Imperial College London

BEng Individual Project
Interim Report

Imperial College London

Department of Computing

An Agent-Based Model of the UK Housing Market

Supervisor:
Dr. Ce Gou

Author:
Max Stoddard

Second Marker:
Dr. Chiraag Lala

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Chapter 1

Introduction

In the UK, the 2008 Global Financial Crisis caused house prices to fall around 20% from the third quarter of 2007 to the second quarter of 2009, along with unemployment rates increasing from 5.2% in the first quarter of 2008 to 7.8% in the second quarter of 2009 [1]. Major global financial crises can be worsened by the housing market as evidenced in a working paper by the International Monetary Fund, who state that, 'the catalyst of the crisis was the overextended U.S. housing and mortgage markets' and then the 'trigger was the turnaround in U.S. house prices' [2, III. A.]. Additionally, the housing market is a particularly distinctive market because changes affect not just the individuals in a society, but also the major financial systems. In the UK, property wealth makes up the largest proportion (40%) of household wealth [3], so when the cost of mortgages and housing prices change, this affects individual households' wealth and debt, but also banks' capacity to lend and their asset quality. Because of this, housing is key for policy makers and regulators, who aim to target the highest-risk mortgages and the banks most exposed to them. These policymakers need to know which households have high debt relative to income and how many of these risky mortgages there are, so they can make policies that affect the riskiest cases without making mortgages less accessible to the majority. These policy makers clearly need tools that represent the diversity of households and the edge-targeting mortgage policies.

Agent-Based Models (ABMs) are simulations in which a system is modelled as many 'agents', each with their own calculated decisions in an environment, based on their own parameters and rules. Each of these agents interacts with many other agents through a series of many small micro decisions. This leads to larger macro trends to form across a system. ABMs are more useful for these housing-market policymakers than other traditional economic model types like Dynamic Stochastic General Equilibrium (DSGE) models and reduced-form models for several reasons [4]. Firstly, ABMs are well suited to scenarios, like the housing market, where there are many diverse characters in the playing field interacting. In the housing market, students have hugely different housing requirements to a retiree and are far more likely to be renting, due to lower income and total wealth. ABMs represent this heterogeneity far more effectively than these other model types because they do not force every agent into a small number of averaged groups. Macro trends are created directly through agent decisions and interactions, unlike DSGE and reduced-form approaches where the simulation is assumed to reaching an equilibrium state, which does not suit the continually rise and fall in costs in the housing market. Secondly, ABMs are better for policy testing than these traditional models. Different policy changes affect separate groups in the housing sector differently. Rather than having one average household affected, you can see how policy changes affect these distinct groups. If policymakers are trying to make it easier for first-time buyers to buy houses, an ABM can show if a policy helps this group and if knock-on effects emerge elsewhere in the system, unlike traditional models in which report a single average response. Finally, ABMs naturally capture the boom-and-bust dynamics in the housing market. In the housing market, houses take time to build, it takes time for buyers/renters to find a house to move into and banks can suddenly reduce how much they are lending. Slight changes in policy can lead to a stronger market or a crash and ABMs can show the steps which lead to these reactions directly, unlike other models which assume the market will always settle towards an equilibrium.

For this individual project, I am aiming to build upon an existing ABM of the UK Housing Market, initially created by Baptista et al in 2016 [5] and later improved by Carro et al. in 2022 [6], whilst collaborating with the Bank of England. The aims of my project are to:

- Ensure my version of the UK Housing Market ABM is faster than the current model.
- Update the ABM to show the latest trends and insights into the post-Covid UK Housing Market and Economy (post-2023).
- Improve the ABM interpretability by improving visualisation for highly multidimensional model outputs.
- Validate my version of the UK Housing Model reproduces seleced real-world patterns.

As of authoring this report, so far for this project I have:

- Updated income tax, national insurance, and person allowance rates in the model.
- Updated 5 major calibration sources with new recent data from Wealth and Assets Survey.

I will discuss these improvements in depth in Section 4.

Chapter 2

Background

2.1 Stylised ABM of the UK Housing Market

In 2009, Gilbert et al. created one of the first Agent-Based Models of any housing market worldwide, which happened to be a model of the UK [7]. Their aim was to create a model in which housing trends are created through interactions between buyers, estate agents, and sellers and not due to aggregates assigned in the model. This aligns with the concept that the housing market is very heterogeneous, and trends form through interactions of many different players, as explained in Chapter 1. In each period, individual households start out as buyers or sellers. Local estate agents then provide valuations that sellers can use to set asking prices and buyers make offers on these prices. This creates a cycle of valuation, listing, search and buying which gives rise to trends in a variety of statistics, for example, average house price to earnings ratio.

