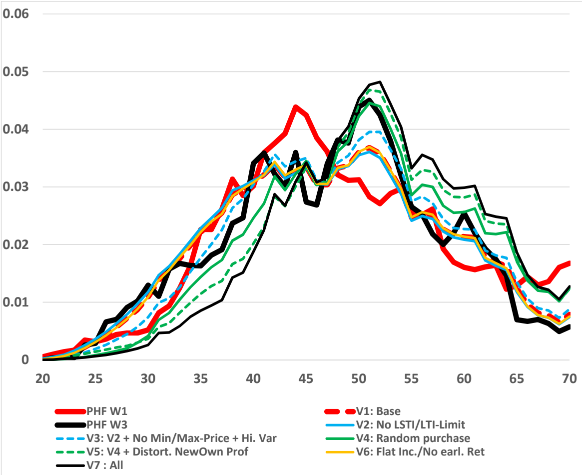
(a) Distribution of ownership (stock)



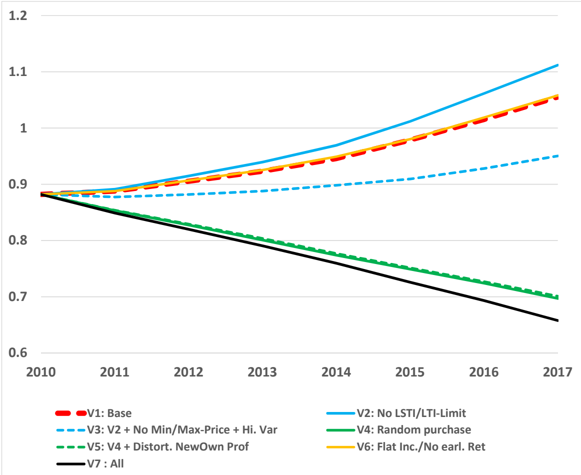
(b) Number of owners (stock)



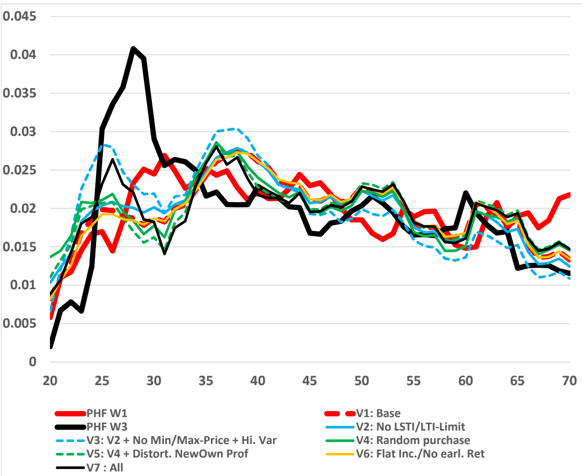
(c) Distribution of debt (stock)



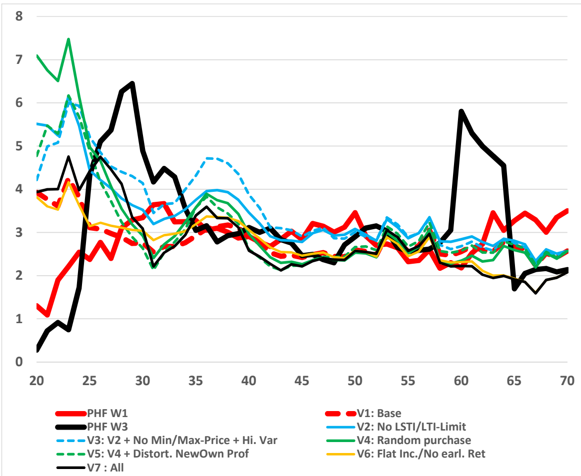
(d) Level of aggregate mortgages (stock)



(e) Avg. debt of indebted owners (stock)



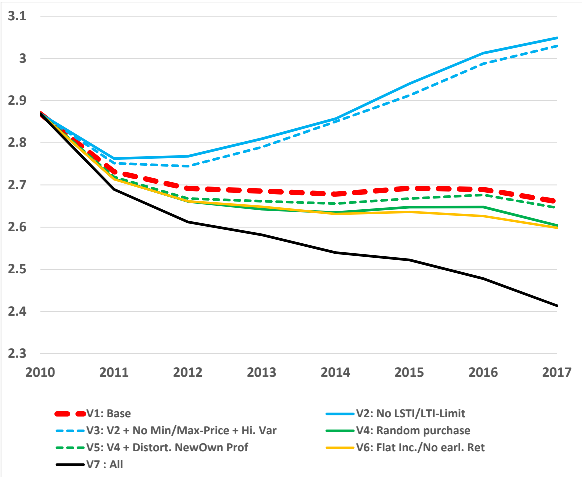
(f) Avg. DTI of indebted owners (stock)



