Where and how do people live? Modelling the occupation of the German building stock by households

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Abstract

Living space needs to be heated in winter and partially cooled in summer and the construction of new buildings requires high amounts of energy and materials. Total living space is increasing, driven by continuously rising average per-capita spaces. The reasons for this are numerous and include the trend to smaller households who live in larger flats, increasing numbers of single-family houses, elderly people remaining in oversized dwellings, e.g. after their children moved out, the unavailability of adequately sized and priced dwellings on the market, and ongoing construction of new buildings even in regions with shrinking or stagnating populations. Prospective scenarios for a sustainable transition of the building stock thus need to account for these factors, in order to be able to endogenously model impacts of different policy measures and other influencing parameters on the distribution and amount of living space. This paper presents the approach of the INHABIT model for the German building sector which is currently under development. Based on Socio-Economic Panel (SOEP) data, we model dwelling occupancy, by matching the German population to the dwelling stock. Historical data shows that dwelling space is increasing for older and wealthier households, even more so in single family homes, and that under-occupation of dwellings concerns exactly these groups: over 50 % of households aged >60 live in under-occupied dwellings. Finally, we find that also moving rates follow similar patterns and are on average lower for these groups, perpetuating the situation. The proposed model will aim at a simulation of the future of possible occupancy pathways, also as a function of policies that may address prevailing inequalities and inefficiencies in German dwelling occupation.

Introduction

Total living space is increasing worldwide and throughout Europe, driven by continuously increasing per-capita spaces. Since 1991 average floor space per capita has increased in all EU countries but Sweden (see Figure 1). Levels vary widely, however. Especially Eastern EU countries started from levels around 10–20 m²/cap, while Central and Northern EU countries started from around 35–40 m²/cap and reached levels of up to 50, Cyprus, Finland and Estonia even above. Especially in large Central EU countries with a growing population this leads to strongly increasing total living space.

This service-level development is a crucial issue for energy and climate policy, as living space needs to be heated in winter, potentially cooled in summer, and new buildings require high amounts of energy and emission-intensive resources. While energy efficiency requirements lead to continuous improvements of the building stock, growing per-capita living spaces increase activity levels – as a result, total energy consumption does not decrease. Figure 2 shows this exemplary for German data.

The reasons for increasing living space are numerous, explanations complex. Some key background developments include a growing number of smaller households who live on average in larger flats, increasing numbers of single-family houses (SFH) that drive up averages, elderly people remaining in oversized dwellings for various reasons, also after their children moved out. Often, households are looking for adequately sized and

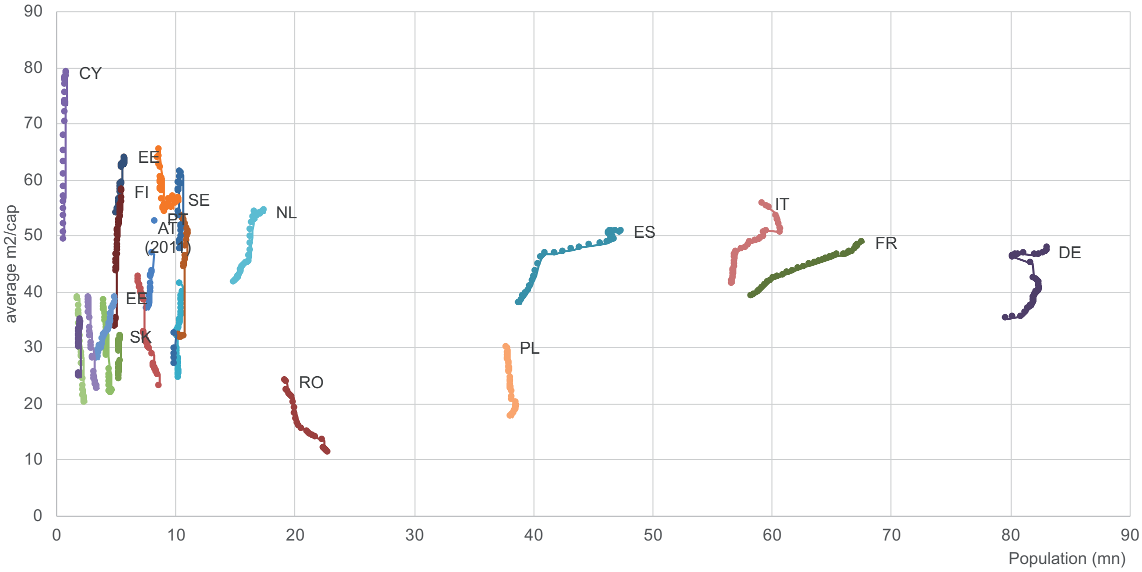

Figure 1. 1991–2021 development of m²/cap by country and population size in EU member states. Country code denotes end of time trajectory (2021). Data source: Eurostat (2024).

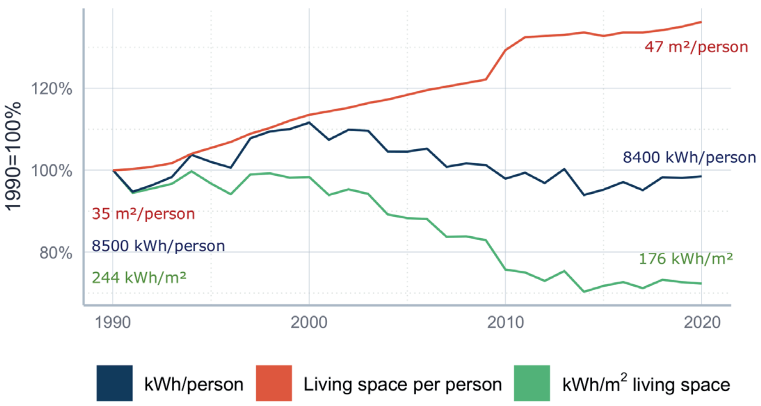

Figure 2. Development of per-capita living space, building energy efficiency and per capita energy consumption. Published in Gräbner-Radkowitsch et al. (2022). Data sources: (AGEB, 2021; DESTATIS, 2000, 2021).

priced dwellings on the market, but when looking for smaller apartments for downsizing, prices are often higher than older contracts for larger dwellings, creating a lock-in. This generates a shortage of larger dwellings for larger households, while in general, not enough small apartments are on the market for increasing number of single households. At the same time, and in spite of often stagnating population numbers, there is ongoing construction of new buildings, also of single-family houses. Prospective scenarios for a sustainable transition of the building stock thus need to account for these factors, in order to be able to endogenously model impacts of different policy measures and other influences on the distribution and absolute amount of living space.

