Wealth Distribution and Household Leverage over the Housing Cycle - an Agent-based Analysis

Ruben Tarne

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Abstract

Since the Great Financial Crisis of 2007-2008, household debt became of increased interest to economists. Recent research indicates that a good predictor of deeper recessions and slower subsequent recoveries is strong credit growth and in particular, rising household leverage. In the upswing households might get highly leveraged and depending on their income and asset position even fincially vulnerable. A small macroeconomic shock could trigger significant mortgage defaults, destabilising banks' balance sheets with adverse economic effects. I will build on Baptista et al. (2016) - a model incorporating institutional and behavioural realism and capturing the heterogeneity of agents in the economy, as well as their interactions - by changing the consumption function to allow for more desired leverage behaviour. The paper shows that the wealth distribution is heavily influenced by leveraged households, and that while leverage increases more broadly with procyclical credit conditions, households from the middle of the distribution become more vulnerable.

1 Introduction

Since the Great Financial Crisis of 2007-2008, household debt became of increased interest to economists. Recent research indicates that a good predictor of deeper recessions and slower subsequent recoveries is strong credit growth (Schularick and Taylor, 2012; Mendoza and Terrones, 2012) and in particular, rising household leverage (Mian and Sufi, 2014; Jordá et al., 2016; Bezemer and Zhang, 2019). This could be due to several causes. In the wake of falling house prices and rising loan-to-value ratios, deleveraging and wealth effects may induce households to increase saving in order to restore their net wealth. This way, the housing market may deepen a downturn in the business cycle. Moreover, even before house prices fall households might become financially vulnerable - meaning that they would be in danger of defaulting on their loans in the case of either their mortgages interest rates rising or their income decreasing. A small macroeconomic shock could trigger significant mortgage defaults, destabilising banks' balance sheets with adverse economic effects. To avoid defaults households could be pressed to reduce their spending significantly - given that they have the means to do so. Households could thereby increase the fragility of an economy and possibly produce an economic crisis.

The aim of this paper is to provide a better understanding of how household leverage and vulnerability might evolve over the course of a housing cycle. Households' leverage is deeply linked to the housing cycle, as most of households' debt is acquired for financing housing. To investigate the connections between housing markets and financial fragility, one has to take wealth and income distributions into account. Households are only vulnerable when their income and wealth position are both relatively low. There is a broader interest in wealth dynamics (Benhabib and Bisin, 2018; Hubmer et al., 2016; Kuhn et al., 2019), which is connected, as the largest wealth position of households is housing and in most countries the main debt position by households is mortgage debt. In this broader literature of modelling wealth dynamics, however, housing and leverage has not played a big role, yet. My paper will contribute to the literature in several ways. It shows that household leverage and the housing market have a huge influence on the wealth distribution and it further shows that with procyclical credit conditions leverage increases over most of the middle-upper wealth distribution, while financial vulnerability increases mostly in the middle of the wealth distribution.

For that I will first, improve an existing housing market model by implementing a different consumption function of households in order to prevent some unwanted consumption and following from that leveraging patterns. By doing so, I am able to match the wealth distribution better than the baseline version of the model. This allows me to understand in depth how the wealth distribution changes over the course of the housing cycle. In a second step I will allow for the relationship between credit and house prices to go both ways. Comparing how leverage and financial vulnerability evolves in a system with and without procyclical credit gives insight into who is able and willing to leverage up more and how this affects the fragility of the household sector. The housing market model I will be building on is the agent-based INET housing market model developed by Baptista et al. (2016). Agent-based models are well suited to deal with the combination of individual interactions and heterogeneity of agents. This is relevant for housing markets as can be illustrated by the interaction between households and banks on the credit market. Here, banks decide individually on granting a loan to a loan applicant household. Several variables, like the creditworthiness of borrowers and capital requirements of banks as well as the developments on the housing market influence the specifics of a credit contract. These credit market interactions generate a web of balance sheet dependencies between households and banks. Also, households build leverage and potentially financial vulnerability over the cycle depending on their incomes and asset positions.

While the INET housing market model provides a very detailed simulation of the UK housing and rental market, it has some limitations. First, the model fails to reproduce the UK wealth distribution by implementing an unrealistic consumption function. Yet, in order to understand housing markets, one has to take into account how households' consumption behaviour affects the wealth distribution, as the latter influences the ability of households to enter the housing markets. If wealth is very concentrated, fewer households may have access to the housing market, as they might lack the ability to take on debt. I address this by implementing a standard consumption function, enabling the model to reproduce the real data significantly better. Additionally, the implementation of a wealth effect allows to understand, how the housing cycle might affect consumption and with that aggregate demand. Second, while rising housing prices lead to higher credit demand and therefore higher credit, more credit supply does not lead to higher housing prices, because in the model, households are almost never credit constraint. The bank more or less provides any credit that is demanded. This does not seem to hold too well with reality, where more procyclical credit conditions lead to more credit used for buying houses (Lindner, 2014; Muellbauer et al., 2015). I address this by implementing pro-cyclical credit constraints to understand how these affect deleveraging motives in the downturn.

This paper is structured as follows: in a first step, I will briefly introduce the INET model and how market cycles emerge from it. Then I describe the implementation of an alternative consumption function. In a next step, I will explain the changes I made regarding the consumption function and will look how the changes affect the wealth distribution in relation to the baseline INET model. The results allow me to research the wealth distribution over the housing cycle. In a last step, I research leverage and financial vulnerability over the cycle by implementing procyclical credit constraints.

2 The INET housing market model

In this section I will briefly describe the INET housing market model[1]. It is made up of four different types of households, which interact on the ownership and rental market. The different types are households in social housing, renters, owner-occupiers and buy-to-let (BTL) investors. Moreover, there is a bank lending out mortgage credit and a central bank implementing macroprudential policies, like setting loan-to-income or loan-to-value ratios. The model is simulated in distinct periods, each representing a month. At the beginning of each period every single household can place bids or offers on the housing or rental market, depending on its state and individual characteristics, like bank balance or income. At the end of each period the bids and offers are cleared by a double auction mechanism.

The model does not simulate is the wider macroeconomy. Employment income of households is set exogenously and their consumption expenditures do

[1]For a complete description see Baptista, Farmer, Hinterschweiger, Low, Tang and Uluc (2016).

not serve as revenue for a firm sector or the like. Therefore, consumption decisions of households do not feed back to their employment income. Households age. In the model this implies that they die at a certain point. To keep the population size constant and close to the British age distribution of 2014, each month new households enter the simulation. They are assigned an income percentile, combined with an age, determining the employment income they earn (increasing income up to retirement, then income decreases). The employment income distribution is calibrated to UK data. Provided the new household is in the upper half of the income distribution, it can get a "BTL-gene", according to an exogenously set probability. This allows the household to buy property to rent out beyond its own home. When households die, their wealth is inherited by a random living household. The houses in the model have a quality parameter, serving as a proxy for the houses location, size, and condition. Households not renting or owning a house are in social housing. Households decide their consumption each period depending on the difference between their actual bank balance and their desired bank balance, which is given as

$$\ln(b^d_{i,t}) = \alpha_1 + \beta_1 \ln(y_{i,t}) + \varepsilon_{1,i}, \tag{1}$$

with α_1 and β_1 being parameters calibrated so that the liquid wealth distribution generated in the model is power-law distributed. $y_{i,t}$ is total income, consisting of rental and employment income[2].

2.1 Household decisions

Households can change their type through market interaction, as symbolised in figure 1. They enter the ownership market by either placing bids for houses or by placing offers to sell their home or investment property[3].

2.1.1 Placing bids on the ownership market

New households enter the simulation in social housing (see SH in figure 1). Whenever households are in social housing, they place a bid on either the ownership (arrow 1 in figure 1) or the rental market (arrow 5). On which of both is decided according to the sigmoid function

$$\begin{aligned} &Prob(\text{placing a bid})^{SH\to OO}_{t,k} \\ &\quad = \frac{1}{1 + exp(-\beta_2[12\overline{r_{Q,t}}(1+\tau) - (12 \cdot m^{SH\to OO}_t - p^{SH\to OO}_{t,k} \cdot g_t)])}, \end{aligned} \tag{2}$$

where the probability to place a bid on the ownership market ($SH \to OO$) is based on the difference between the perceived cost of renting versus the perceived costs of buying a house. Where $12\overline{r_{Q,t}}(1+\tau)$ is the yearly costs of renting a house of quality Q, plus a psychological costs factor and where

[2]In the original version there are interest rates on deposits, which I leave out, in order to simplify.

[3]For the sake of simplicity, I will not describe the details of the rental market.