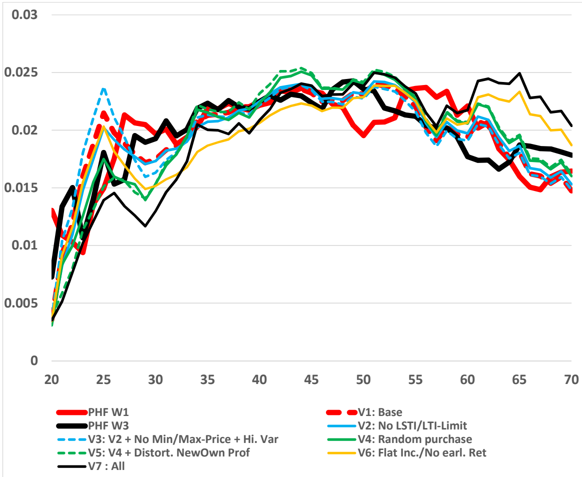
Notes: a): share of total; b) and c): value in 2010 standardized to one; d): in EUR thousands.

Figure A.2: Robustness checks - stock variables (2)

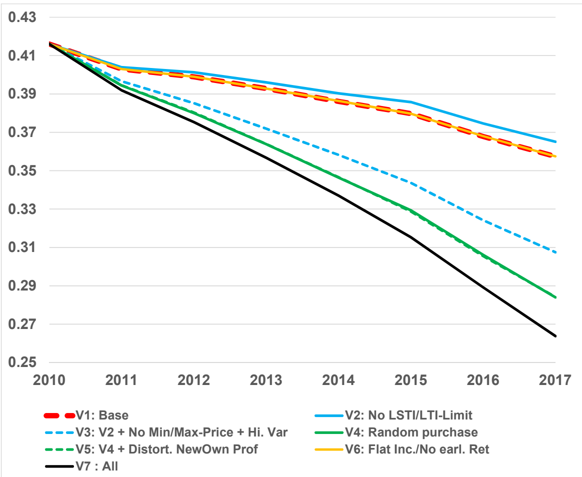
(a) Avg. DTI of indebted owners (stock)



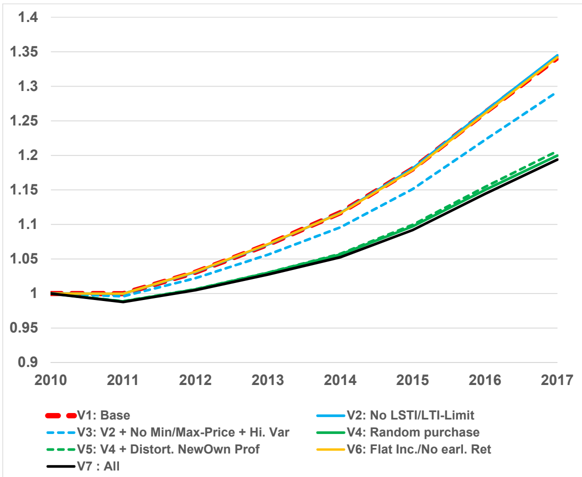
(b) Avg. household income (stock)



(c) Avg. LTV of indebted owners (stock)



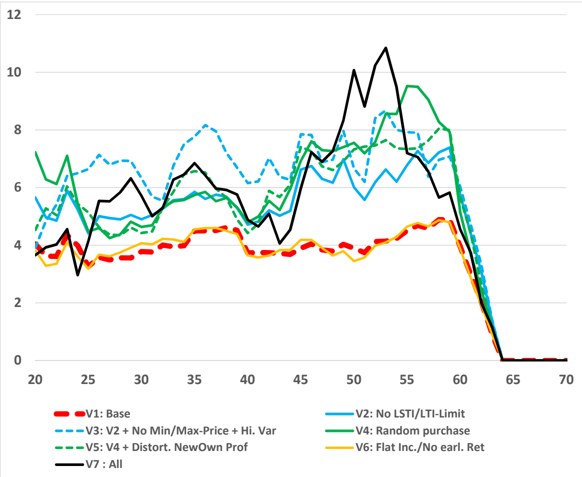
(d) Avg. real assets of owners (stock)