Gilbert et al. met their aim to create a simple model of the UK Housing Market, however, there are several key limitations of this early model. Firstly, their model scale, which has a maximum of only 2500 houses in their 'town', is far smaller than a model would need to be to predict the future of a large, full-scale housing market, like the whole of the UK. Secondly, the rental market was not a part of this model. The rental market is an important part of any housing market. In the UK, around 36% of the population rents privately or socially [8], so incorporating these demographics of the population is a requirement to completely model the UK Housing Market. Thirdly, calibration was done on a macro-level with parameters 'calibrated to match approximately the actual English situation' in 2008 [7]. This is a limitation as it is possible for the model to match macro-trends, like price-to-income ratio, on average, whilst having unrealistic searching and bidding driving it. Gilbert. et al even mention it 'may also be necessary to reproduce a real location in order to validate the model'.

2.2 Washington D.C. Housing Market ABM

In 2014, Axtell et al. created the first large scale Housing Market ABM, which was of Metropolitan Washington D.C. [9]. They simulated Washington D.C. at full scale of over 2 million individual households as agents. This marks a clear increase in scale from Gilbert et al.'s small, stylised scale. They created this model in response to the Global Financial Crisis of 2008 and aimed to use their model to reproduce the crash in Washington D.C. and thereby explain why the crash occurred.

This Washington D.C. model is different and improved from Gilbert et al.'s simple model in several ways. Firstly, Axtell et al. combines many sources of transactional, characteristic, and administrative data to empirically calibrate many micro-components of the model. They then choose to validate the macro trends of the model against different datasets to ensure the model is producing 'correct' outputs. This is different to Gilbert et al.'s model in which there is no validation from the real world. This is significant as Axtell et al. was the first major Housing Market ABM to explicitly use micro data for calibration. For my improvements to the UK Housing Market ABM, I will require validation from datasets within the UK. Although the model currently has some validation, I want to build upon and improve this validation to prove my model is correct. Secondly, Axtell et al. included renters in their model. Agents choose to buy a property if they can with a house where they can get a mortgage and if the house is within their budget. If they cannot buy a house they rent it. Moreover, agents can also become landlords by buying multiple houses and renting them out. This representation of the housing market is more realistic of a real-world property market.

Although Axtell et al. made several improvements from Gilbert et al.'s simple model, their model still has many limitations. The model does not correctly predict the bubble in neither size nor date and their rental market is underdeveloped. This is a clear limitation as the model does not quite fit its intended purpose. Perhaps this was a limitation of the input datasets, there are other external factors influencing the market during this era (the authors specifically mention seasonality and people moving house when schools starting as examples of this) or the fact that the model doesn't use any location sensitivity.

Axtell et al. made major strides in developing a large scale ABM of a Housing Market and in their conclusion, they argue that their contributions to the field are just the beginning and they prove that this new model type is effective for building models of Housing Markets. This is true as most of the modern Housing Market ABMs cite Axtell et al. for inspiration in their models.

2.3 Full-Scale UK Housing Market ABM

In 2016, Baptista et al. created the first full-scale model of the UK Housing Market for the Bank of England, in order to investigate the effect of a loan-to-income portfolio limit (capping how large a mortgage an individual can take out based on their income) and investigating the varying of the size of the buy-to-let market [5]. They found that making the buy-to-let market larger makes house prices more variable and makes market upswings and downswings more pronounced. This model was later improved by Carro et al. in 2022 [6] which I will discuss in the next subsection. This model is significant for my project as it is the first iteration/publication of the model I am improving for my individual project.

2.3.1 Model Details

This model uses households as the main agent type, each of which are an economic unit with their own wealth, income, age, and decisions. For example, each household decides whether they want to buy or rent when they currently do not live in a private house. It is easier to imagine a household as one or more individuals who live together and make collective decisions. Importantly, households themselves are different to actual houses and are also not individual people. There are four types of households in the model: renters, first-time buyers (FTBs), owner-occupiers and buy-to-let (BTL) investors. Although first-time buyers are effectively owner-occupiers (after they have bought a house), they are different in that they have no housing equity to roll-over when they first buy their house and hence, they are treated differently. When 'households' are born into the model they are considered to be in 'social housing', which corresponds to a real-world state where the individuals in the household are homeless, living with parents or in temporary accommodation. Households can re-enter social housing when rental contracts expire or they just sold their house. Because new households must be 'born' into this initial social housing state, the model requires a 'spin-up' phase. This phase initially occurs with no households or houses in the model, followed up by a rapid build-up of population until the population reaches a target size, all in social housing. Then a house construction phase begins with rapid construction of the actual houses in the model. Households then make decisions about where to buy/rent until an equilibrium is reached, after which the model is considered initialised. This spin-up phase is mentioned to last approximately two hundred years in the model.