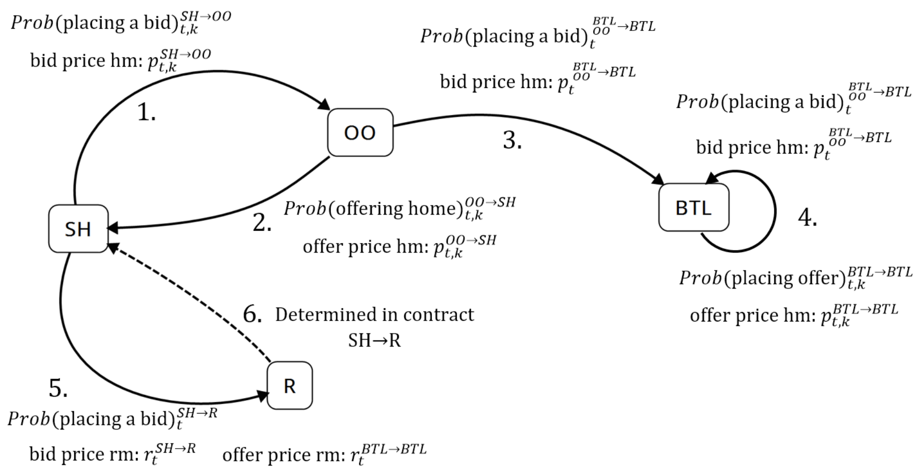


Figure 1: Households states and decisions in the INET housing market model

$(12 \cdot m_t^{SH\to OO} - p_{t,k}^{SH\to OO} \cdot g_t)$ is the yearly cost of buying a house, consisting of the expected monthly mortgage payment necessary, less the expected appreciation (or depreciation) of the house, calculated as the desired purchase price $p_{t,k}^{SH\to OO}$ times g_t, the expected yearly change in house prices. g_t is calculated as the difference between prices of this quarter with the quarter one year past, i.e. backward-looking expectations. The desired purchase price of the house is given as

$$p_{t,k}^{SH\to OO} = \min\left(q_t^{SH\to OO} + b_{i,t}, \quad \frac{\alpha_3 12 y_i^{m,emp}\exp(\varepsilon_3)}{1-\beta_3 g_t}\right), \tag{3}$$

where their desired purchase price is possibly limited by the maximum mortgage credit $q_t^{SH\to OO}$ the bank would grant them plus their own bank balance $b_{i,t}$. Their desired purchase price is mainly determined by their yearly employment income $12y_i^{m,emp}$ times the factor α_3 and increases with expected rising house prices.

Like the households in social housing, buy-to-let agents decide every period if they want to acquire new property (arrow 3 or 4 in figure 1). Their probability to place a bid on the market is given by

$$Prob(\text{placing a bid})_t^{{}^{BTL}_{OO}\to BTL} = \begin{cases} 1, & \text{if } i \text{ has only 1 house} \\ 0, & \text{if } b_i < 0.75 b_i^d \\ 0, & \text{if } p_i < \overline{p_{Q=0}} \\ \frac{1}{1+e^{(-\beta_4 \Omega_{i,t})^{\frac{1}{12}}}}, & \text{if else} \end{cases}, \tag{4}$$

where the investor always places a bid on the ownership market, if it possesses only one house (which is his home), and never places a bid when his actual bank balance is below 75% of his desired bank balance or his desired purchase price is too low to even bid for a house. If none of these conditions are met, the investor decides according to the perceived capital or rental yield of buying a house. The model has two types of investors, the first,trend-following, tries to buy property predominantly when expected capital gains are high, the second, fundamentalist, if the expected rental yield is high. Their desired purchase price is given by

$$p_t^{OO \to BTL} = q_t^{OO \to BTL}, \tag{5}$$

where it is only limited by the banks maximum mortgage it is willing to grant.

2.1.2 Placing offers on the ownership market

Owner-occupiers sell their home on average every 11 years on the housing market (see arrow 2 in figure 1). This is in line with UK data and reflects households moving. Their offer price depends on the average selling price they observed to be realised on the market for houses of this quality, plus a mark-up and adjusted for the expected time the house will be on the market before being sold. If the expected sale price is below the principal of the mortgage on the house, then the household will not sell their home. If their properties are not rented out at the moment, BTL investors decide if they want to sell their property according to the probability function

$$Prob(\text{placing offer})_{t,k}^{BTL \to BTL} = \begin{cases} 0, & \text{if } i \text{ has only 2 houses} \\ 0, & \text{if } k \text{ has a tenant} \\ 1 - \left(\dfrac{1}{1 + e^{(-\beta_4 \Psi_{k,i,t})^{\frac{1}{12}}}} \right), & \text{else} \end{cases} \tag{6}$$

Their price setting mechanism of BTL investors selling properties is the same as for owner-occupiers.

2.2 Market mechanism

When all bids and offers are made, they are matched in a double-auction process. In a first step, bids of households in social housing are matched with the cheapest house of the highest quality it can afford. If there are two houses of quality 20, then a bid that could afford both would be matched with the cheaper house. Investors' bids are matched with the houses with the highest rental yield they can afford. In a first step all offers are sold to bids, if there is only one bid for that house. The realised price is the offer price. In a next step, all offers matched with more than one bid increases the offer price by a small fraction and is then randomly sold to one of the bids still high enough. After this first iteration, all bids and offers that are left are matched again and the process starts anew. This is done until either all offers or all bids have been matched. Households whose bid did not match any offer will decide again in the next round if they want to bid on the rental or housing market and households whose offers did not match any bids will decide if they want to reduce the offer price in the next round.

2.3 Market cycle dynamics

The core mechanism of the market cycle can be reduced to two main contributors. The households in social housing switching between bidding on the rental and the housing market and the BTL investors switching from buying to selling investment property.

Looking at agents in **social housing**, when **house prices rise**, more households place bids on the market as they expect prices to increase even more and increase their bid price at the same time. A more or less stable number of normal households offer their homes on the housing market, but to higher prices. This leads to higher realised average prices, reinforcing the upswing. With ever rising offer prices, bid prices become restricted by households' income. Households that cannot afford to even bid for the lowest quality house enter the rental market. The upswing continues until at least half of the highest offers cannot be sold. When not all houses get sold, only the comparatively cheapest get sold, as households bid for the lowest priced house given its quality. Because the cheaper houses get sold, the average realised sale price drops. This implies that even without any singular offer on the market having to be lowered, the **market price drops**. The lower average sale prices are then used as basis for the new offers on the market, which will then be lower. Offers not sold will themselves slowly lower their price (but this is not necessary for the cycle to turn).

When prices fall, the number of bids decline as households in social housing expect prices to fall even more, as households compare the cost of housing and renting before deciding if to bid on the housing or rental market (equation (2)). Expected falling house prices increase the perceived cost of buying a house (this can be understood as stronger depreciation). Therefore, they rather enter the rental market. Households still entering the housing market will reduce the value of their bids. This will lead to house prices falling further. Several effects reverse the downfall. First, the decision to either buy or rent is also based on stochastics, i.e. there will always be a minimum of bids on the housing market, even when renting is comparatively much cheaper. Second, while expected falling house prices increase the cost of buying (due to depreciation), lower house prices itself lower the cost of buying, counterbalancing the former effect. Third, with more households entering the rental market, prices rise, making renting comparatively more expensive to buying a house. Taking these effects together, bids begin to increase again in the downturn. Sale offers on the other hand decrease when expected sale prices of a house drop below the mortgage principal outstanding. Falling number of offers and increased bids eventually leads to all houses getting sold. New offer prices of a house are based on the same average sale price, the prices rise. For bid prices to rise as well, at least half of the quality bands need to show a price increase, so that the overall HPI increases.

The mechanism for **BTL investors** is similar as they, too, decide if entering the ownership or the rental market seems to be more financially sensible. With **rising prices**, BTL investors increase their bids on the housing market, as they expect capital yield to go up (this effect is weakened by the fact that rental yield goes down). The further prices rise, at some point investors cannot afford the higher offers which leads to falling prices (with the mechanism described above). When prices fall, investors want to sell their houses due to shrinking expected capital yield (which is weakened by the effect of rising rental yield). As prices fall, households in social housing push on the rental market. When houses are rented out, they cannot be put on the ownership market.