For EU-level and German modelling of building energy consumption scenarios, typically building stock models are employed that use population and average per-capita floor spaces as exogenous assumptions (see e.g. ifeu, 2024). We have not found EU-level or German models that estimate or forecast the development in the occupation of the building stock by the population within the model.

On the other hand, there exists a large literature body on "building occupancy modelling", with a number of reviews available (Chen et al., 2018; Hou et al., 2020; Jin et al., 2021; Rueda et al., 2020). This research strand is engineering research and aims at a detailed time-series analysis of occupancy behaviour of building users (work force, inhabitants), in order to model energy use and performance due to time-varying use patterns in heating, ventilation, air conditioning (HVAC) and other uses. Research also involves modelling and forecasting, the presence state of occupants, their trajectory and number, location in a certain space in the building, the number of occupants, and how they are moving (Jin et al., 2021). It is focused on the building level and building management, such as HVAC control, building systems and flexibility management. It does not focus on the distribution of living space between different household types and the development of living space per household over time – this would be an additional occupancy metric defined differently from existing occupancy research.

We have not found a model in the European context that models how household types distribute in the existing dwelling stock. We consider this a major research gap given the utmost importance of living space development for building energy consumption, and the potential impacts that future policies may have on the distribution of occupancy. We thus outline the respective modelling approach in this work and present the results of the analysis of current relocation behaviour and distribution of living space in relation to various housing characteristics.

Material and methods

The INHABIT building occupation model departs from the distribution of household types on the building stock represented in the *inhabit matrix*. We then apply household-specific moving rates and model how moving households re-distribute to the freed-up living space. This chapter first describes the data used as empirical basis for the INHABIT model. As a second step, the calculations are explained that lead to the generation of the *inhabit matrix* as the key data base for the model, and to the move-out rate as a key model variable. These calculations are applied in this paper (with findings presented in the following results chapter). The final methods section outlines the INHABIT model structure that is currently being set up as an open python framework available from gitlab (Thema et al., 2024).

DATA

The main database for the model under development is the German Socio-Economic Panel (SOEP) in its version 38 (DIW, 2024). The SOEP is one of the world's longest-running panel data sets that covers about 30,000 individuals from 15,000 households surveyed every year. From the many datasets, we use the following sets: hl, ppathl, hpathl, hgen, hbrutto, movedist; we use years from 1986 to 2015 and the variables listed in Table 1.

For the population forecast, we use BBSR (2024) data. The *household* forecast is disaggregated by household size, spatial planning region, years 2020–2040 in 5-year steps. On a NUTS3 level, it includes total number of households, but not disaggregated by household size. The *population* forecast includes additionally age, sex and region type classes.

EMPIRICAL ANALYSIS BASE

As a first step in the model development, we do empirical analysis of the panel data, and develop baseline macro-tables that are used for the model. Analysis is done with python and all calculation routines are openly available from our model development repository (Thema et al., 2024).

Inhabit matrix: how people live

For the model under development, for computational reasons we do not use microdata, but macro-level data tables derived from SOEP survey data. To this end, we apply the following disaggregations:

- Household (h): income quintile (5 groups), household type (single, single parent, couple without children, couple with children, other), household size (number of persons: 1, 2, 3, 4, 5+), age [of oldest hh member] (<40, ≥40), Data not yet available: regions (growing, neutral, shrinking + urban, suburban, rural)
- Dwelling (d): building type (Single Family Houses/SFH, Multi Family Houses/MFH), ownership (nonprofit/ private dwelling, private owner/tenant), condition (renovated, not renovated), rooms (1, 2, 3, 4+)

Table 1. List of variables used for INHABIT, SOEP source datasets, data availability by years.

Variable category	Variable name	SOEP dataset	Name/description	Years
General	Hnetto	Hpathl	Survey status (completed)	1986–2021
	Hid	Hgen	Household ID	1986–2021
	Pid	Ppathl	Person ID	1986–2021
	Hhrf	Hpathl	Household weight (DE representativeness	1986–2021
Household specific	Hgtyp1hh	Hgen	Household type	1986–2021
	Gebjahr	ppathl	Birth year	1986–2021
	Hhgr	Hbrutto	Household size (nr. pers.)	1986–2021
	Hghinc	Hgen	Household income	1986–2021
Dwelling specific	Hgcondit	Hgen	Dwelling condition (renovated)	1986–2021
	Hgowner	Hgen	Ownership (owner/tenant)	1986–2021
	Hlf0013_h	hl	Ownership (non-Profit dwellings)	1986–2021
	Hgroom	Hgen	Number of rooms in dwelling	1986–2021
	Wum1	hbrutt	Dwelling type (single/multi-fam.)	1986–2018
	Hlf0154_h	Hl	Dwelling type movers	2019–2021
	Housing1	Housing2021	Dwelling type 2021 (generated)	2021
Spatial categorization	Resmove	Movedist	Person moved to new dwelling	2001–2015
	Regtyp	regionl	Rural/urban/suburban region type	1986–2021

This disaggregation results in the following number of dimensions for the inhabit matrix of household times dwellings: h*d = (5*5*5*2) * (2*4*2*4) = 250 * 64, or, once the data for the regions is available in h*d = (5*5*5*2*6) * (2*4*2*4) = 1,500 * 64.

The starting base for the INHABIT model is a table with dwelling type categories as columns and household categories as rows. In the model, the base year table is derived from empirical G-SOEP data and subsequent tables are modelled. This subsection outlines the proceeding for the generation of tables for empirical analysis.