The two other agent types in the model are banks and the central bank. The central bank defines the type of regulation used, if any, for mortgages. For example, the central bank may impose a hard limit on the amount a bank can loan compared the value of a house (referred to as a hard loan-to-value ratio). The central bank is effectively the policymaker for this simulation. The bank, on the other hand, decides the mortgage pricing and approve mortgages for households, based on the policies imposed by the central bank. The bank is a single aggregated lender and is not profit-incentivised.

Households go through a strict process when deciding to buy or let a house. When a household is in social housing for any reason, they must decide they want a (non-social) house. Households choose a desired expenditure budget, find the highest quality of house they can afford, decide whether to rent or buy a house and then place a bid on the sales market. if buying a house, households will pay fully in cash wherever possible or go through a bank for a mortgage if not. This cycle repeats whenever a household is in social housing, which keeps a dynamic housing market going.

2.3.2 Model Limitations

The first clear limitation of this model I noticed in this model is scale. Although the model is said to model the entire population of ∼27 million households, only 10,000 household agents are included in the model, so each household "agent" is representative of ∼2,700 households in the UK. Baptista et al. states this is for computational reasons/complexity, but this could potentially cause a variety of issues. They explicitly state some housing quality bands have a limited number of transactions per month leading to a 'unrealistic distributions of price with quality'. This is something I am keen to investigate further to quantify the effects of and ideally provide a fix for. Because of this, I've set a speed-up of the model as my first project aim in Section 3.1.

Another limitation mentioned by Baptista et al. is that households defaulting on loans are not considered in the model. They explicitly state they ensure 'payments are always made by artificially injecting as much cash as necessary to the bankrupt. households'. This is clearly unrealistic of a real-world housing market, and I am keen to investigate how much money is supporting this economy in the model and perhaps leading on from this investigate if we could investigate foreclosure and defaulting in the UK housing market.

A final limitation of this model is that no macro-economic dynamics are considered in this model; economic growth, recession, unemployment and population changes are not considered in this model. This means we are currently unable to use this model to consider how other economic factors affect the UK Housing Market. It would be interesting to see how a thriving economy influences the house prices, or if we are able to simulate/reproduce a housing market crash through unemployment shocks.

2.4 Full-Scale UK Housing Market ABM Improvements

In 2022, Carro et al. published several improvements to Baptista et al.'s UK Housing Market model in order to conduct experiments for the Bank of England [6]. Their findings from the model are that, firstly, using both a hard loan-to-value limit and a soft loan-to-income limit reduce the house price cycle (booms and busts) by reducing credit availability. Secondly, policies targeting owner-occupiers often affect the rental sector as there is a shift from people being owner-occupants to becoming buy-to-let investors. Thirdly, there is lots of policy 'spillover' to different household types when enforcing policies, which gives evidence that the effect of policies needs to carefully be considered for all groups of people and not just the group of people the policy is aimed to target. This model is significant for my project as this is the version of the model I am improving for my project. The repository for this model can be found at `https://github.com/INET-Complexity/housing-model` and the last commit with actual code modification was in October of 2021, six months before Carro et al.'s working paper was published on the Bank of England's website.

2.4.1 Model Improvements

Carro et al. make a variety of improvements to the model, all of which are targeted at making the model more representative of the UK Housing Market, therefore making the model more reliable and accurate for running experiments and giving policymakers insights.

The first clear improvement to the model from Carro et al. is expanded use of micro-data. Carro et al. collect and utilise a much larger set of micro data from a variety of sources, such as Zoopla housing/rental listings and loan level regulatory data. Using a greater variety and quantity of micro data for calibration and validation allows use of full distributions, rather than just using averages, making the model better representative of the UK.

A second major improvement is their buy-to-let heterogeneity calibration. In Baptista et al.'s initial model, they assume a fixed distribution of whether a house owner becomes a buy-to-let investor across all income percentiles. This is not a great assumption, as logically those with higher incomes are more likely to look for investment opportunities. However, Carro et al. flips this by using survey data to estimate the chance of someone becoming a buy-to-let investor at the different income percentiles. Again, this improvement, alongside validation, makes the households in the model more representative of households in the UK, improving model reliability.

2.4.2 Model Limitations

The limitations of this model are mostly the same as the limitations I mentioned for Baptista et al.'s initial model version. Carro et al. again explicitly mention the dynamics for defaulting on loans, not being able to vary macroeconomic factors and the down sampling of the model as clear limitations in the model.

A further significant limitation I have currently noticed from working with this version of the model is visualisation. The model output, similarly, to the original model is a monthly time-series of core indicators, presented as large comma-separated value (CSV) files. No visualisation for runs is currently included in the model, making insights harder to gain and see between runs. I personally want to make visualisation and comparison tools for this model, so it is easier for insights to be made and visualised quickly. Because of this, I've set improving model visualisation to be my third project aim in Section 3.1.