3 Expanding the model

3.1 Consumption function with wealth effects

As seen in the model description, the consumption function in the baseline (equation (1)) serves to keep liquid wealth power-law distributed. This results in high fluctuations of aggregate consumption, as households selling a house usually consume half of the revenue in the following period (given that their current bank balance is higher than their desired bank balance). As most sales happen in the upswing of the housing cycle the model, consumption peaks here at around 100% of total income and then quickly falls back to 50%. This does not seem to be supported by the evidence, as consumption levels do change rather slowly. This has potentially adverse impacts on the wealth distribution and on their leverage. Households selling their homes would reduce their financial wealth position quite drastically, leading to them moving down in the wealth distribution and at the same time requiring them to take on new debt when they decide to buy a new home, which happens frequently in the model. This way, leverage could be overestimated. To address these issues, I implement a different consumption function (I will call the resulting model wealth effect model or alternative consumption model interchangeably) where households' consumption is induced by disposable income and their financial and net housing wealth position. The model assumes an essential consumption that matches the UK monthly income support for a married couple (which are £492.7). Above that, I implement a simple non-essential consumption function, so that non-essential consumption is:

$$c_{i,t} = \begin{cases} \text{if } b_{i,t} - c_{i,t}^{desired} < \zeta y_{i,t}^{m,disp} & , c_{i,t} = \alpha_i y_{i,t}^{m,disp} \\ \text{if } c_{i,t}^{desired} > b_{i,t} & , c_{i,t} = b_{i,t} \\ \text{if } c_{i,t}^{desired} < 0 & , c_{i,t} = 0 \\ \text{if equity position negative} & , c_{i,t} = \delta c_{i,t}^{desired} \\ \text{else} & , c_{i,t} = c_{i,t}^{desired} \end{cases} \tag{7}$$

with

$$c_{i,t}^{desired} = \alpha_i y_{i,t}^{m,disp} + \beta_i \left(b_{i,t} + \gamma (w_{i,t}^h - q_{i,t}) \right) \tag{8}$$

with $y_{i,t}^{m,disp}$ being the monthly disposable income, $b_{i,t}$ the bank balance, ζ works as liquidity preference and is set to twice the monthly disposable income, δ is a deleveraging motive, reducing the desired consumption by 20% if the equity position of the household turns negative. $w_{i,t}^{h}$ is housing wealth and $q_{i,t}$ the mortgage debt, which is the only type of debt in the model. α_i and β_i are dependent on the employment income quartile of the agents, allowing for lower income households to consume more out of disposable income and wealth. α_i is set at 0.99 for the lowest income quartile, 0.96 for the second, 0.93 for the third, 0.9 for the highest excluding the top 10% for which it is 0.85 and 0.6 for the top 1%. [4]. β_i is set accordingly to 0.015, 0.012, 0.01, 0.008, 0.001 and 0.0001. This follows the observation that wealthier households tend to have a lower consumption out of wealth than poorer households (Arrondel et al., 2019). The coefficients in the consumption function are held constant over time. There is however, a growing body of research suggesting this might be a simplification (Carroll et al., 2017; Aron et al., 2012). As the model does not implement a pension system, which is a significant part of household expenses, I account for them by increasing the consumption propensities. This way, more of the income - which would otherwise be paid into a pension fund - is consumed and "leaves the model". Retired households then continue to get some income exogenously. γ gives the relation of the strength of consumption induced by liquid wealth to net housing wealth and is set to 0.25. That the consumption out of housing wealth is lower than that of financial wealth can be supported by the literature (Arrondel et al., 2019; Jawadi et al., 2017; Chauvin and Muellbauer, 2018; Christelis et al., 2015). However, some findings do suggest larger wealth effects of housing wealth than financial wealth (Bostic, Gabriel and Painter, 2009). In the following the model with this adaptation I will call 'wealth effect' or WE for short interchangeably with 'alternative consumption' model or AC .

3.2 Sensitivity analysis

The INET model has in its current form 70 parameters, which are for the main part micro-calibrated from UK data. To understand in a systematic way, which influence on the models outcomes the variables have, I employ the Morris screening method (Morris, 1991) in its improved form developed by Campolongo, Cariboni and Saltelli (2007) as the method is very well suited for ABMs, as one does not have to know in advance in which direction the parameters influence the outputs (i.e. if an increase in the parameter increases or decreases or even has non-linear effects on the output value) (Thiele, Kurth and Grimm, 2014). It calculates the relative importance of each parameter for each model output in question.

[Implement sensitivity analysis here - not finished yet]

[4] As a starting point, these values are in line with US data following Dynan (2004), where the first quintile has an MPC of 0.986, the second 0.9, the third 0.889, the fourth 0.827, and the fifth 0.764. The top 5% have an MPC of 0.628 and the top 1% 0.488.

3.3 Calibration

[Implement MSM here - not finished yet]

4 Model performance

4.1 Housing cycle

The changes to the model are bound to affect several of its outputs. The focus of this chapter is the comparison between the baseline and the WE version. The procyclical version of the model will be introduced in chapter 5.1. To understand if the house price cycles change, I check their cycle length, their volatility, as well as their average level, skewness and kurtosis in table 1. The housing cycle length of both versions is in line with empirical observations, like Strohsal, Proaño and Wolters (2017), estimating it to be 13.1 years. The coefficient of variation - the overall average of all standard deviations of all runs in a Monte-Carlo simulation, normed by the respective runs average - stays constant, as well as the house price index average, its skewness and kurtosis, reflecting overall similar sale patterns.

	Cylce length (years)	Coeff. of Variation	Average	Skewness	Kurtosis
Baseline model	12.43	0.33	0.79	0.35	1.58
Wealth effect	12.58	0.33	0.79	0.29	1.59
Wealth effect and procyclical credit	13.21	0.43	0.85	0.45	1.69

Table 1: House price cycle characteristics - Monte-Carlo simulation

The findings of the coefficient of variation are supported by the histogram of housing cycles (figure 2), showing higher and frequent peaks of the housing cycle when procyclical credit constraints are employed as opposed to fixed credit constraints.

The cylce length in the model is predominantly determined by the price expectation of households. When households look at a longer time horizon in the past to extrapolate into the future, the cycle becomes longer, and vice versa. For reaching the 13 years, households take the last three years into account. If they only take the last year into account the cycle length is reduced to about 7 years. What the model is not yet able to match as well is the stylized fact that upswings usually span over a longer time than downturns, see figure 3. House prices rise pretty strongly in the upswing and then take longer to fall in the downturn.

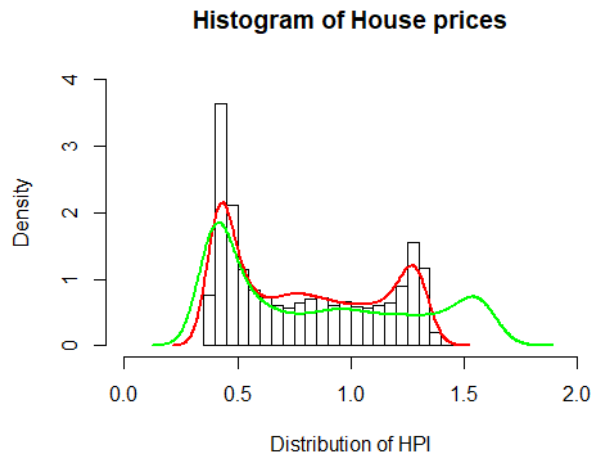


Figure 2: Histogram of the House Price Index, Baseline(bars), wealth effect (red), wealth effect and procyclical credit (green)

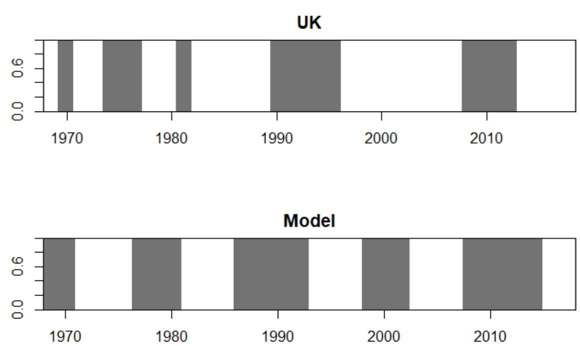
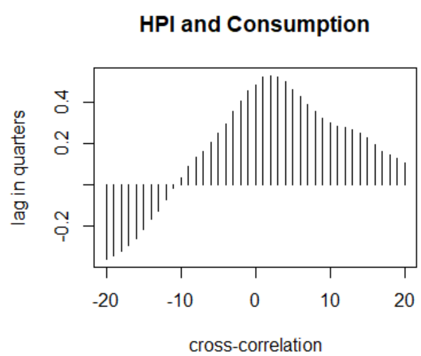
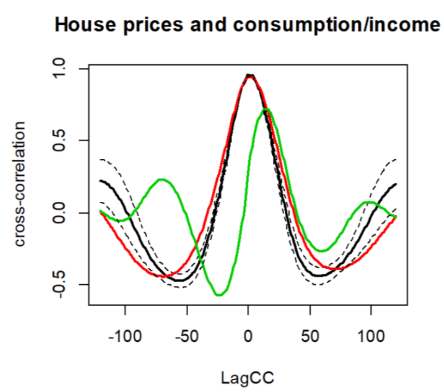


Figure 3: Housing cycles upswings (white) and downturns (grey)), for the UK and the Model; Harding-Pagan filter with minimum cycle 3 years and minimum phase 1 year; UK real house price index, Model single run house price index

As the changes introduced are expected to affect the relationship of consumption and the housing cycle, figure 4b shows the cross-correlations of house prices and consumption of the different model versions. In the baseline (green) consumption is leading house prices as it is highly connected to the sales of houses, which happen mostly in the first part of the upswing. This is mainly due to housing and liquid wealth increasing in the upswing. Liquid wealth increases because households take out more credit in order to buy houses. This credit then ends up on the balance sheet of other households where it induces higher consumption out of disposable income according to equation (3). With the new consumption function house prices and consumption are highly correlated at lag zero. As the INET housing market model has no long-term growth mechanism, like income or population, there is no long-term change in the economic indicators. However, one can observe short- and medium term cycles being generated by the agents economic interactions. When comparing the model to real UK data, I have to therefore detrend it. For that, I use the Hamilton method and apply a 5-year look ahead filter for financial cycle variables and 2-year look ahead for business cycle varibles, as suggested in Hamilton (2018). UK data (figure 4a) suggests consumption to lead by about two quarters, indicating that the model matches this relationship quite well. The HPI is de-trended with a 5-year look ahead and consumption is detrended with 5-years ahead as well, although the relationship also holds with a 2-year detrending.