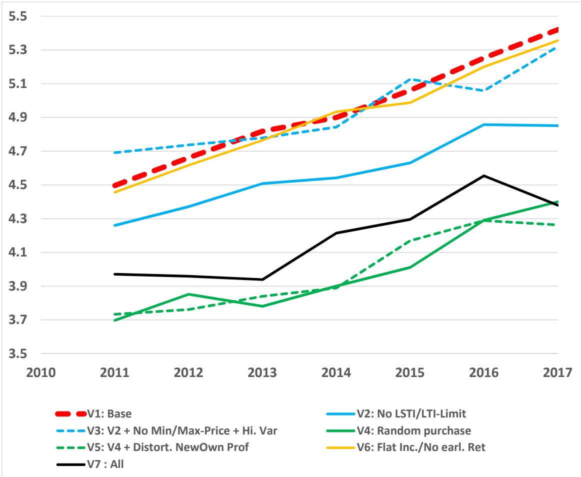
Notes: a): share of total; d): value in 2010 standardized to one.

Figure A.3: Robustness checks - flow variables

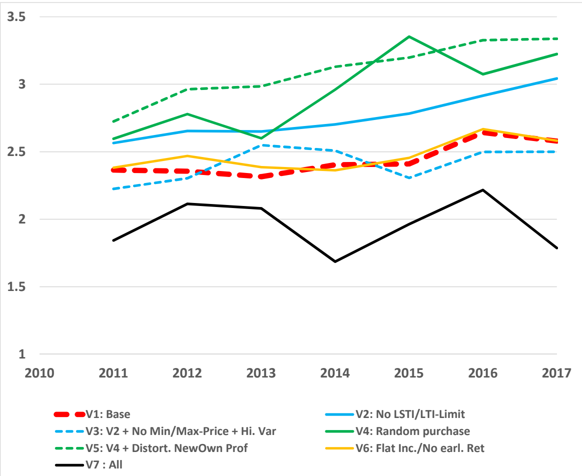
(a) Avg. DTI of new owners (flow)



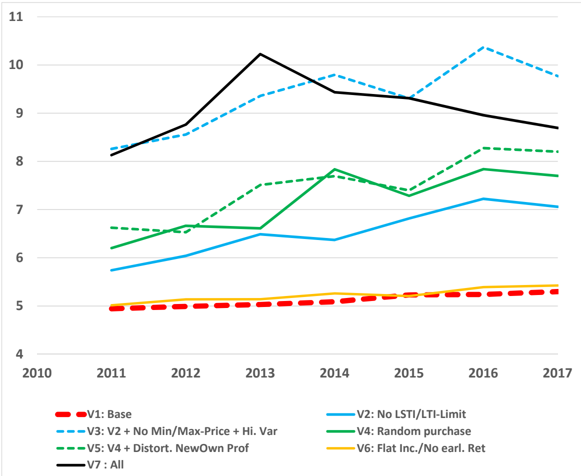
(b) Avg. household income of new owners (flow)



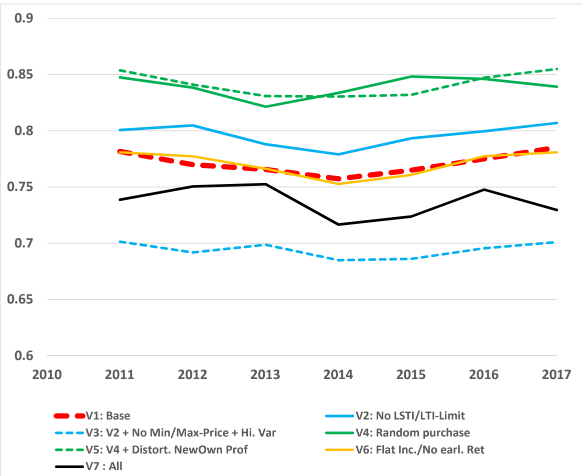
(c) 25th percentile of DTI for new owners (flow)