Chapter 3

Project Aims, Evaluation and Planning

3.1 Project Aims

As discussed in the Introduction (Chapter 1), my project aims are to:

- **Aim 1**: Ensure my version of the UK Housing Market ABM is faster than the current model.
- **Aim 2**: Update the ABM to show the latest trends and insights into the post-Covid UK Housing Market and Economy (post-2023).
- **Aim 3**: Improve the ABM interpretability by improving visualisation for highly multidimensional model outputs.
- **Aim 4**: Validate my version of the UK Housing Model reproduces seleced real-world patterns.

3.2 Project Aim Evaluation

We can evaluate these aims via the following methods:

- **Aim 1 Evaluation**: Run runtime benchmarks, profiling, and regression performance tests to prove speed-up made.
- **Aim 2 Evaluation**: Recalibrate input data sources to more recent sources.
- **Aim 3 Evaluation**: Create some tools within the model to visualise model outputs.
- **Aim 4 Evaluation**: Create and improve unit testing for key mechanisms, create more empirical validation, run parameter sensitivity testing.

3.3 Project Plan

There are 20 weeks from the date of this interim report submission (22nd January 2026) to the date of final report submission (12th June 2026). With this in mind, I have outlined a 17-week approximate project plan for my project below:

- **Weeks 1-5** (26th January to 27th February): 4 weeks to update the model with new housing price/rental data, gain and visualise new insights clearly in preparation for meeting with bankers from the Bank of England.
- **Weeks 6-8** (2nd March to 20th March): 2 weeks of revision and 1 week of final exams.
- **Weeks 9-10** (23rd March to 3rd April): 2-week optimisation sprint, with an aim to drastically increase the speed of the model.
- **Weeks 11-12** (6th April to 17th April): 2-week research sprint 1 (sprint aim to-be-decided).
- **Weeks 13-14** (20th April to 1st May): 2-week research sprint 2 (sprint aim to-be-decided).
- **Weeks 15-16** (4th May to 15th May): 2-week research sprint 3 (sprint aim to-be-decided).
- **Weeks 17-18** (18th May to 29th May): 2-week research sprint 4 (sprint aim to-be-decided).
- **Weeks 19-20** (1st June to 12th June): Finish authoring final report and working on presentation slides.

Chapter 4

Initial Improvements

The majority of my work towards this project in the Autumn Term of University have been through updating the model with more recent data in the repository at `https://github.com/max-stoddard/uk-housing-model-individual-project`, which is a fork of Carro et al.'s 2022 model [6] and can be found at `https://github.com/INET-Complexity/housing-model`.

4.1 Wealth and Assets Survey

4.1.1 Introduction

The Wealth and Assets Survey (WAS) is a biannual survey conducted in the UK to better understand household and individual capacity in terms of their 'assets, savings, debt and planning for retirement' [10, p. 4].

The micro data from this survey is vital for both model calibration and validation. In the model, a household's age, income, and wealth affect which houses they can afford to rent or mortgage. This in turn affects which households buy or rent, which renters become first-time buyers and which quality of houses households bid for. Currently, the following calibration sources use WAS data:

- **Household Age Distribution** - Household agents are assigned an age based on the bins calculated using WAS data.
- **Joint Age Gross-Income Distribution** - Households are then given gross income based on their age via a joint age-income distribution
- **Buy-to-let Probability per Income Percentile** - Every household has a probability to be buy-to-let based on this income.
- **Joint Gross-Income Net-Wealth Distribution** - Every household has a net-wealth based on their assigned income.
- **Total Wealth Distribution** - How much wealth each household has from a variety of sources

Currently the model is calibrated in all of these cases with data from *Wave 3* of the WAS, where data was collected in 2010-2012 [11]. As of 2026, this data is over 14 years out of date. For this improvement, I am aiming to update the calibration and validation source to be the latest iteration of the WAS: *Round 8*, which was collected from 2020-2022 [12]. It would ideal to have slightly more recent data, but a statement from the Office of National Statistics stated 'Data collected on the Wealth and Assets Survey covering the period April 2022 to March 2024 (Round 9) are currently undergoing post-collection data processing' and that their 'current expectation is that this data will be released in 2026' [13]. If this data is released during the timeline of this project, I am aiming to integrate this new data from the survey to ensure the model is as up to date as possible.

4.1.2 Household Age Calibration

Age is a particularly crucial factor in modelling the UK Housing Market, as it dictates a variety of factors. When people earn different incomes at different ages households have varied wealth at different ages. This means different age groups are more or less likely to rent, own and occupy or buy to let, significantly influencing our model. The House of Commons states the UK population is currently ageing [14] and our model should ideally show shifts in these different age groups.

Within the model itself, an age distribution is used to maintain a constant overall age distribution by varying birth and death rates. This means for the duration of the simulation, the household age with stay constant with the age distribution of the target year.