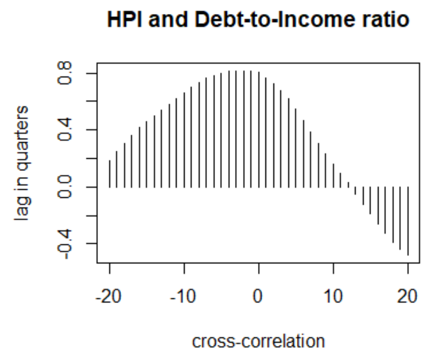
(a) Cross-Correlation House Price Index and Consumption (both detrended with Hamilton 5-year ahead)



(b) Cross-Correlation House Price Index and Consumption-to-income

Figure 4: Cross-correlations INET model, Baseline (green), wealth effect (black), wealth effect and procyclical credit (red)

The debt-to-income ratios follow house prices in UK data (figure 5a), matching the models outcome quite well, regardless of its version.



(a) UK

(b) Model

Figure 5: Cross-correlation House Price Index and Debt-Income Ratios UK (1987-2018) (both detrended with 5-year ahead) and INET model, Baseline (black), wealth effect (red), wealth effect and procyclical credit (green)

Comparing the core indicators of the Bank of England with the models output some important similarities but also divergences arise. The similarities are marked green and mirror number the mortgage approvals, as well as the mean above the median loan-to-income ratio of the owner-occupiers and the mean loan-to-value ratio of BTL households. There are, however, important divergences. The first being the Owner-occupier debt-to-income ratio with a value of above 2 for the baseline and below 2 for the alternative consumption function model, as opposed to be more below 1. Another is that the price to income ratio (average house price to average yearly disposable income) which is significantly higher in the INET model. These two parameters go hand in hand, as higher house prices can only be afforded by more debt. Interest rates do not seem to hampen the housing market significantly, as the high number of transactions are accompanied by very high interest rate spreads. While the model is able to match some of the core indicators, while it matches others only loosely. Important to note is that as expected from the baseline's consumption function, its overall debt measures are significantly higher than with the new consumption function, due to homeowners spending their transaction revenue between moving houses. This is not a desirable model outcome, especially when looking at the distribution of leverage. The new model version improves on this.

Core indicator	Financial Stability Report November 2018, Bank of England				INET housing market model (average of 10 Monte-Carlo runs, adjusted for N households in UK)	
	Minimum since 1987	Average 1987-2006	Maximum since 1987	Previous value (oya)	Baseline	WE
OO mortgage LTI ratio (mean above the median)	3.6	3.8	4.2	4.2	4.16	3.66
BTL LTV ratio (mean)	0.57	-	0.75	0.61	0.75	0.74
Household credit growth	-0.007	0.11	0.22	0.04	0.0	0.0
OO debt to income ratio	0.65	0.78	0.97	0.82	2.33	1.67
Housing transactions (month)	51,660	129,508	221,978	101,100	119,076	120,557
Mortgage approvals	26,284	97,905	132,709	65,742	116,501	109,359
Advances to homemovers	14,300	48,985	93,500	32,100	64,149	60,571
Advances to FTB	8,500	39,179	55,800	30,800	35,962	30,885
Advances to BTL purchasers	3,600	10,128	29,100	6,400	16,390	17,903
House price growth (QoQ)	-0.058	0.017	0.066	0.012	0.0	0.0
House price to income ratio(*)	2.1	2.9	4.6	4.5	6.51	6.22
Rental yield	0.048	0.058	0.076	0.05	0.063	0.078
Spreads (basis points)	35	80	369	121	583	322

Table 2: Core Indicators by the Bank of England and the different model versions, Bank of England (2018)

4.2 Wealth distribution

The second aspect where the new model improves on the baseline is in matching the overall UK wealth distribution. Table 3 shows the models and the UKs wealth distribution divided into net housing wealth (house value less mortgage debt), net financial wealth (their bank balance in the model and overall financial wealth less unsecured credit for the UK) as well as the total net wealth (the sum of both). The distributions are divided up into phases of upswing and downturn. Unfortunately, the UK data is only collected in waves that take two years to complete and the data is limited to the time from 2006-2016. Total net wealth is higher in the UK data than in both model versions. Looking at the sums it is clear that this is due to net housing wealth. In the model the house prices fall to significantly lower levels before picking up again as opposed to UK data. This will become even more clear in figures 7 and **??**. The levels of net financial wealth on the other hand match very closely. The total wealth share of the top 10 % of households in the UK data lies roughly between 43 and 45 % points. The baseline model overshoots with shares between 50 and 54% while the AC model matches closer with shares between 47 and 49%. The 9th decile is also matched better than in the baseline. Looking at net financial wealth, the baseline overshoots the UK data by about the same amount as the AC model undershoots it. The deciles below are overall matched better by the AC model. The same is true for the top decile looking at net property wealth. The 9th and

8th decile are matched better by the baseline, while the rest of the distribution is more or less even. Apart from the first decile which is more closely matched by the AC model. Looking at the UK data, the top decile experiences a decline in wealth shares, driven by net financial as well net property wealth. This is not reflected in both versions of the model. This will be discussed in more detail below. In conclusion, the AC model is able to match the UK wealth distribution with more accuracy. Therefore, I will continue the evaluation of the wealth distribution with the AC model alone.

	UK Data				**Baseline**				**Wealth Effect**			
Total net wealth deciles	Up-swing (ths)	Down-turn, (ths)	wealth share upswing	wealth share downturn	Up-swing (ths)	Down-turn, (ths)	wealth share upswing	wealth share downturn	Up-swing (ths)	Down-turn, (ths)	wealth share upswing	wealth share downturn
					Net property wealth							
1st	-2	-1	-0.1%	-0.1%	-20	-29	-2.2%	-3.4%	-10	-14	-1.1%	-1.7%
2nd	1	1	0.0%	0.0%	0	-1	-0.1%	-0.1%	0	0	0.0%	0.0%
3rd	10	10	0.6%	0.7%	0	-1	0.0%	-0.1%	0	0	0.0%	0.0%
4th	44	42	2.8%	3.0%	17	4	1.8%	0.5%	11	4	1.2%	0.5%
5th	86	84	5.5%	6.0%	44	25	4.7%	3.0%	41	30	4.6%	3.6%
6th	131	122	8.3%	8.6%	69	53	7.5%	6.4%	69	59	7.8%	7.0%
7th	170	160	10.8%	11.4%	97	84	10.5%	10.1%	99	91	11.2%	10.8%
8th	223	204	14.1%	14.4%	132	120	14.3%	14.4%	135	129	15.3%	15.3%
9th	298	268	18.9%	19.0%	191	180	20.7%	21.7%	187	186	21.3%	22.1%
10th	617	521	39.1%	36.9%	394	394	42.7%	47.5%	349	358	39.7%	42.5%
SUM	1,577	1,411	100.0%	100.0%	923	830	100.0%	100.0%	880	843	100.0%	100.0%
					Net financial wealth							
1st	-5	-5	-0.9%	-1.0%	8	11	1.5%	2.0%	6	8	1.1%	1.4%
2nd	0	0	0.0%	-0.1%	2	2	0.4%	0.4%	1	1	0.1%	0.1%
3rd	2	1	0.3%	0.2%	6	4	1.2%	0.8%	2	2	0.4%	0.3%
4th	6	6	1.0%	1.2%	15	13	2.7%	2.4%	11	7	1.9%	1.2%
5th	12	11	2.0%	2.2%	18	19	3.4%	3.7%	22	21	3.8%	3.8%
6th	20	19	3.6%	3.8%	23	24	4.3%	4.6%	28	28	4.9%	5.2%
7th	35	32	6.1%	6.5%	30	29	5.5%	5.6%	35	34	6.2%	6.3%
8th	58	50	10.3%	10.2%	40	39	7.4%	7.4%	50	46	8.8%	8.6%
9th	92	85	16.2%	17.4%	55	54	10.2%	10.2%	87	78	15.2%	14.6%
10th	346	292	61.3%	59.7%	341	332	63.4%	63.0%	330	314	57.8%	58.4%
SUM	564	490	100.0%	100.0%	537	527	100.0%	100.0%	572	538	100.0%	100.0%
					Total net wealth							
1st	-7	-6	-0.3%	-0.3%	-12	-18	-0.8%	-1.3%	-4	-7	-0.3%	-0.5%
2nd	1	0	0.0%	0.0%	2	1	0.1%	0.1%	1	0	0.0%	0.0%
3rd	11	11	0.5%	0.6%	6	4	0.4%	0.3%	2	1	0.1%	0.1%
4th	50	48	2.3%	2.5%	31	17	2.2%	1.2%	21	11	1.5%	0.8%
5th	98	95	4.6%	5.0%	62	44	4.2%	3.3%	62	51	4.3%	3.7%
6th	151	140	7.1%	7.4%	92	77	6.3%	5.7%	96	87	6.6%	6.3%
7th	205	192	9.6%	10.1%	127	113	8.7%	8.3%	134	125	9.2%	9.0%
8th	281	254	13.1%	13.3%	171	159	11.7%	11.7%	185	175	12.8%	12.7%
9th	390	353	18.2%	18.6%	246	234	16.9%	17.2%	274	265	18.9%	19.2%
10th	962	813	44.9%	42.8%	734	726	50.3%	53.5%	679	672	46.8%	48.7%
SUM	2,141	1,901	100.0%	100.0%	1,461	1,356	100.0%	100.0%	1,451	1,381	100.0%	100.0%