The yearly inhabit tables are generated for all years from 1986 to 2015 (leaving available years to 2021 for calibration). After calibration, the latest year can serve as a baseline year. The originally more detailed SOEP variable categories are grouped to reduce complexity and size of the resulting matrix. Only SOEP data of complete surveys are used in our findings.

Dwelling and household variables are merged for each year to one table (stacked and unweighted, each column represents one variable, each row represents one household). Household weights provided by SOEP for representativity are applied to the observations. In the resulting macro-level inhabit table, each cell contains the number of weighted observations for the respective set of household and dwelling. In the final inhabit table, a cell is identified by the dwelling variables category $j \in \{1, \ldots, m\}$ denoted in the columns and the household variables category $i \in \{1, \ldots, n\}$ denoted in the rows of the inhabit table I_t in the year t. The inhabit table has thus the dimension *hxd*:

$$I_{hd} = \begin{pmatrix} i_{1,1} & \cdots & i_{1,d} \\ \vdots & \ddots & \vdots \\ i_{h,1} & \cdots & i_{h,d} \end{pmatrix} \tag{1}$$

Move-out matrix: which people move from which buildings

In order to model changes to the building occupation, it is crucial to model which households (hh) move, and where. The first question is thus which households move out, to derive a moving rate by household and dwelling category that can be used for scenario modelling. We calculate this from empirical microdata as follows.

For creating the move out matrix the same steps are executed as for the generation of the inhabit table, with additional steps. The SOEP variable *resmove* indicates whether a person has moved in the previous year. This information is written back to the previous year in the variable *will_move*, indicating that a person will move until the next survey year. The households are then filtered based on the value in the generated variable *will_move*. Only households that fulfil one of these criteria are kept:

a. Full household moves: only the oldest person per moved household is kept as a representative for the whole household that is moving.

b. Single person moves: of the households where only a single person is moving out, only this person is kept as a new "moving household".

All other households are removed, giving the final move out table with dimensions of the inhabit table (*hxd*:):

$$M_{hd,out} = \begin{pmatrix} m_{1,1} & \cdots & m_{1,d} \\ \vdots & \ddots & \vdots \\ m_{h,1} & \cdots & m_{h,d} \end{pmatrix} \tag{2}$$

For later usage in the model, move out *rates* are needed instead of absolute numbers of households moving out. Move out rates are calculated by dividing the number of moving households in each cell by the number of households in the same cell of the inhabit table for the respective year t. This yields a move-out rate matrix mr_{hd} with rates of households moving per category, of same dimensions as the inhabit matrix.

Calculation of over-/underoccupancy

Underoccupancy refers to a dwelling with significantly more rooms than persons in the household. In non-profit housing in Switzerland, the following concept is applied (Blumer, 2012): occupancy rules mandate as example a maximum room number of *hh size+1* to avoid underoccupancy. To evaluate the fit of rooms to household size, we generate a variable *underoccupancy*:

$$underoccupancy = rooms - hh_{size} \tag{3}$$

For analysing average underoccupancy by groups, average values of the *underoccupancy* variable are calculated for groups of income quintiles, ages and other variables. An *underoccupancy* of 0 implies that nr. of rooms = household size, underoccupancy ≤1 implies meeting the Swiss minimum occupancy criterion and values >1 indicate underoccupancy. Negative values imply overoccupancy (#rooms <hh_size).

MODEL OUTLINE

The INHABIT model is a macro-level simulation model that simulates the distribution of the German household population disaggregated by socio-demographic and economic variables over the dwellings disaggregated by descriptive variables over time. Baseline starting year data is based on empirical micro-data from the German Socio-Economic Panel (G-SOEP, see methods and data section). It takes a stepwise modelling approach that iterates in yearly steps over macro-level data. In the following and presented in Figure 3, we outline a simplified presentation of the model architecture.

Modelling move-outs

The model is initiated with the generation of the inhabit matrix I_{hd} with following dimensions: *h* different household categories and *d* different dwelling categories (see section on inhabit matrix). The baseline inhabit matrix for year t is filled with numbers of households in the respective cell $I_{a,b}$ from G-SOEP micro-data (with $a \in \{1, \ldots, h\}$ and $b \in \{1, \ldots, d\}$).

In a second step, the move-out rate Mor_{hd} is used. This is as a baseline matrix also derived from empirical moving rates in the G-SOEP data (see section on move-out rate), but moving rates can be adjusted by applying factors $morf_{hd}$ from exogenous inputs. Application of the moving rate yields

$$\text{Stay matrix: } S_{hd} = I_{hd} \odot (J_{hd} - Mor_{hd}) \tag{4}$$

$$\text{Move out matrix: } M_{hd} = I_{hd} \odot Mor_{hd}$$

With J_{hd} being a h x d all-ones matrix.

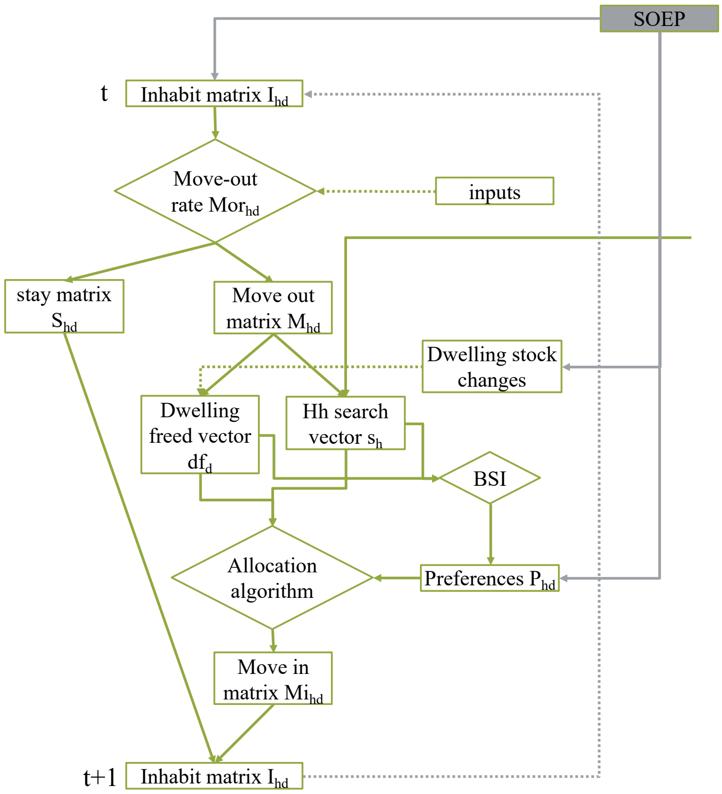

Figure 3. INHABIT model structure.