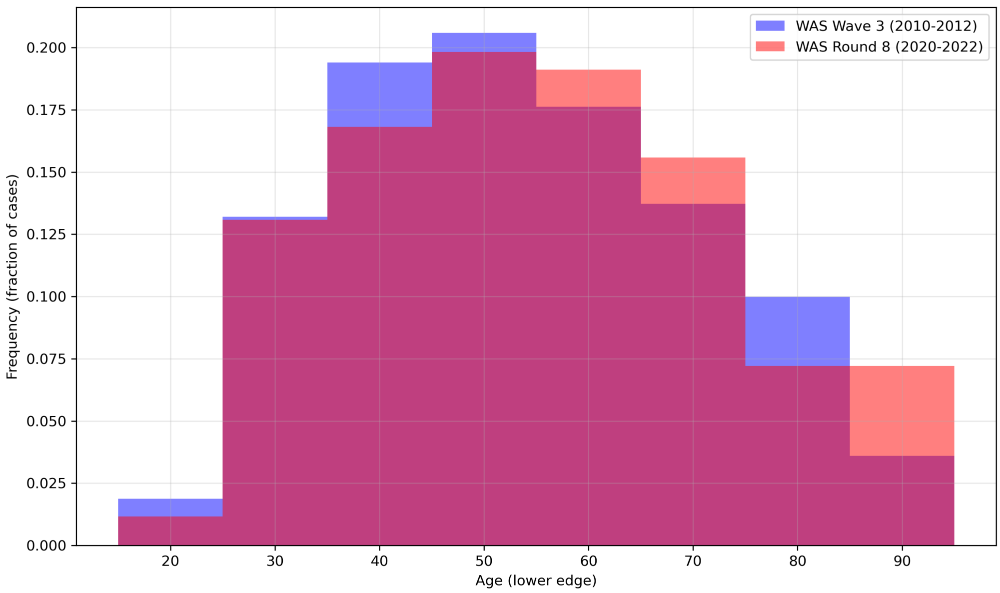


Figure 4.1: Age Distribution Bins between 2010-2012 and 2020-2022

Dataset	Period	Mean	Std. Dev.	Skew
WAS Wave 3	2010-2012	53.797	17.165	0.218
WAS Round 8	2020-2022	55.434	17.661	0.224
Percent diff (Round 8 vs Wave 3)	–	3.04%	2.89%	2.35%

Table 4.1: Age Distribution Summary Statistics

Through updating our dataset from the WAS in 2010-2012 (Wave 3) to the WAS in 2020-2022 (Round 8), we can see that average household age in the UK has increased by 3.04% in 10 years, from 53.8 to 55.4, which is consistent with the histogram shifting to slightly older bins. It is important to note that the WAS Wave 3 dataset has nine age bins, whereas the WAS Round 8 dataset only has eight bins, likely leading to the increase of variation in Round 8 data. Updating the model using this newer WAS data will lead to more households with an older age, which in turn will affect average wealth and income per household, as I will explain in sections 4.1.4 and 4.1.6.

4.1.3 Total Wealth Distribution

Different households in the UK have different wealth. Similarly to income, average total wealth increases over time due to nominal growth and steady inflation in the UK. Wealth also gives households the ability to make deposits and buy houses outright.

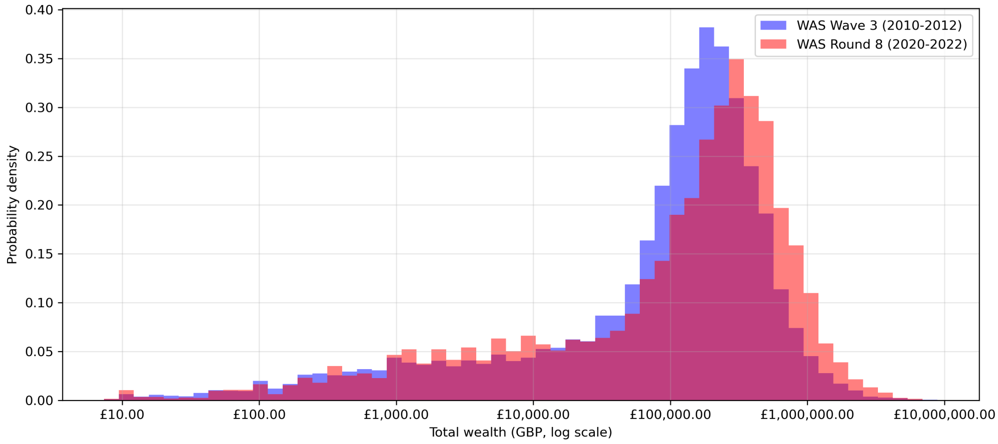


Figure 4.2: Total wealth distribution comparison: 2010-2012 (WAS Wave 3) vs 2020-2022 (WAS Round 8)