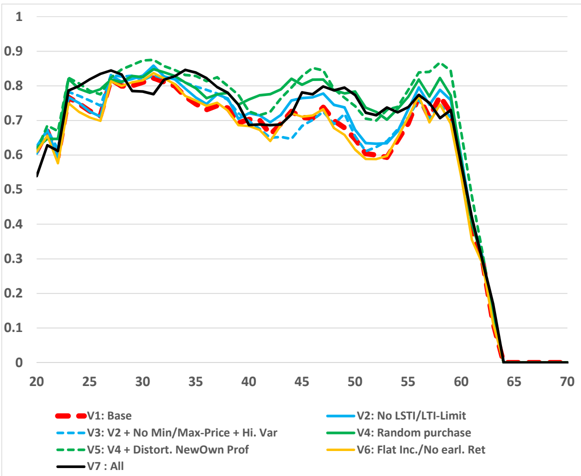
(d) 75th percentile of DTI for new owners (flow)



(e) Avg. LTV of new owners (flow; time series)



(f) Avg. LTV of new owners (flow; cross section)



Notes: c): value in 2010 standardized to one.

A.3 Estimation of the probability of becoming an owner household and of the house price

To estimate a function that assigns a probability of purchasing a house to households, we need data on ownership status and some explanatory variables such as the size of the household or income, wealth, education or age of the household's members. Ideally, these data should contain a longitudinal dimension that allows us to track households that switch from renters to owners. To the best of our knowledge, there is no German panel dataset that contains a sufficient amount of households with a change in ownership status. PHF data include information on house ownership and a rich set of explanatory variables, but so far lack a considerable panel dimension. PHF data only include households that are renting today and owner households that purchased a house in the past. To estimate the probability of households purchasing a house, we need to compare households that become owners and those that do not at the same point in time. We therefore first need to transform the data.

PHF data include information on the year in which a household purchased a house that can be used to scale other variables back to that point in time. This allows us to treat owners as if they purchased their house today. However, we can only use variables that are available for the time of house purchase: information on the age of household members today is used to generate a variable on the age of the household head when the house was purchased. The number of household members and the presence of children in the household can be constructed in a similar way. The PHF also includes a variable on the years of labor market experience of the household head and spouse that can likewise be scaled back to the day when the house was purchased. Information on the price of the house when purchased and on the original amount of the loan used to finance the house is used to generate a variable on the own funds used by the household ($Price - Loan = OwnFunds$). For non-owners we use the sum of their liquid assets (deposits, stocks, bonds, etc.) as the value of their own funds (the value of own funds for owners is deflated by the consumer price index to make it comparable to the value for non-owners). Finally, we treat the educational attainment of the household head and spouse as being constant over time. The resulting function we estimate with PHF data from 2017 is thus:

$$\begin{aligned} Ownership\,(0/1) = f(&Age^{HHhead}, Experience, No.\,of\ Adults,\\ &No.\,of\ Children, Education, OwnFunds) \end{aligned}$$

We choose to estimate this relationship with a logit model. We include squared terms for the age and experience variables to allow for nonlinear relationships. We further use the logarithm of the own funds variable since it fits the data better than linear or quadratic specifications. The regression is weighted with the cross-sectional household weights of the PHF to account for the oversampling of specific households in the data. Since the PHF data are built on multiple imputations, we compute standard errors with the help of Rubin's Rule. Coefficients and standard errors are first estimated separately for each imputation, then the results are pooled. We use Rubin's Rule to properly account for the variance between the different imputations.

The results of the regression can be found in the first column of Table A.2. Not all the variables included there have a significant explanatory power for the decision to purchase a house. For the purpose of the simulation, we include only variables that have a significant explanatory power and, therefore, use the results that can be found in the second column of Table A.2. To capture the uncertainty of the estimated regression results, we add a disturbance term to the deterministic outcome. The disturbance term is drawn from a standard logistic distribution, as in the underlying logit model.

The relationship of the house price and household characteristics is estimated in a similar way to the probability of purchasing a house. For the regression we can, however, use only households that have already purchased a house, i.e. we lose observations. The dependent variable is the price of the house when purchased, deflated by the consumer price index. The third column of Table A.2 shows the results when all potential explanatory variables are included in the regression. In this case, we include a linear and a quadratic term of own funds as it fits the data better than a log specification. Owing to the relatively low number of observations, only a few variables exert a significant influence on the house price. After dropping one insignificant variable after another, we obtain the specification depicted in the fourth column of Table A.2. This specification was also used for the simulation.