Marginal distributions of M_{hd} yield a vector df_d of freed dwellings after households have moved out and a vertical vector of household types s_h now searching for a new dwelling. As both the building stock and the population are not static, we at this step adjust respective vectors with exogenous inputs: the dwelling vector df_d is adjusted according to demolition, new-build and renovation rates and the searching household vector s_h is adjusted, so that total households in t+1 will match exogenous population projections.

Preferences and allocation

In the following core step, we present an allocation algorithm that iteratively assigns households in search of dwellings to available dwellings. For this, we develop a preference profile matrix P_{hd}, that describes preferences by household type h, which dwelling type d they would prefer to move in. Preferences profiles are derived from empirical data from the SOEP, and different preference profile assumptions can be selected as inputs for modelling. In a first step, baseline preference profile options can be selected, based on the observed distribution of households to dwellings in the inhabit table:

- $P_{h\{q\}} \triangleq I_{h\{q+1\}}$ *(preference equals the distribution in inhabit matrix of the income quintile above own)*
- $P_{h\{q\}} \triangleq I_{h\{q=5\}}$ *(preference for all equals the distribution in inhabit matrix of the highest income quintile)*
- $P_{h\{q\}} \triangleq I_{h\{q\}}$ *(preference to live in dwelling type where respective household had lived)*
- $P_{h\{q\}} \triangleq \frac{1}{2}\left(I_{h\{q\}} + I_{h\{q+1\}}\right)$ *(preference for average between own and above quintile)*

Where $P_{h\{q\}}$ denotes the entries of the preference profile matrix P_{hd} for households with type h (whole row) with the income quintile q. Similarly, $I_{h\{q\}}$ denotes the observed distribution of households with type h and income quintile q to the dwelling types.

Subsequently this selected baseline preference can be adjusted by factors for

- owner/tenant: preference to move into an owned dwelling
- building status: preference to move into a renovated dwelling
- SFH: preference to move to a single-family house
- number of rooms: aspired size of dwelling (hh_x).

The allocation algorithm uses these preferences and allocates households to available dwellings in iterative steps. This allocation mechanism can follow various logics that can be selected for model runs. We currently plan to implement the following options:

1. By income quintiles: (a share of) the highest quintile is allocated first, in iterative steps the below quintiles.
2. Balanced/solidarity: households are allocated to achieve a more balanced outcome in the distribution (e.g. by minimizing the spread between over- and underoccupancy)
3. Monte Carlo: an iterative aleatoric selection of households for allocation until all households are allocated

The rationale behind option 1 is to mimic the fact that wealthy households are able to realise their preferences by their acquisition power. Model calibration can be done by exogenously varying the share of households in each income quintile that is allocated according to their preferences in each allocation iteration. The goal of Option 2 is to simulate a scenario with a more balanced distribution of preference realisation between income quintiles, leading to a more "just" distribution of living space. Option 3 (that can also be combined with others) is to simulate what happened if living space allocation was less dependent on income but order of selecting-in aleatoric. Additional allocation options including mixed version will be derived depending on the calibration as well as depending on policy and framework conditions whose effect is to be tested in the model.

Once all searching households are matched with available dwellings by the iterative allocation process, the resulting move-in matrix $M_{hd,\in}$ is finalised for the respective model year *t*. Adding move-ins to the non-movers St_{hd} yields the new inhabit matrix for the next model year *t+1*.

$$I_{hd}(t+1) = S_{hd}(t) + M_{hd,\in(t)} \tag{5}$$

Recursive preference adjustment

It is possible and even likely that preferences for certain dwelling types, such as new, large or renovated dwellings cannot be satisfied for all households by the available dwellings, especially when adding urban/rural or growing/shrinking regions with tight housing markets to the model. Households thus may scale down their aspirations for future dwellings.

To reflect this effect, we create a building shortage index BSI_{rooms} that indicates for each *dwelling size* category by *nr of rooms* whether there is a shortage (less dwellings of this room number available than resulting from the preferences, ($BSI_{rooms}<1$) or affluence ($BSI_{rooms}>1$). From the available dwellings vector df_d, we first retrieve the number of dwellings available per *nr of rooms* d_{rooms}, then from preferences and searching households, we generate a vector of desired dwellings by *nr of rooms*, dd_{rooms} and calculate the building shortage index:

$$BSI_{rooms} = d_{rooms} / dd_{rooms} \tag{6}$$

In addition, we calculate an index of total living space shortage $BSI_{total,}$ that indicates overall shortage. Depending on the outcomes of the shortage index for specific dwelling size categories, household preferences are then adjusted, before the allocation algorithm is applied.

Iterative yearly time-step scenario modelling and calibration

The above-outlined modelling approach simulates the changes in the occupation of the building stock in a given year and yields the starting inhabit matrix I_{hd}(t+1) for the following year t+1. Simulation then proceeds in yearly time steps with the inputs of moving rates and preference profiles that can be set also according to future developments. The model will be calibrated by first developing the quantitative calculation infrastructure and starting the model based on a base year in the past, e.g. the year 2000, and then calibrating model outputs (i.e. development of the inhabit matrix I_{hd}) to the empirical evolution of this matrix. After calibration, the last year of available data can be used as base year and scenario modelling into the future can be applied.