Dataset	Period	Mean	Std. Dev.	Skew
WAS Wave 3	2010-2012	£221,888.59	£344,844.56	-1.472
WAS Round 8	2020-2022	£310,608.50	£447,169.15	-1.291
Percent diff (Round 8 vs Wave 3)	–	39.98%	29.67%	-12.31%

Table 4.2: Total Wealth Distribution Summary Statistics

Through updating our dataset from the WAS in 2010-2012 (Wave 3) to the WAS in 2020-2022 (Round 8), we can see that there is a higher average household wealth in the UK of £447k, a 40% increase in 10 years. Moreover, there is a higher average wealth dispersion, evidenced by a 30% increase in total wealth standard deviation. Updating households using this distribution in the model will lead fewer buyers that are limited by the deposit they can make. However, we also need to adjust house prices and rental costs in the model to gain greater insights into how the modern-day market is performing.

4.1.4 Gross-income by Age Calibration

In the model, households are assigned a fixed income percentile for life at their birth. Every month, the household is then assigned an income based on the household's age. Income in real-life, alongside wealth, determines the capacity of a household to afford mortgages or rent houses, the probability they become buy-to-let investors and the household wealth. We expect updating the WAS to a more recent dataset to increase average income at every age group due to nominal growth and steady inflation in the UK over time.

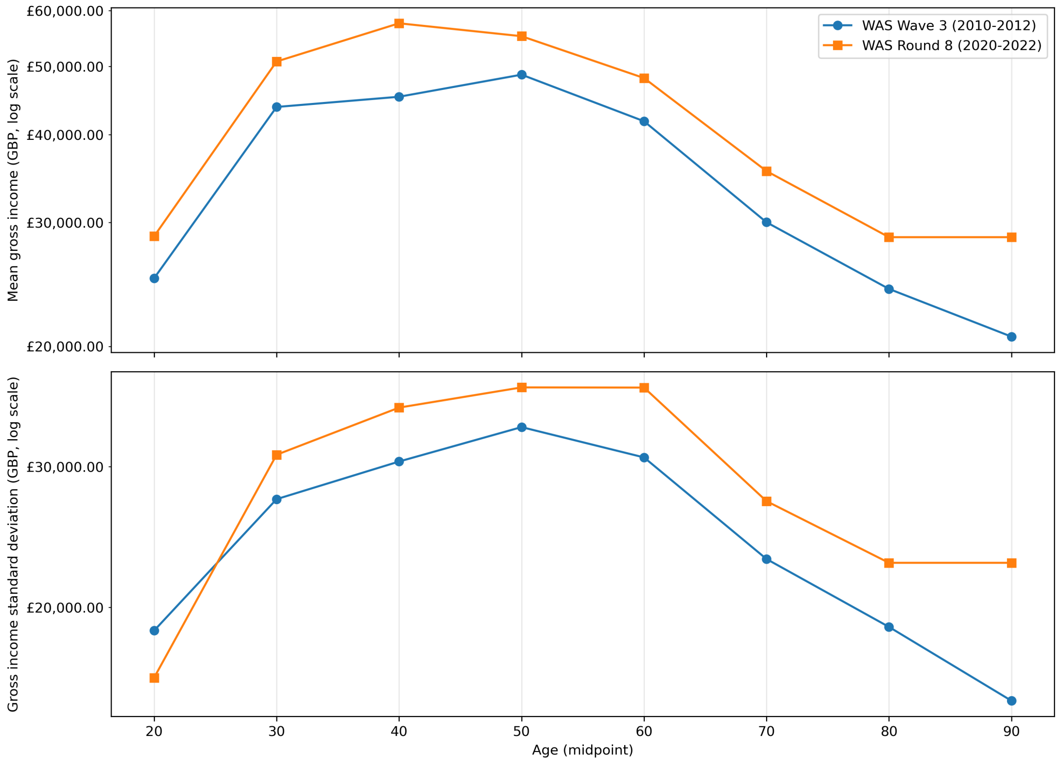


Figure 4.3: Joint gross-income by age distribution comparison: 2010-2012 vs 2020-2022

Dataset	Period	Mean	Std. Dev.	Skew
WAS Wave 3	2010-2012	£39,378.54	£28,940.44	1.654
WAS Round 8	2020-2022	£46,113.65	£34,007.57	1.610
Percent diff (Round 8 vs Wave 3)	–	17.10%	17.51%	-2.68%

Table 4.3: Joint gross-income by age distribution summary statistics

Through updating our dataset from the WAS in 2010-2012 (Wave 3) to the WAS in 2020-2022 (Round 8), we can see that there is higher gross-income on average overall, with mean household gross income increasing by 17.1% in 10 years, from £39.4k to £46.1k (table 4.3). Interestingly, in Round 8, peak income appears earlier in the distribution, around age forty rather than fifty. Updating the model using this dataset will cause the model to reflect these changes in income distribution.