Table 3: Wealth Composition and Distribution UK and Model Output, Wealth and Asset survey 2018 aggregated data,averaged over five 2-year periods from 2006-2016, excluding physical and pension wealth, upswing from 2006-2008 and 2012-2016, downturn from 2008-2012. Model data averaged from single run with 1200 periods

Wealth inequality in the UK did fall continuously over the course of the last century, from before the first World War until around 1980. While the top

1% of the wealth distribution owned 70% of total wealth around 1900, they owned only 16% by 1980. This trend then came to an abrupt stop and the wealth shares of the top 10% have been relatively stable, while the top 1 % saw an increase (Alvaredo et al., 2018). One would assume that rising house prices increase the wealth for all households with housing wealth. This would presumably lead to a decrease in the top wealth shares, as a majority of the population are home owners, while at the same time the inequality between home owners and renters would increase. To see how the share of total wealth of the top 10 and 1% changes with regards to the housing cycle, figure 6 shows their cross-correlation from 1980 - 2012. The HPI is de-trended with a 5-year look ahead to account for the underlying longer waves of the financial cycle, while the wealth shares are either de-trended with 5- or 2-years look ahead, allowing for wealth inequality being more influenced by the shorter business as well as the longer financial cycle. The result for the top 10% wealth share (top

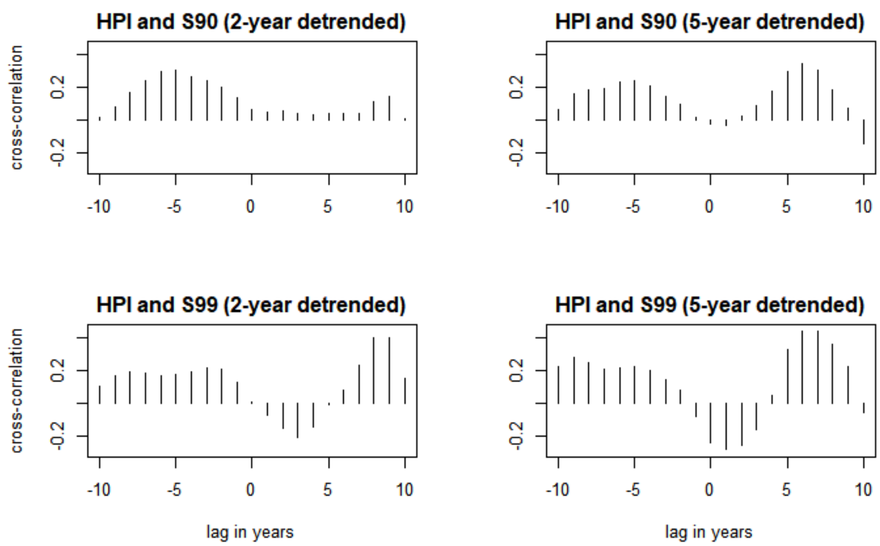


Figure 6: Cross-correlation of the house price index (detrended with 5-year look ahead) with the top 1% and 10% wealth shares, detrended with either 2- or 5-year look ahead; sources: OECD, Wealth top income data base (Alvaredo et al., 2018), from 1980-2012, imputed values 2004, 2007-08, 2010-11

of the figure) show no correlation with the housing cycle at lag=0, while the housing cycle seems to lead by five years, regardless of the de-trending method. However, the correlation seems to be not very strong. De-trended with 5-year look-ahead, top 10% wealth share seems to be positively correlated with the housing cycle 6 years in the future. This correlation is stronger for the top 1% share of total wealth (bottom figures). Moreover at lag=0, the top 1% wealth share seems to be slightly negatively correlated with the housing cycle, in line with what we expected.

Another data source than Alvaredo et al. (2018) is the aforementioned Wealth and Asset Survey. While this gives a clearer picture of the rest of the wealth distribution, instead of only the top 10%, the survey waves are taken over the course of two years, making it more difficult to connect changes in wealth composition to changes in the housing cycle. Figure 7 shows on the left hand side the five waves of the asset survey, divided by the financial and housing wealth positions (excluding physical and pension wealth) of the bottom 10%, the 10%-50%, the 50-90% and the top 10%, as well as the averaged cycle component of the house price index (right scale). On the right hand side is the wealth distribution of the AC model from a housing cycle peak over a trough to the next peak. This is to mimic the time frame from the UK data. The first thing that is immediately obvious is the stronger pronounced drop in house prices as opposed to the time frame in the UK. This is rather a calibration issue of when households start buying houses again so that the cycle turns. It will not really diminish the value of the analysis because first, the underlying mechanisms are the same and second, the peak is values are very close to the data. The UK data shows that the bottom 50% do not see a significant change of their wealth share over the course of the period. The bottom 10% see negative wealth positions in the boom, and in the bust phase. The top 10% share in total wealth decreases in the beginning of the crisis (2008-10) but then bounces back, while their wealth composition changes from housing to more financial wealth. In the last period, with rising house prices the top deciles wealth share decreases again, rather due to their financial wealth than their housing wealth. The change in total wealth share for the 50-90% of the wealth holders is mainly driven by changes in housing wealth. Their financial wealth as part of total wealth stays almost constant. The wealth distribution in the model is driven by the housing cycle. Overall level of wealth changes most with changing gross housing wealth, then with the change in credit and financial wealth. In the upswing not only gross housing wealth increases but also credit gets expanded and with that its flipside, money gets created. While all wealth deciles experience an increase in wealth, their share depends on the difference in growth rates between deciles. Intuitively, any group increases its wealth share when its wealth growth rate is higher than that of the whole population.

The share of gross housing wealth of a wealth decile can change due to several factors. As the housing stock is fixed in the model, the aggregate value of housing is completely determined by the house price index. Changes in the house price index affect all houses equally, which is why deciles only experience a change in their wealth share when there are deciles without any houses. A change in the share of gross housing wealth of a decile can be caused by changes in the number as well as the quality of houses held. They can change due to transactions, social movement and inheritance. Then an increase in house prices will reduce its share and vice versa increase the share of all deciles with housing. Transactions between households in different wealth deciles are at first only an asset swap, not influencing the wealth distribution. They only lead to changes over time when house prices change. Social movement describes households changing the wealth decile between two points in time. When households die, they inherit