To prevent a deterministic simulation and to capture estimation uncertainty we also add a disturbance term here. The disturbance term is normally distributed with a mean of zero and a variance that mimics the variance of the regression residuals.

Table A.2: Regression results

	(1)	(2)	(3)	(4)
	Owner(0/1)	Owner(0/1)	House value	House value
Age_hhh	0.213	-0.057	12570.9	5535.8
	(0.151)	(0.027)	(6873.4)	(937.3)
Age_sq	-0.003		-130.6	-58.4
	(0.002)		(90.9)	(19.3)
Exp	0.140	0.214	-1349.7	
	(0.066)	(0.059)	(3019.2)	
Exp_sq	-0.003	-0.005	-0.6	
	(0.002)	(0.001)	(73.0)	
D.Adults=2	0.893	0.912	36662.7	31808.7
	(0.336)	(0.278)	(16390.5)	(13459.4)
D.Adults>2	0.134		-7683.8	
	(0.669)		(22715.6)	
D.Kids=1	0.661	0.696	-8541.9	
	(0.321)	(0.277)	(13957.8)	
D.Kids=2	0.129		4171.6	
	(0.382)		(18270.7)	
D.Kids>2	-0.005		28527.7	
	(0.485)		(24318.2)	
D.mid_educ	-0.036		16364.5	
	(0.903)		(47419.8)	
D.high_educ	0.071		48590.5	37800.0
	(0.924)		(47020.6)	(12326.8)
Ln_ownfunds	0.813	0.824		
	(0.082)	(0.079)		
Ownfunds			1118.9	1074.1
			(87.3)	(38.9)
Ownfunds_sq			-0.1	
			(0.1)	
Constant	-9.251	-4.887	-148332.2	
	(2.419)	(0.776)	(127026.3)	
Imputations	5	5	5	5
Observations	1,556	1,556	576	579

Note: Standard errors in parentheses.

A.4 Estimation of shadow wage

We rely on the Heckman selection model to estimate the unobserved shadow wage. The relationship between wages and the explanatory variables is described using two equations. The first (selection equation) models the decision to work as a function of personal characteristics.

$$Prob(Work = 1) = X_{work} + u_1.$$

The second describes the wages (wage equation):

$$ln(Wage) = X_{wage} + u_2,$$

where $ln(Wage)$ is observed if $Work = 1$, $u_1 \sim N(0; 1)$, $u_2 \sim N(0; \sigma)$ and $Corr(u_1; u_2) = \rho$.

$Wage$ is the observed gross personal labor income as reported in the PHF, the variable vector X_{wage} includes age, gender, education and the region where the person lives. X_{work} includes the same variables as X_{wage} plus two dummy variables indicating if the person is married and has children. Marital status and children are believed to affect the probability of working but are unlikely to affect the wage, and for this reason can be used to identify the model.

The estimation results are reported in Table A.3. Based on the model estimates, the average predicted annual gross shadow wage amounts to 21,760 euro. To compare, the observed sample mean wage based on the PHF data is 39,699 euro.

Table A.3: Regression results for the Heckman selection model

	Selection equation Prob(Work=1)		Wage equation ln(Wage)	
	Coef.	Std. Err.	Coef.	Std. Err.
Male	0.208	0.074***	0.578	0.032***
Married	-0.279	0.086***		
Male x Married	0.527	0.122***		
Children	-0.277	0.077***		
Age	0.215	0.015***	0.093	0.012***
Age^2	-0.002	0.000***	-0.000	0.000***
Vocational training	0.392	0.095***	0.444	0.063***
Higher education	0.802	0.106***	0.829	0.067***
West	-0.005	0.094	-0.058	0.055
South	0.173	0.088*	0.078	0.051
East	-0.139	0.102	-0.148	0.059**
Constant	-3.029	0.327***	7.134	0.244***
Observations	31,420		13,875	

Notes: * p<0.10, ** p<0.05, *** p<0.01.