4.1.5 Buy-to-let Probability by Income Percentile Calibration

In this model, the rental market is considered as important as the owner-occupier market. Households in this model can be assigned a buy-to-let gene based on their income percentile assigned. We must compute a joint distribution between income bracket and chance a household becomes a landlord. The probability of a household becoming a landlord in real life is heavily dependent on household income, as households with more disposable income are more likely to be able to afford to buy a house to rent. The results of the update of the distribution in Figure 4.4.

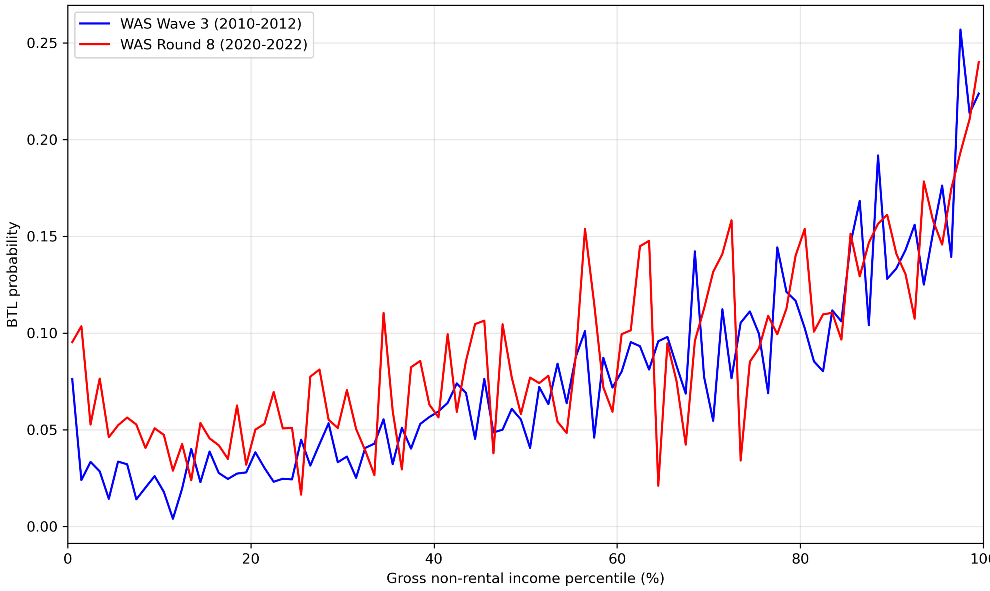


Figure 4.4: Buy-to-let (BTL) probability by income percentile: 2010-2012 vs 2020-2022

Visually from Figure 4.4, we can see that Wave 3 and Round 8 follow a similar pattern of the chance a household tries to buy-to-let increasing as gross non-rental income increases. Importantly, the mean percentile of income of which are buy-to-let investors has decreased by 8.18%, perhaps showing more people at lower income percentiles are becoming a landlord than in 2010. Updating the model distribution with this new data will reflect these changes in the model.

Interestingly in the original model, the top and bottom percentiles of non-rental income are trimmed from the distribution, likely due to the lowest non-rental income percentile having an unusually high chance to be BTL. I am aiming to run an experiment to show if this trimming is an invalid assumption, as I hypothesise that these households with the lowest percentile of non-rental income simply get most of their income from being a landlord. On the other hand, this could be a column definition artifact in the data. This is therefore something I will need to experiment with and validate.

4.1.6 Net-wealth by Gross Income Calibration

To improve accuracy in the model, household wealth is selected by first obtaining a household's gross income, then sampling a joint net-wealth by gross-income distribution to obtain the household's net wealth. This is important to update to more recent household wealth data to ensure household wealth is consistent with the household's income percentile, as explained in section 4.1.4. Changes to the joint distribution are visualised in Figure 4.5 below.