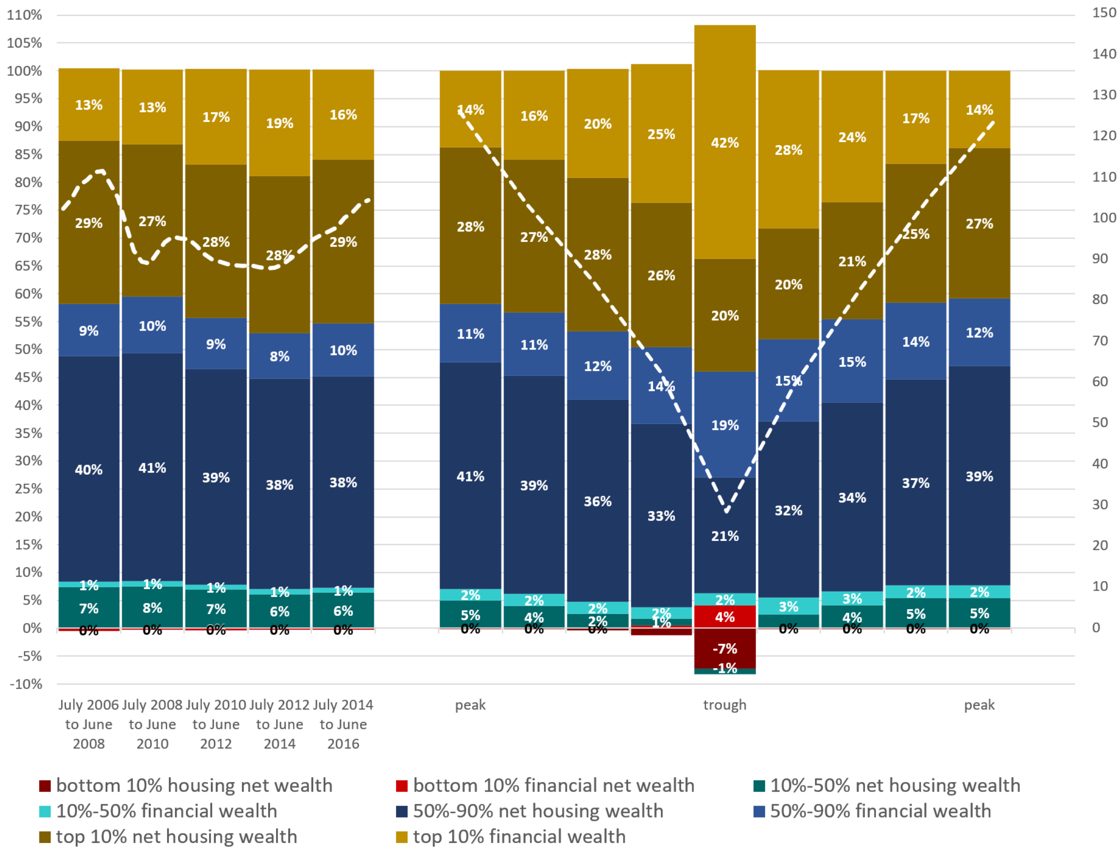


Figure 7: Share of total net wealth by households sorted for their net wealth position over the housing cycle (lhs) and UK house price index (rhs), Source: Wealth and Asset Survey 2018, OECD Economic Outlook, UK constant house prices, 2006 = 100, AC model from a peak over trough to peak. Models house price index: 100 = UK house prices of 2011.

their housing and financial wealth to random living household. Depending on the wealth position of the heir she will land in a different household than the bequeather, leading to shifts in the wealth share of deciles. In the housing market upswing, there are two main effects driving the decrease in the top wealth share. In the beginning of a housing upswing there are a substantial part of houses on the market which has not cleared since the last cycle. The houses not being sold until then are mostly higher quality houses put there by normal owner-occupiers. Owner occupiers sell their home on average every eleventh year, due to reasons not addressed in the model (like moving, divorces, etc.). The frequency is based on the English Housing Survey from 2013. There are more higher quality houses on the market, as households' bid prices (equation (3)) are constrained by their bank balance, income and future price expectation. In effect this leads to cheaper and lower quality houses to be transacted more than higher quality and more expensive houses. Higher quality houses are rather being held by wealthier household. In the first part of the upswing these houses get finally sold, until the offer side of the market is completely cleared. As the houses are sold to households more dispersed over the wealth distribution this leads to a swap from housing to financial wealth for these wealthier households. As house prices continue to rise, these households having sold their homes fall back. The top wealth decile looses wealth shares in this part of the upswing as it is selling more houses than it is buying, thereby not profiting as much from rising house prices. This mechanism is probably not found or at least less pronounced in reality. However, there is another effect in the same direction, which most probably is. After the market has been cleared the decline in the top 10% wealth slows down considerably, yet without stopping. While the top decile is experiencing an increase in their net housing wealth position higher than the rest of the distribution, their relative financial position declines. This is mainly due to a replacement of households with a higher financial wealth share for households with a higher net housing wealth share. The households moving up in the wealth distribution have on average higher leverage than the households leaving the top wealth share. At the top of the housing cycle the median and mean above median LTI ratios of the top decile increase steadily. Households that bought houses in the previous periods see their wealth position improve. As they are leveraged their net wealth rises faster with increasing house prices. However, when the house cycle turns, this leverage becomes problematic. Their equity position is hit harder than that of less leveraged households and they move down the wealth distribution. This is the main effect why the top decile increases its wealth share in the downturn. The top decile improves its relative position mainly by amassing more of the financial wealth. As this model does not incorporate any financial asset movements, it shows how strongly leverage can affect the wealth distribution all else equal (Kuhn et al., 2019), and that this is vital in understanding wealth distributions and their dynamics.

5 Household leverage and vulnerability

Leverage can have strong effects on the wealth distribution and can potentially lead to households becoming financially vulnerable. There are several measures discussed in the literature about how to measure households' financial vulnerability. A prominent one is the debt-measure-to-income ratio of households, where a value above 0.3 and especially 0.4 is attributed to a higher probability of default (BoE, 2017). Another measure is a financial distress index, considering apart from the debt-service-to-income ratio the financial wealth of households (Ampudia et al., 2016). Before looking at these measures over the course of the housing cycle in the AC model, I introduce procyclical credit conditions into the model.

5.1 Procyclical credit constraints

In the baseline version of the model rising house prices lead to an increase in credit demand, as households and investors expect rising house prices in the future which increases their bid-values. This leads to higher sales prices and therefore higher need for credit. Yet not the other way around, as agents are never really constrained by credit restrictions, such as the loan-to-value ratio or the interest rate. In fact, their desired purchase prices are the limiting factor. In the real economy, there seems to be a very strong push from mortgage credit to housing prices (Favara and Imbs, 2015; Lindner, 2014; Muellbauer et al., 2015). The liberalisation of credit supply and the push of banks to lend out loans seems to have led to rising asset prices. In order to allow for this channel to be active in the INET model, I make the bank's credit constraints depended on the yearly house price appreciation rate, so that the LTV ratio χ, which is the most limiting credit constraint in the baseline model[5], dependant from the change in house prices is

$$\chi = \min(\alpha_{10} g_t + \chi_{param}, \quad 1.0), \tag{9}$$

with α_{10} being 0.6 and χ_{param} 0.8. In the following I will call this version of the model 'wealth effect with procyclical credit' or WE procyclical, for short. Overall it can be said that the procyclical credit constraint leads to higher housing prices and higher volatility as well as higher household indebtedness as the WE version. The procyclical credit conditions lead indeed to higher overall credit and to more pronounced housing cycles, as can be seen in figure 2 and table 1. How these aggregate changes over the distribution and over the cycle will be discussed below.

5.2 Leverage and financial vulnerability

Figure 8 shows the median LTI of all households and the I break the cycle down into four periods and take the average measures between start and endpoint. On the left hand side is the AC model and on the right hand side AC with procyclical credit. Median LTI ratios are generally highest in the middle-top of the distribution. In the upswing the leverage of the top deciles increases. Partly due to taking on new credit, but also due to more leveraged households moving up the distribution. They move back once prices fall again. The first decile is populated by households with negative equity when house prices are low. The share of households with a debt-service-to-income ratio above 0.4 show a similar movement, however, both top wealth deciles have significantly lower shares of these households. Looking at the median LTI in a procyclical environment, we see that households from a broader spectrum of the distribution can leverage up. Especially in decile three and four. In the lowest decile we see an even higher LTI ratios in the downturn. These are households with high DSR ratios, but these are mainly BTL investors with otherwise higher financial asset positions,

[5] To simplify and make the results more attributable to this change I deactivated all other credit constraints - also in the baseline - without it affecting the simulations significantly.

as shown in figure 9. The share of households with high DSR ratios almost doubles and spreads as well, as poorer households can leverage up and there being more mobility over the cycle.