A.5 Unemployment replacement rates

Table A.4: Unemployment replacement rates

		Short term				Long term	
Income	Children	Single	Married	Income	Children	Single	Married
	0	59%	74%		0	36%	54%
Low	1	72%	81%	Low	1	48%	59%
	2+	85%	89%		2+	60%	64%
	0	59%	71%		0	26%	42%
Medium	1	65%	75%	Medium	1	36%	37%
	2+	71%	80%		2+	46%	52%
	0	57%	65%		0	19%	32%
High	1	62%	70%	High	1	26%	36%
	2+	66%	75%		2+	34%	40%

A.6 Calibration of steady state matrices

The steady state transition matrix for agents in the labor force is

$$\begin{bmatrix} \pi_{ee}, \pi_{es}, \pi_{el} \\ \pi_{se}, \pi_{ss}, \pi_{sl} \\ \pi_{le}, \pi_{ls}, \pi_{ll} \end{bmatrix} \tag{30}$$

where e denotes employment, s short-term unemployment, and l long-term unemployment. We impose the restriction that the long-term unemployed cannot return to short-term unemployment ($\pi_{ls} = 0$) and that agents cannot move directly from employment to long-term unemployment ($\pi_{el} = 0$). The other restriction is that the sum of transition probabilities equals one. This leaves four transition probabilities to calibrate. Two targets are given by the short-term and long-term unemployment rates, which we estimate from GSOEP data and transfer (impute) to the persons in the PHF data (the PHF has information only on unemployment but not on the duration). The parameters π_{se} and π_{le} are chosen so that the average duration of short-term and long-term unemployment are as reported by Bremus and Kuzin (2014). This gives the following matrix.

$$\begin{bmatrix} \pi_{ee}, \pi_{es}, 0 \\ \pi_{se}, \pi_{ss}, \pi_{sl} \\ \pi_{le}, 0, \pi_{ll} \end{bmatrix} \tag{31}$$

The labor market state of the household in period t is determined by using the corresponding entry from the matrix $t-1$, i.e. the state in period t is determined – given state $t-1$ – by the transition matrix from $t-1$.

When stabilizing the economy at a higher unemployment rate (after a hypothetical shock), we apply the same procedure. The only difference is the target unemployment rate(s) and the duration of unemployment. This approach allows us to simulate a simultaneous increase in unemployment and a separate change in duration. For instance, we can also simulate that the duration of long-term unemployment has increased.

A.7 Calibration of transition matrices

When simulating the unemployment scenarios, we adjust the transition probabilities in a way that – starting from the initial distribution – we match a target unemployment rate in *expected* values.[54] To calibrate the transition probabilities we proceed as follows. First, we compute the unemployment rate by age/education group in the last period u_{ij}^{t-1}. Second, we compute the aggregate unemployment rate u_{agg}^{t-1}. Third, we compute a scaling factor SF from $SF = u_{agg}^{t-1}/u_{agg}^{*}$ where a star denotes the aggregate target unemployment rate. Finally, we apply this scaling factor to each age/education pair by unemployment type to compute the age/education-specific target unemployment rate $(u(s)_{ij}^{*})$. This ensures that if all age/education-specific unemployment rates are scaled by

[54] Given the nature of the simulation, we cannot ensure that the target unemployment rate is hit in each round.

the same factor, the expected aggregate unemployment rate will match the target. The labor force L_t is defined as $L^t = E^t + U_s^t + U_l^t$ and known in advance (predetermined). Inserting the target unemployment rate yields

$$\begin{aligned} E_{ij}^* &= L_{ij}^t(1 - u_{ij}^*) && (32) \\ U_{ij}^{s*} &= L_{ij}^t u_{ij}^{s*} && (33) \\ U_{ij}^{l*} &= L_{ij}^t u_{ij}^{l*} && (34) \end{aligned}$$

Using the above transition matrix as a starting point, the relevant age/education-specific target (un)employment aggregates are given by

$$\begin{aligned} E^* &= E^{t-1}\pi_{ee} + U_s^{t-1}(1 - \pi_{ss} - \pi_{sl}) + U_l^{t-1}(1 - \pi_{ll}) && (35) \\ U_s^* &= E^{t-1}(1 - \pi_{ee}) + U_s^{t-1}\pi_{ss} && (36) \\ U_l^* &= U_s^{t-1}\pi_{sl} + U_l^{t-1}\pi_{ll} && (37) \end{aligned}$$

where we have substituted the above restrictions $\pi_{le} = 1 - \pi_{ll}$, $\pi_{es} = 1 - \pi_{ee}$ and $\pi_{se} = 1 - \pi_{ss} - \pi_{sl}$. This leaves four parameters $(\pi_{sl}, \pi_{ll}, \pi_{ss}, \pi_{ee})$ to be determined with only three equations. Further, from equation (37) it is obvious that by fixing one of the transition probabilities, π_{ll} or π_{sl} pins down the other one. Further, π_{sl} also enters equation (35). That leaves equations (37) and (35) to determine π_{ss} and π_{ee}. Using a hat to denote the calibrated values (i.e. the values set by assumption) for π_{ll} and π_{sl} gives