INCLUSION OF POLICY LEVERS

The first task of the model under development is to project current trends based on a model calibration to historical data into the future. In a second step, variations to these projections will be carried out based on sensitivity analyses for variations in key input parameters such as moving rates, dwelling

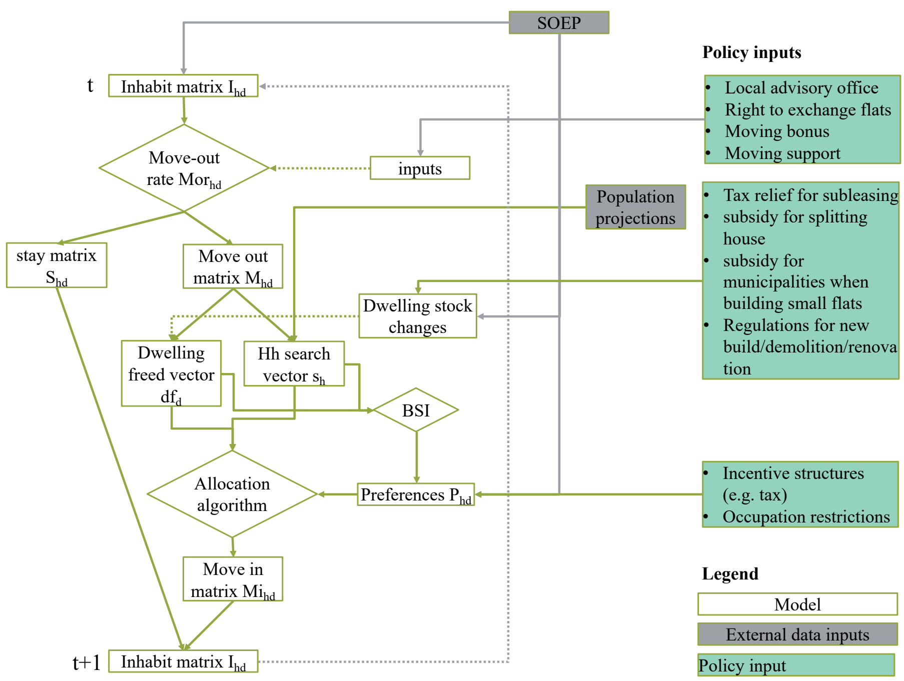

Figure 4. Policy lever inclusion in the INHABIT model.

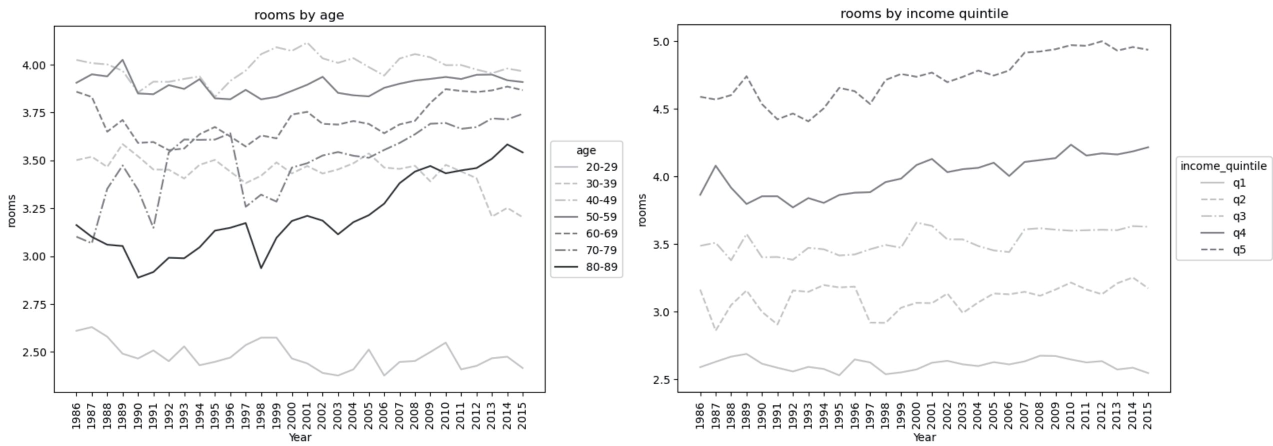

Figure 5. Average number of rooms by age and income.

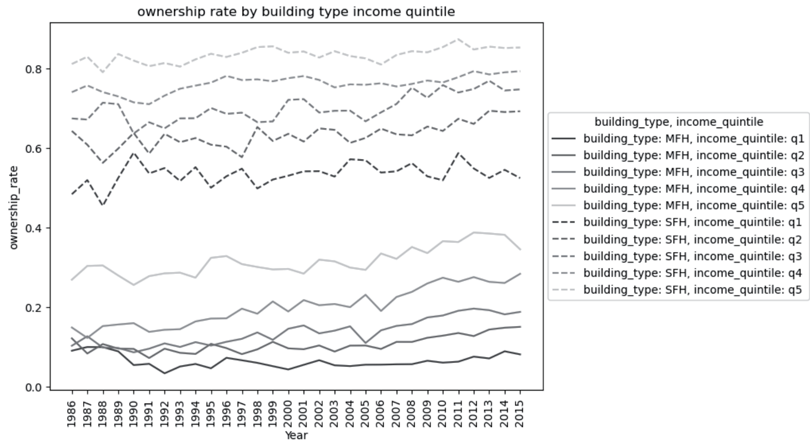

Figure 6. Ownership rate by building type and income.

stock variations, preference adjustments or differing allocation mechanisms.

A future goal is to implement policy impact chains (Zell-Ziegler & Thema, 2022) to the model: based on literature, we derive impacts from policies that change input parameters in order to model policy scenarios for building occupation. Policies can change various input parameters of the model. At the moment, we expect to be able to implement policy-induced changes to moving rates, to the building stock/dwellings and to the preferences or allocation of households to dwellings. Figure 4 shows first ideas for policy lever inclusion.