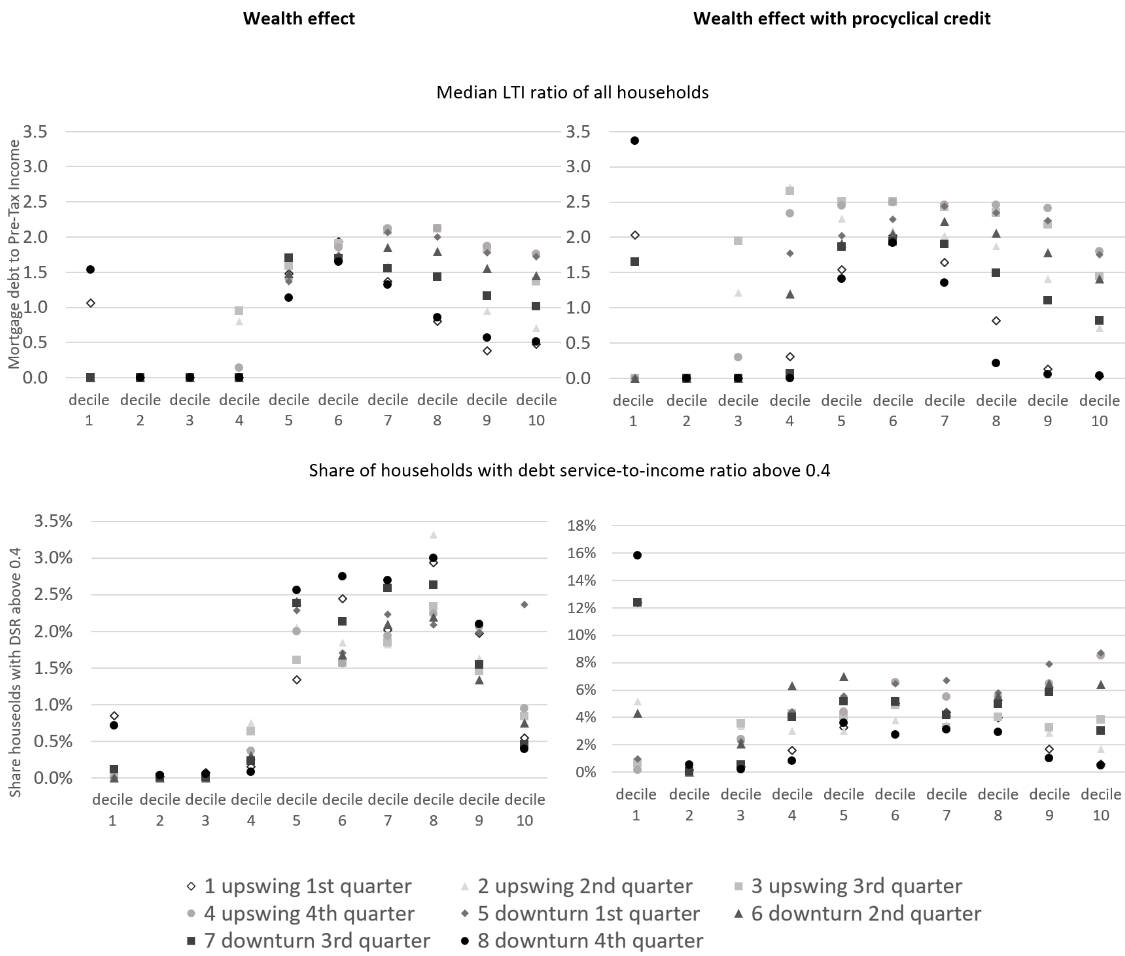


Figure 8: Median LTI and DSR above 0.4 for WE and WE procyclical over the course of one cycle.

In figure 9 we see the share of households that are financially distressed, measured following Ampudia et al. (2016) taking into account the debt-service-to-income ratio and the financial wealth of a household. As households with high DSRs could have a high amount of financial wealth, making them less vulnerable. Only when both come together, the probability of default or consumption reduction increases significantly. The results show that it is more the lower-middle part of the distribution that is financially distressed. Procyclical credit increases the vulnerability especially in the upswing and over almost the whole part of the distribution.

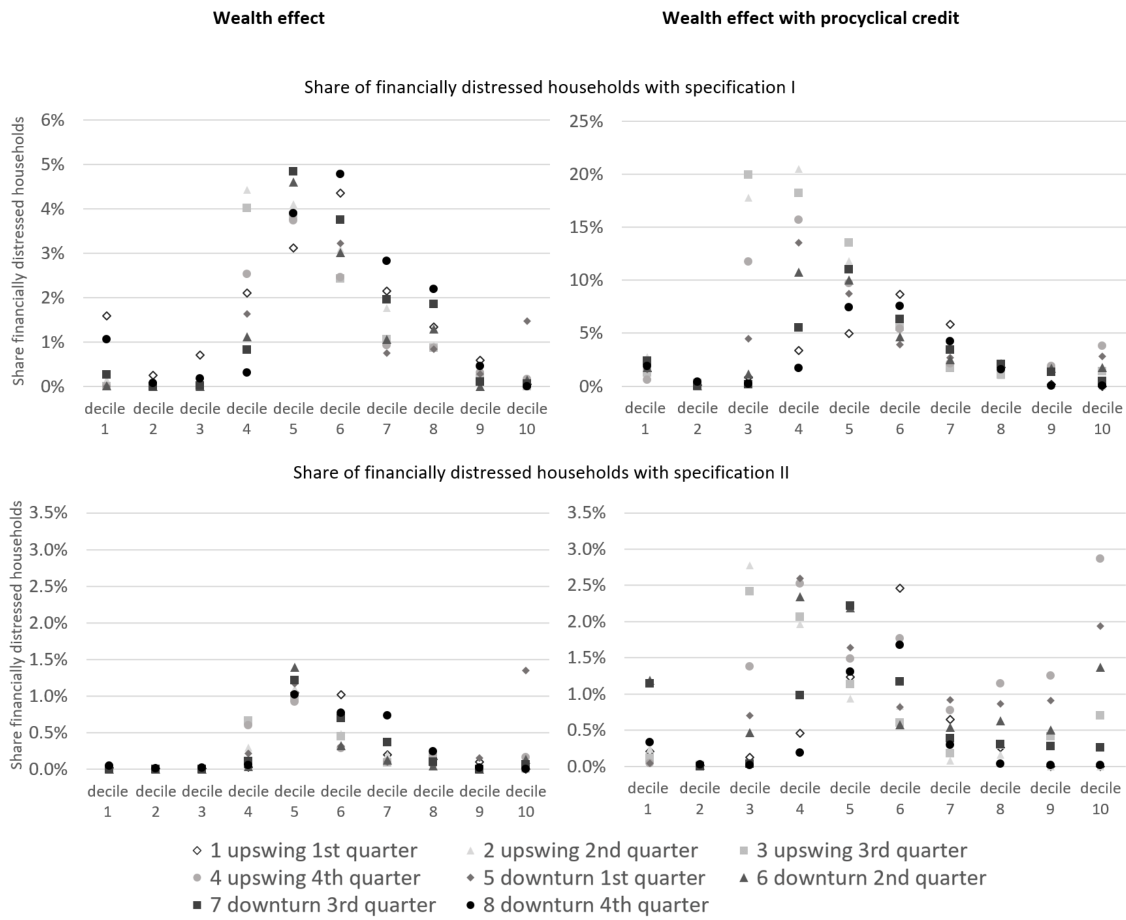


Figure 9: Share of households being financially distressed, following (Ampudia et al., 2016). Specification I: household can pay one month of mortgage payments out of their liquid wealth, when calculating with the basic living costs spent every month with 70% of the median income. Specification II: household can pay half a month of mortgage payments out of their liquid wealth, when calculating with the basic living costs spent every month with 40% of the median income.

Table 4 gives a breakdown of the mean above median measures for LTI and LTV ratios for different kinds of agents over the course of the cycle. It gives insight into who is driving the leveraging the most. From the mean above median LTI values the BTL investors seem to be clearly driving the credit expansion. They also take the most advantage of the procyclical credit conditions. Households in their first homes are also getting more leveraged. They are also able to buy a house at the average age of 38.7 in the procyclical model versus 40.4

without procyclical credit[6]. LTI ratios tend to be higher in the upswing, as the income of households stays mostly the same (with the exception of BTL investors who can rent out their properties). The LTV ratios fluctuate more with the housing cycle. Here we do not see this stark of a difference between BTL investors and the rest of the population. This measure rather obfuscates the financial vulnerabilities of households.

6 Conclusion

Mortgage debt plays a huge role when looking at wealth distributions and financial fragility. Higher leveraged households move up in the wealth distribution in a housing market upswing and lead to a lower total wealth share of the top 10%. This effect is reversed in the downturn. The wealth distribution becomes more volatile. It shows that for understanding wealth distributions one should include housing and mortgage debt. Regarding the fragility side of the housing cycle, households in the middle and middle-top of the wealth distribution leverage up most. The most financially vulnerable households are found at the lower-middle of the wealth distribution, especially in the middle part of the upswing. Procyclical credit conditions increase the access for a broader set of households while the the lower-middle of the wealth distribution in the upswing becomes most financially distressed.