$$\begin{aligned} E^{t-1}\pi_{ee} - U_s^{t-1}\pi_{ss} &= E^{t-1} - U_s^* && (38) \\ E^{t-1}\pi_{ee} - U_s^{t-1}\pi_{ss} &= E^* - U_s^{t-1}(1 - \hat{\pi}_{sl}) - U_L^{t-1}(1 - \hat{\pi}_{ll}) && (39) \end{aligned}$$

which shows that the system is still colinear. Intuitively speaking, this is because when targeting a specific (un)employment rate, it does not matter whether fewer agents leave unemployment or whether more agents move into unemployment. Therefore, we take the probabilities of remaining in short and long-term unemployment (π_{ss} and π_{ll}) as given and solve for π_{ee} and π_{sl} by

$$\pi_{sl} = \frac{U_l^* - U_l^{t-1}\hat{\pi}_{ll}}{U_s^{t-1}} \quad (40)$$

$$\pi_{ee} = \frac{E^{t-1} - U_S^*\hat{\pi}_{ss}}{E^{t-1}} \quad (41)$$

These choices mean – in economic terms – that a rising unemployment rate decrease the probability of finding a job (π_{ee} decreases), increasing the probability of becoming short-term (π_{es}) and long-term unemployed (π_{sl}), and lowers the probability of finding a job out of short-term unemployment (π_{se}). The probability of leaving long-term unemployment $\pi_{le} = 1 - \pi_{ll}$ decreases in π_{ll}.

Table A.5: Summary of the existing literature

Study	Goal	Approach	Data	Input	Output	Result
Gross and Población (2017)	Assess efficacy of borrower-based instruments	'fully integrated micro-macro model'	HFCS micro database + macro data	HH balance sheets & employment (micro simulation), GVAR (macro trends)	PDs & LGDs at HH level	LTV caps reduce LGDs, DSTI caps reduce PDs
ECB (2016) TF Op. Mac. R.	Provide toolkit to assess costs and benefits of macroprudential policies	Presentation of four different kinds of models	Credit register data or HFCS data	Maximum credit available per HH	Effect of credit available on house prices	Results differ significantly between SSM countries
Verbruggen et al. (2015)	Costs and benefits of a further reduction in the LTV limit to 90%	Descriptive analysis & 3 micro-macro approaches	Loan-level data	Number of housing transactions after LTV	Effect on house prices and private consumption	Benefits: lower volatility, cost: first-time buyers have to save more
Ampudia et al. (2016)	Identify distressed HHs (solvency + liquidity situation), check response to shocks	Stress test of euro area HHs	HFCS data, NPL data	New measure of distressed HHs	Responses to interest rate-, income-, house price-shock	Euro area-HHs are resilient, but large variation between countries
Djoudad (2012)	Assess risks to financial stability from HH debt burdens	Microsimulation	Canadian Financial Monitor (survey)	Defined macro scenario (interest rate, income growth)	HH debt service ratio, aggregate PDs, NPL ratios	Only presentation of methodology
Faruqui et al. (2012)	Assess risks to financial stability from HH debt burdens	Microsimulation	Canadian Financial Monitor (survey)	Defined macro scenario (interest rate, income growth)	HH debt service ratio, aggregate PDs, NPL ratios	Asset prices have only small effect on NPL ratios since distressed HHs hold few assets
Chambers et al. (2008)	Show how different mortgage products affect housing decision and indebtedness	Theoretical model of mortgage choice	PSID data on HH wealth	Different kind of mortgage products (Fixed rate, ARM, combo loans)		ARMs increase homeownership of younger HH
Albacete and Lindner (2017)	Impact of borrower-based instruments on the real estate sector in Austria	Micro-econometric approach of ECB	HFCS data	Maximum credit available per HH	Effect of credit available on house prices	DSTI and DTI are binding, instruments affect less affluent HH significantly
Baptista et al. (2016)	Study the impact of macroprudential policies (LTI) on key housing market indicators	ABM of the UK housing market	HH survey data, housing market data (for calibration)			LTI limit attenuates house price cycles

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