First results from data analysis

HOUSEHOLD AND BUILDING TYPES

Historical data (1986–2015) shows that average rooms per household increased for the higher-aged generations, and decreased for households below age 40. Average number of rooms vary largely by income quintiles. The gap widens for higher incomes, number of rooms keeps rising, while for lower incomes it stagnates (Figure 5). We find ownership rates to be correlated with income and at 10–30 % MFH and 50–80 % in SFH (Figure 6). The only pattern visible are rising rates for higher incomes in MFH.

OVER- AND UNDEROCCUPANCY

The analysis of under-occupation also reveals expected patterns (see Figure 7): it increases on average with age (again slightly decreasing for age group >80) and income, decreases with household size and is substantially higher in SFH than MFH. Increases are especially strong for households above age 50 and in SFH, with a stagnation for the lowest income quintile. An analysis of the share of the population that exceeds the Swiss occupation standards (see Figure 8) repeats the same pattern. In the population below age 40, less than 25 % lived in under-occupied dwellings in 2015, while in the population aged 40–49, this rises to 35 and above age 50 to 50 % and higher. In SFH, the share of underoccupied dwellings has increased from 50 to 70 %, a result of increasing SFH sizes and smaller households. While only 20 % of large households (with 5+ members) live in under-occupied dwellings, the figure is over 50 % for one- and two-person households, and the share is 35 % for low-income households while it has risen to 60 % in the highest income quintile.

Figure 9 shows how underoccupancy is distributed in the different groups in one year (2015). This underlines that in all

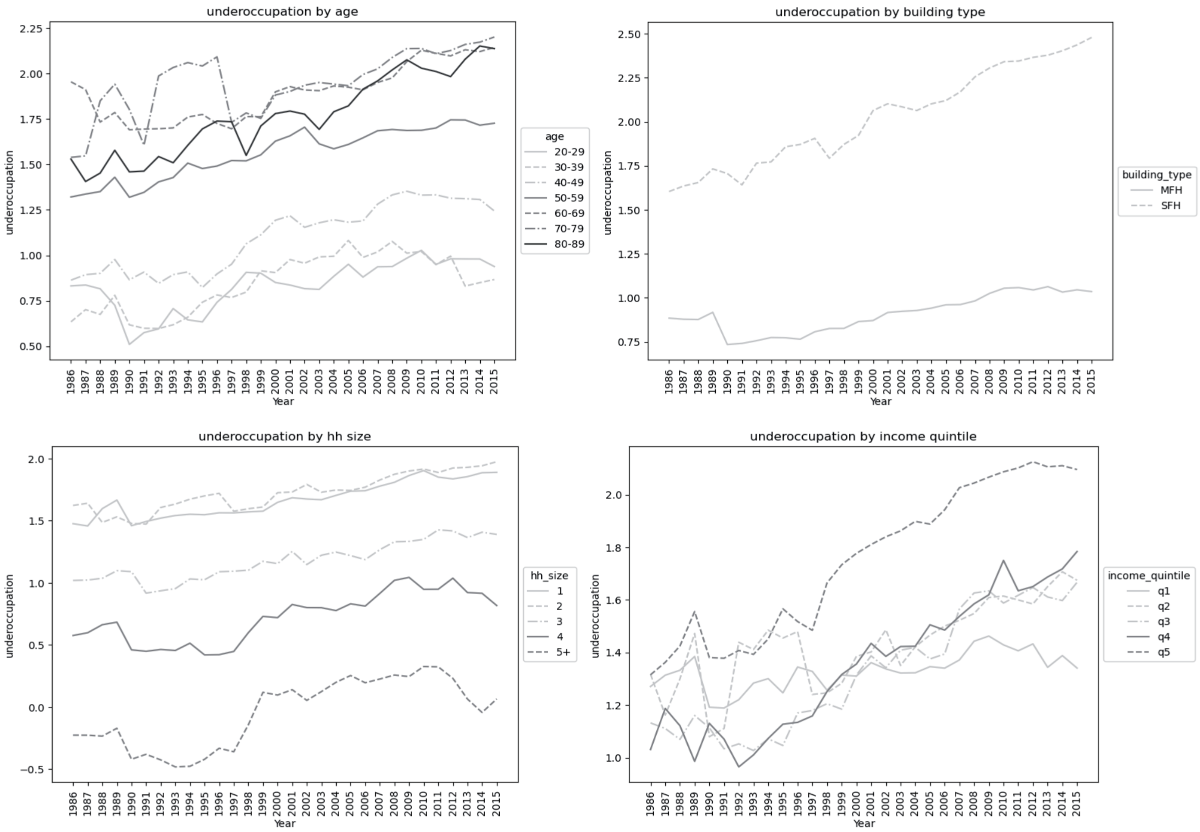

Figure 7. Average underoccupation (number rooms – hh size) by age, building type, hh size, income. Values > 1 = underoccupation.