[6] This is the average over the whole of 1200 months and not only over one cycle.

time \decile	Alternative consumption function										Alternative consumption function, procyclical credit									
	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
mean above median LTI all debt holders																				
I	3.42	2.72	2.77	2.86	3.13	3.36	3.18	2.86	2.56	2.32	6.98	3.68	3.37	3.28	3.32	3.33	3.14	2.95	2.88	2.33
II	3.72	-	1.73	2.95	3.16	3.26	3.32	3.40	3.00	2.90	12.58	5.15	4.74	3.99	3.70	3.53	3.59	3.54	3.63	3.39
III	3.36	-	-	3.11	3.31	3.42	3.42	3.51	3.38	3.43	13.73	5.32	5.19	4.57	4.32	4.27	4.02	4.13	4.52	5.31
IV	2.46	-	2.38	3.17	3.38	3.37	3.36	3.42	3.33	3.83	8.29	5.35	4.97	4.61	4.65	4.92	4.88	4.83	5.42	7.44
V	2.54	-	-	3.26	3.39	3.28	3.37	3.35	3.26	3.72	5.27	5.03	5.25	4.59	4.64	4.84	4.96	4.62	5.22	7.04
VI	2.66	3.97	2.45	3.50	3.41	3.26	3.29	3.25	3.16	3.30	6.57	4.45	6.22	5.17	4.78	4.14	4.25	4.10	4.37	5.80
VII	2.83	2.48	2.86	3.74	3.46	3.20	3.15	3.06	2.93	2.87	8.26	4.32	4.53	4.90	4.05	3.69	3.60	3.62	3.96	4.14
VIII	3.20	2.70	2.97	3.57	3.41	3.21	3.03	2.70	2.52	2.35	6.45	3.45	3.36	3.64	3.68	3.37	3.18	3.15	2.90	2.63
mean above median LTI BTL investors																				
I	3.21	-	1.99	1.88	1.89	2.04	1.99	2.55	2.66	3.04	10.63	1.60	1.67	1.77	2.15	3.41	4.46	3.71	5.05	3.56
II	4.09	-	-	1.87	1.65	1.90	2.13	2.96	3.06	3.49	16.41	-	4.32	3.01	2.81	3.86	4.43	4.61	5.46	4.69
III	-	-	-	1.57	1.74	1.94	2.26	3.04	3.59	4.01	30.28	-	12.48	8.07	7.74	8.35	7.88	9.84	9.12	8.54
IV	1.91	-	-	1.54	1.29	1.87	2.28	2.84	3.62	4.71	34.06	-	12.40	10.23	12.05	13.09	13.46	14.89	13.64	12.27
V	2.31	-	-	1.84	1.14	1.85	2.13	2.80	3.41	4.59	5.91	5.51	11.03	12.75	13.04	12.39	13.57	14.16	12.88	11.51
VI	2.41	-	1.85	1.90	1.22	1.79	1.90	2.66	3.22	3.99	16.41	-	12.98	13.51	12.44	9.05	10.59	11.52	9.78	10.50
VII	2.29	1.55	1.81	2.03	1.54	1.62	1.85	2.68	3.01	3.60	15.36	-	5.23	9.37	7.41	6.96	7.13	7.93	8.48	7.55
VIII	2.70	1.40	1.49	1.55	1.98	1.72	1.88	2.40	2.63	3.17	10.75	1.71	1.60	2.58	4.62	4.80	5.59	4.87	5.48	4.42
mean above median LTI households in their first home																				
I	2.71	1.98	2.14	1.98	2.62	2.96	2.67	2.68	1.83	1.55	3.72	3.42	3.20	3.03	2.95	2.91	2.79	2.67	2.31	2.15
II	3.30	-	1.73	2.41	2.57	2.79	2.90	3.42	2.52	1.96	5.71	5.15	4.73	4.03	3.48	3.13	3.21	3.08	3.25	2.76
III	3.24	-	-	2.53	2.61	2.94	3.06	3.52	3.40	2.50	5.24	6.01	4.71	4.39	4.12	3.93	3.72	3.62	3.50	3.17
IV	2.46	-	2.38	2.66	2.58	2.89	2.98	3.34	3.24	2.71	5.34	5.45	4.86	4.45	4.20	4.11	3.97	3.87	3.69	3.45
V	2.50	-	-	2.73	2.58	2.74	3.05	3.17	3.08	2.71	5.21	5.02	4.99	4.31	4.15	3.96	3.98	3.73	3.52	3.10
VI	2.58	3.97	2.11	2.81	2.52	2.75	2.97	2.97	2.91	2.35	5.02	4.81	4.67	4.26	4.13	3.75	3.72	3.46	3.14	2.76
VII	2.49	1.72	3.08	3.20	2.62	2.64	2.80	2.64	2.58	1.84	4.71	4.36	3.43	4.08	3.94	3.63	3.29	2.96	2.83	2.38
VIII	2.46	2.14	2.26	2.94	2.73	2.76	2.59	2.27	1.91	1.53	3.97	3.23	3.03	3.44	3.60	3.24	2.80	2.72	2.33	2.16
mean above median LTV all debt holders																				
I	1.85	1.53	1.43	1.30	1.24	1.07	0.95	0.90	0.89	0.83	2.45	1.63	1.42	1.29	1.07	0.98	0.90	0.83	0.82	0.78
II	1.38	-	1.49	1.08	0.85	0.73	0.68	0.65	0.66	0.62	1.43	1.00	0.99	0.79	0.63	0.59	0.57	0.55	0.56	0.53
III	1.12	-	-	0.77	0.61	0.57	0.54	0.51	0.51	0.46	1.14	1.00	0.80	0.60	0.54	0.52	0.47	0.46	0.47	0.41
IV	1.05	-	1.00	0.70	0.52	0.48	0.46	0.42	0.40	0.37	1.06	0.99	0.79	0.52	0.48	0.46	0.43	0.41	0.41	0.36
V	1.10	-	-	0.80	0.55	0.49	0.47	0.43	0.41	0.37	1.10	1.01	0.93	0.57	0.50	0.47	0.45	0.41	0.39	0.35
VI	1.19	1.11	1.05	0.91	0.65	0.58	0.53	0.48	0.46	0.41	1.25	1.06	1.03	0.75	0.60	0.53	0.49	0.45	0.42	0.39
VII	1.45	1.27	1.22	1.13	0.87	0.73	0.65	0.60	0.58	0.52	1.49	1.05	1.13	0.98	0.73	0.62	0.56	0.51	0.50	0.44
VIII	1.87	1.38	1.41	1.33	1.19	1.01	0.90	0.84	0.80	0.75	2.34	1.54	1.53	1.30	1.12	0.95	0.84	0.80	0.77	0.73
mean above median LTV BTL investors																				
I	1.67	-	1.31	1.19	1.15	0.96	0.89	0.96	0.89	0.84	2.58	1.58	1.40	1.20	1.27	1.74	1.61	1.26	1.27	1.11
II	1.41	-	-	0.93	0.76	0.71	0.64	0.64	0.64	0.57	1.48	-	1.24	0.83	0.70	0.79	0.86	0.88	0.64	0.47
III	-	-	-	0.69	0.51	0.49	0.51	0.50	0.45	0.41	1.17	-	0.95	0.79	0.76	0.76	0.71	0.71	0.60	0.41
IV	1.02	-	-	0.69	0.36	0.40	0.40	0.41	0.37	0.35	1.06	-	0.90	0.75	0.74	0.72	0.70	0.66	0.60	0.40
V	1.10	-	-	0.85	0.36	0.40	0.40	0.43	0.37	0.35	1.09	1.00	0.97	0.83	0.78	0.72	0.71	0.66	0.61	0.41
VI	1.14	-	1.07	0.93	0.44	0.47	0.44	0.49	0.41	0.39	1.21	-	1.04	0.93	0.84	0.77	0.76	0.71	0.64	0.47
VII	1.37	1.12	1.10	1.11	0.71	0.59	0.56	0.61	0.52	0.49	1.39	-	1.11	1.04	0.96	0.86	0.80	0.79	0.76	0.52
VIII	1.75	1.07	1.06	1.08	1.08	0.89	0.82	0.86	0.78	0.71	2.32	1.67	1.29	1.28	1.18	1.19	1.15	0.99	1.02	0.76
mean above median LTV households in their first home																				
I	1.98	1.51	1.33	1.20	1.20	1.08	0.87	0.88	0.86	0.82	2.43	1.58	1.43	1.29	1.07	1.00	0.94	0.89	0.81	0.85
II	1.39	-	1.49	1.08	0.81	0.72	0.65	0.65	0.67	0.64	1.29	1.00	0.99	0.81	0.63	0.59	0.62	0.57	0.58	0.62
III	1.13	-	-	0.78	0.58	0.52	0.52	0.50	0.50	0.51	1.11	1.00	0.80	0.60	0.53	0.49	0.45	0.44	0.46	0.45
IV	1.05	-	1.00	0.71	0.48	0.43	0.41	0.41	0.39	0.40	1.06	1.00	0.81	0.53	0.46	0.42	0.39	0.38	0.38	0.36
V	1.10	-	-	0.79	0.50	0.43	0.43	0.41	0.40	0.41	1.10	1.01	0.94	0.56	0.46	0.41	0.41	0.37	0.34	0.32
VI	1.19	1.11	1.05	0.90	0.58	0.50	0.49	0.45	0.45	0.45	1.26	1.04	1.04	0.70	0.54	0.47	0.45	0.42	0.37	0.35
VII	1.48	1.25	1.26	1.13	0.79	0.65	0.59	0.56	0.57	0.56	1.52	1.03	1.13	0.95	0.68	0.57	0.51	0.47	0.44	0.38
VIII	2.01	1.36	1.37	1.26	1.11	0.92	0.85	0.78	0.78	0.80	2.43	1.58	1.53	1.25	1.09	0.90	0.78	0.80	0.71	0.77

Table 4: Leverage ratios for different kind of agents over the course of one housing cycle. I - upswing 1st quarter II - upswing 2nd quarter III - upswing 3rd quarter IV - upswing 4th quarter V - downturn 1st quarter VI - downturn 2nd quarter VII - downturn 3rd quarter VIII - downturn 4th quarter

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