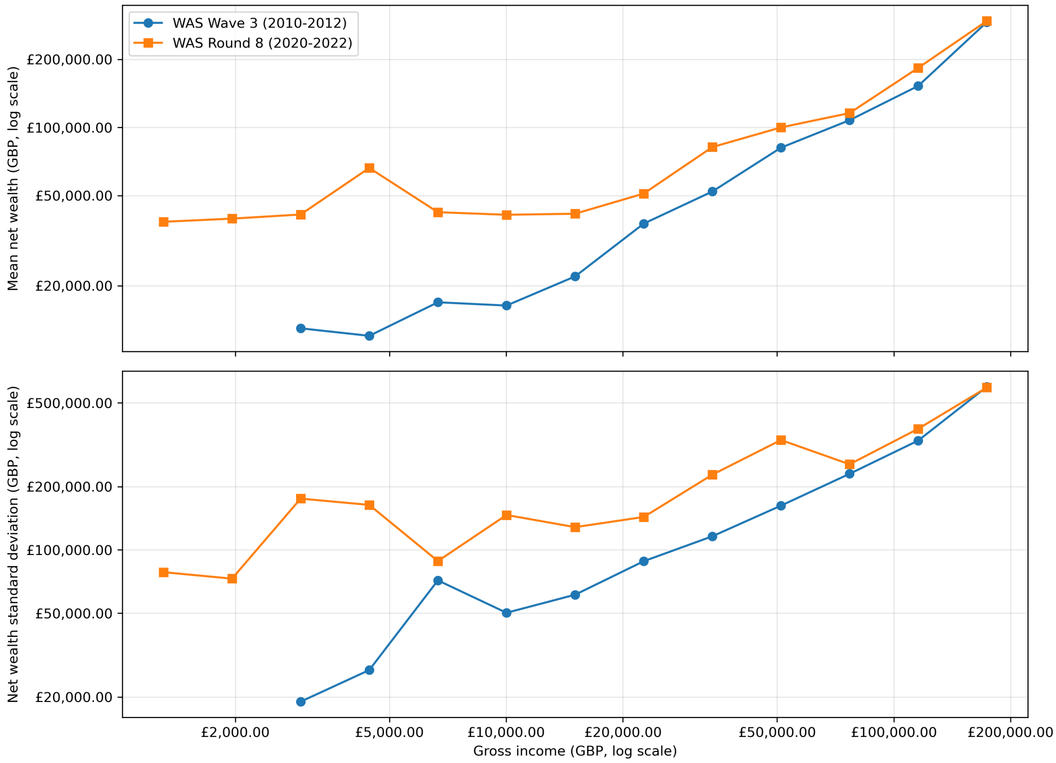
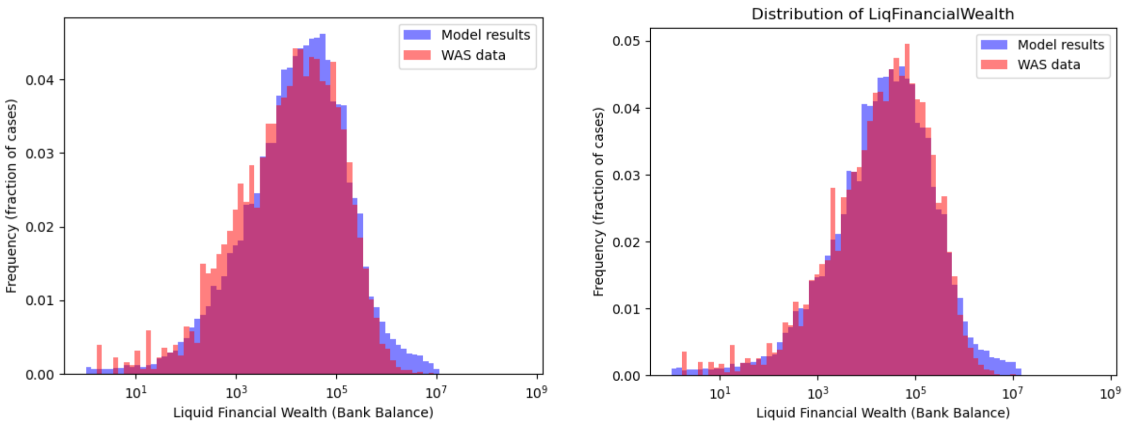


Figure 4.5: Joint gross-income by net-wealth distribution comparison: 2010-2012 vs 2020-2022

Through updating our dataset from the WAS in 2010-2012 (Wave 3) to the WAS in 2020-2022 (Round 8), we can see that household wealth is higher in 2020-2022 at every income than in 2010-2012. This is an interesting trend and cannot be clearly explained by inflation or nominal growth like in sections 4.1.3 and 4.1.4. I hypothesise this is likely due to house prices rising considerably during this period and since property wealth makes up the largest proportion. (40%) of household wealth [3], this drives up wealth, even at lower income brackets.

4.2 Income Tax Rates, National Insurance Rates and Benefits

In the UK, about 42% of all tax receipts come from two tax sources; Income Tax (27%) and National Insurance Tax (15%) [15, p. 1.3]. Taxes significantly affect the capacity of households to live in different quality of households through having more or less disposable income. In this improvement I modify the model's tax and benefits system to ensure the model taxes according to the latest UK tax system. For the UK's rates of Income Tax rates, National Insurance Tax rates and Personal Allowance rates I used official government statistics [16] [17] [18].



(a) Before Policy Integrations (b) After Policy Integrations

Figure 4.6: ABM Financial Wealth Distribution Comparison

As visualised in Figure 4.6, integrating these government policy changes in the model alongside integrating the more recent WAS data (Section 4.1) reduced the difference between the model's financial wealth distribution and sampled WAS financial wealth distribution by 20.4% (from 14.88% difference to 11.85% difference). This change is therefore a clear improvement in model accuracy.

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