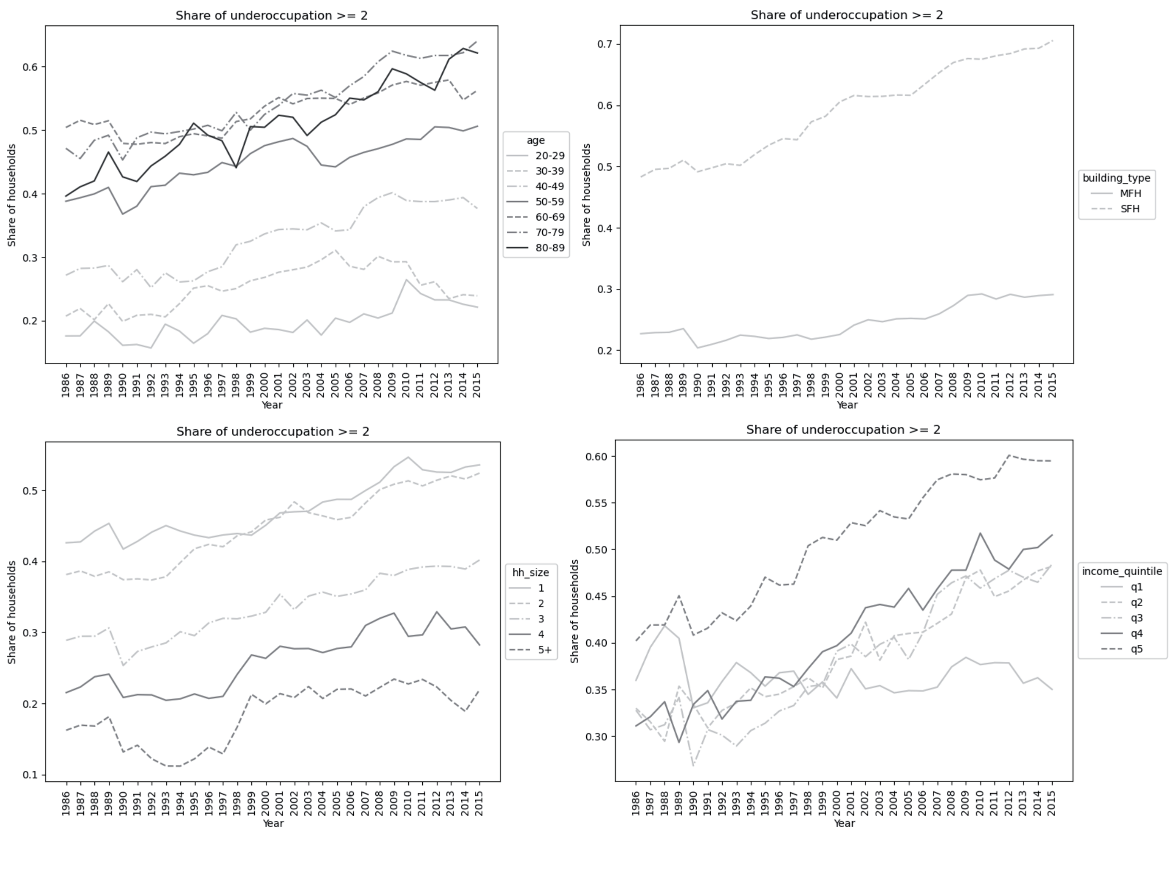

Figure 8. Share of households with underoccupation ≥ 2 (number rooms – hh size) by age, building type, hh size, income. Values > 1 = underoccupation.

groups there is both over- and under-occupation and gives a more detailed understanding for distributions underlying the averages in Figures 7 and 8.

MOVING PATTERNS

Our final results section shows how moving rates vary between groups (Figure 10). Oscillating curves results from relatively small numbers of movers in individual sub-categories. Moving rates are therefore subject to stochasticity resulting from the limited sample size. However, some patterns can be observed. While the average annual moving rate is at around 7 % of all households and has been slightly decreasing over the last decades, it is substantially higher for households below age 30 (25 %), in MFH (decreasing from 10 to around 8 %) while in SFH it is around 3–4 %. Smaller households tend to move more often and wealthier households less, probably due to higher ownership and SFH rates.

Discussion and conclusion

Historical increases in per-capita living space have outweighed efficiency increases and thus building energy consumption stagnates. Therefore, a better understanding is essential of how the population distributes to the dwellings, how moving and living trends develop and can be projected – and how they can be addressed by policy. This paper presents a conceptual outline for a building occupation model targeted at answering these questions.

Our analysis of German survey micro data matches official macro-level statistics on increasing living spaces and uncovers some of the underlying explanations by disaggregating the historical development of number of rooms, underoccupancy and moving rates by age, building type, household size and income classes. We find empirical evidence for high correlations of these variables, but also large variations in the distributions. Rising per-capita floor spaces are driven especially by older generations living in large and growing single-family houses, by one- and two-person households living in more under-occupied dwellings and by the higher income classes. The mobilisation and flexibilisation of living is necessary for a more efficient and fair distribution of existing living space as presented data shows the high remanence effect of elderly people staying in large dwellings.

However, not all households contribute to the rising averages, in all categories also a substantial fraction without underoccupancy or even overoccupancy exist, but distributions are skewed according to the averages above. This finding is exacerbated by the fact that moving rates are lower precisely in those population segments with higher underoccupancy (higher age and income, single-family housing) – leading to a lock-in to oversize, while younger and growing households with higher moving rates move to larger dwellings. The consequence are thus further increases in average living spaces.

Our proposed INHABIT model that is currently under development will be based on these empirical findings and simulate pathways how the population distribution may develop in the future – following current trends and including policies that may alter framework conditions shaping moving patterns, the building stock, or occupancy patterns when moving.

The proposed modelling framework is highly innovative as it serves to project dwelling occupation and can cover key sufficiency issues related to living space development. However,

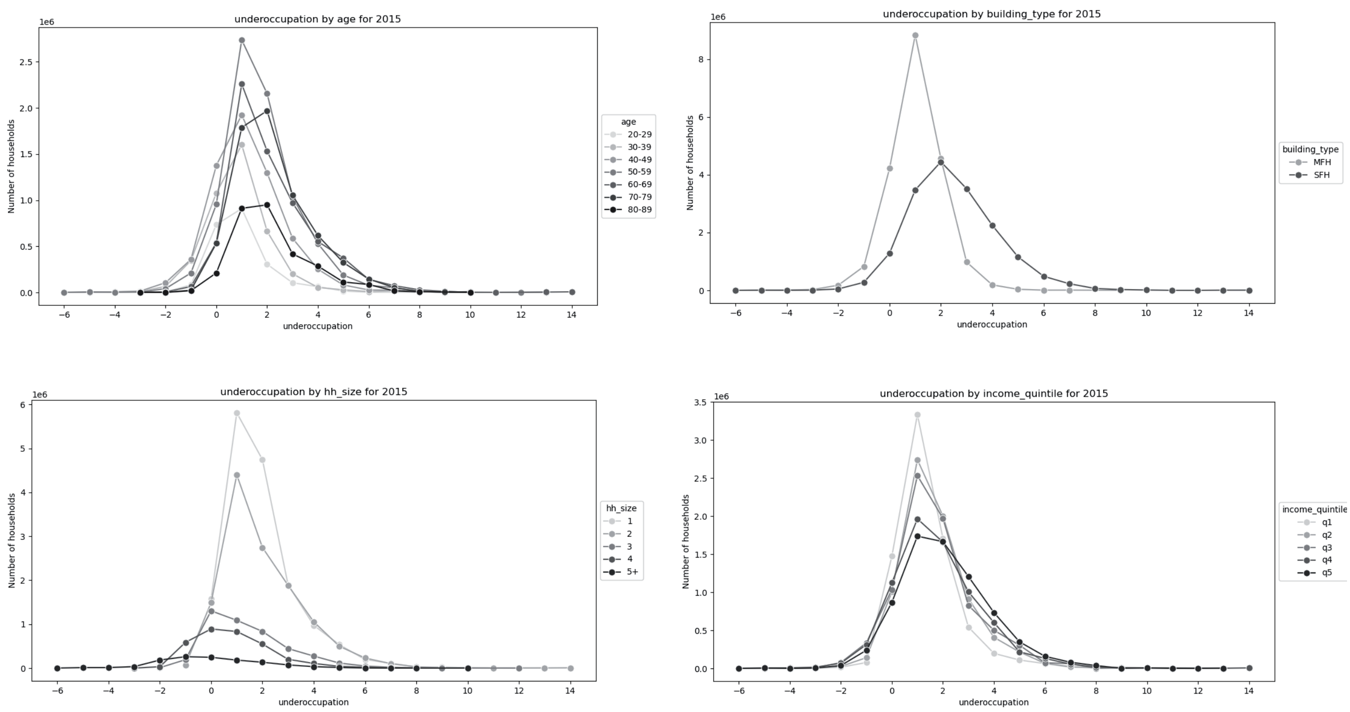

Figure 9. Distribution of underoccupation (number rooms – hh size) by age, building type, hh size, income (year=2015). Values > 1 = underoccupation. Year: 2015.

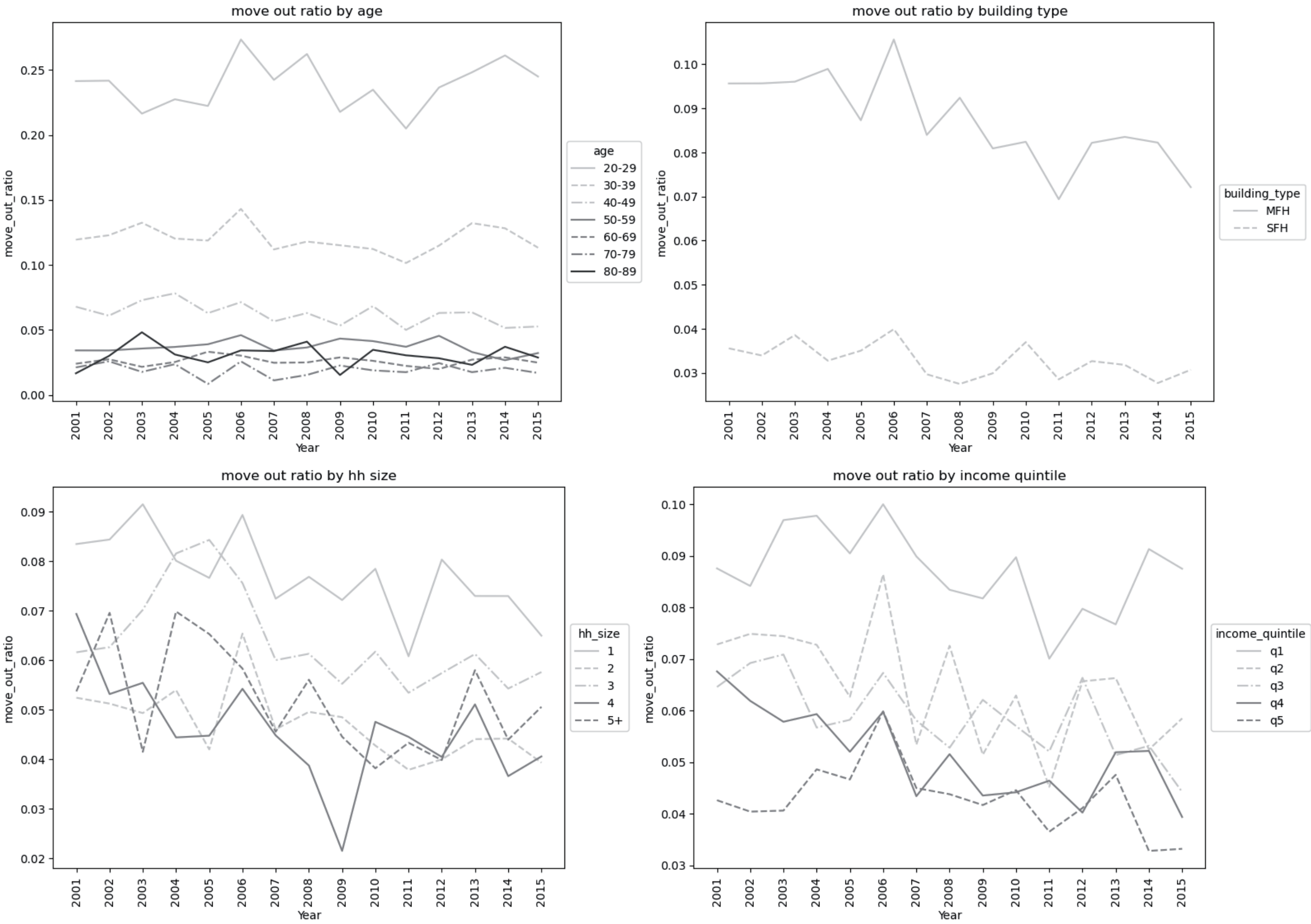

Figure 10. Move-out rates by age, building type, hh size, income.

albeit available data allows for distinguishing a high number of hh type/dwelling type combinations, we do not model technical specificities of buildings. For modelling energy or GHG impacts, the INHABIT model will need to be coupled with more conventional building stock models in the future.

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