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Understanding Relocation Behavior: A LightGBM Model for Switzerland

GEO 511 Master's Thesis

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Abstract

Residential relocation is a key mechanism shaping housing markets, urban structures, and population dynamics. This study analyzes residential relocation in Switzerland from 2013 to 2023 using nationwide individual and household register data combined with housing-market indicators. This comprehensive scope allows for the observation of relocation behavior across the full demographic and spatial spectrum of Switzerland, providing a more complete and representative understanding of the mechanisms driving residential mobility at both local and national scales. The study provides a stratified view of relocation rates across average household age and building categories. This descriptive analysis is complemented by a LightGBM model that estimates the relocation probabilities of households. In doing so, this study determined both the magnitude and direction of the driving factors behind residential mobility. Relocation behavior was found to be primarily driven by a combination of life-course dynamics and dwelling characteristics. Among these, average household age, household size, and building type emerged as the most influential factors. Real estate market indicators, such as micro and macro location ratings, exhibit contrasting effects across housing types. Vacancy rates did not show strong effects on the observed household relocation rate. High median asking prices of dwellings at the municipality level were found to inhibit residential mobility. In addition to real estate ratings, a municipality typology was used to control for spatial effects. Incorporating these determinants into a LightGBM model yielded a balanced accuracy of 0.601 with a sensitivity of 0.278. Overall, this work highlights the complex dependencies between household variables, life course events, dwelling characteristics, the real estate market, and spatial dependencies shaping residential relocation behavior in Switzerland.

Table of Contents

1 Introduction

The scientific field of demography focuses on the size, composition, and spatial distribution of populations, as well as the processes driving their change over time. Today, migration has become the main driver of population change in Switzerland, while natural growth has decreased. Migration between countries, along with its push and pull factors, has been studied widely. Various models have been developed to describe international migration flows driven by climatic and economic factors (Millock, 2015; Willekens, 2019). Research on internal migration focuses mainly on distribution patterns within countries, often in the context of urbanization trends (Ichimura, 2003; Dyson, 2011; Lerch, 2023). While the FSO sheds light on demographic differences in the relocation patterns of individuals (FSO, 2024), this study seeks to determine and measure the various factors that shape the relocation behavior of households. To expand the understanding of relocation dynamics, this study focuses on identifying the main variables that drive relocation among the Swiss population by combining person-level data with information on the Swiss housing stock and real estate market. Such variables include rent prices, general availability of land and housing, and the overall attractiveness of a municipality or neighborhoods. Household characteristics, such as the age of residents, type of home or building, and the composition of inhabitants, also provide valuable information on relocation behavior (Schmid & Schläpfer, 2023; Schmid et al., 2024). Finally, life cycle events, such as family formation, marriage, divorce and widowhood, overall health, and educational and economic opportunities, play a crucial role in relocation behavior (Lehner et al., 2023).

This study aims to quantify the key factors that influence individual and household relocation behavior and to explore their effects at the household level using exploratory and machine learning approaches. The following research questions were formulated:

1. What are the key variables influencing the relocation behavior among different age groups in Switzerland?
2. How strong are the effects of these variables on the relocation behavior?

3. Can relocation probability and densification potential be combined to improve estimates of demographic change at the parcel and neighborhood scales?

To answer the formulated research questions, the existing literature on relocation behavior in Switzerland is reviewed. While international studies provide valuable insights, research focusing on Switzerland is particularly relevant. It reflects the country's specific legal framework, housing market conditions, and economic context and relies on comparable data sources. In addition, studies addressing methodological and modeling approaches to residential mobility are considered to inform the analytical framework of this research.

Relocation rates at the individual and household levels were calculated for Switzerland over the period 2014–2023. Sociodemographic and building stock characteristics were analyzed with respect to their influence on household relocation behavior. An experimental LightGBM-based predictive model was developed to estimate relocation probabilities at the household level.

The model shows potential for future applications in predicting relocation patterns. However, further methodological development is required to improve prediction accuracy. Although the analysis also examined densification potential and regional patterns, no direct relationship between relocation behavior and inner densification was established within the scope of this thesis.

2 Background

This section situates the present study within the broader literature on demographic change, housing markets, and spatial population dynamics in Switzerland. It begins with an overview of national-level demographic developments and projections, with a particular focus on the evolution of the housing stock and tenure structures. The section then narrows to regional and municipal scales, where studies on internal migration, residential mobility, and urban–rural differentiation are reviewed. Finally, recent methodological contributions in spatial demography and probabilistic population forecasting are considered in order to highlight how existing approaches inform, complement, and differ from the modeling framework adopted in this work.

2.1 Demography

Demography, as a scientific discipline, examines the size, structure, and geographical distribution of populations, alongside the mechanisms that drive their evolution over time. The key factors influencing demographic shifts include fertility, mortality, and migration, which are the core elements of any population model (Poston & Bouvier, 2010). These factors operate within a broader socioeconomic and political context, shaping structural attributes like age distribution, gender composition, and dependency ratios that are essential for interpreting long-term social and economic trends. Consequently, comprehending population dynamics is vital for effective policymaking across all levels, from local to global (Apenteng, 2009; Poston & Bouvier, 2010). On an international scale, demographic trends have significant implications for tackling global environmental issues such as climate change, pollution, and escalating ecological stress. In addition, the aging population in developed nations poses unique public health challenges for the future, such as an increasing need for healthcare services and suitable housing for the elderly (Kanasi et al., 2016). Conversely, the growing number of young individuals in the global south imposes substantial socio-economic demands, heightening the need for jobs, education, and infrastructure (Sommers, 2011). At a local level, rising urbanization presents further challenges. The rapid concentration of populations in urban areas necessitates meticulous planning for infrastructure, including transportation, housing, healthcare, and education services (Ichimura, 2003; Bloom et al., 2011; Valencia, 2012; Schmid et al., 2024).

Over the past fifty years, Switzerland's demographic changes have been influenced by both natural population change and immigration trends. Net migration has become the main factor in population expansion, as the natural increase has persistently diminished. Switzerland's permanent resident population has grown from 7.1 million in 1995 to nearly 9 million in 2024. Population projections indicate continued growth, with the reference scenario by the Federal Statistics Office (FSO) estimating 10.5 million residents by 2055. From a structural perspective, even under moderate reference conditions, Switzerland is anticipated to face continued population aging, an increasing proportion of foreign-born residents, and a heightened regional concentration of growth within metropolitan areas (FSO, 2025b).

While demographic forecasts are generally available at regional levels, precise predictions of demographic changes at the neighborhood level remain challenging. Therefore, planning entities often depend on assumptions derived from regions larger than the actual resource catchment area, potentially causing mismatches in capacity. For example, in smaller cities, there are often several primary schools, each serving unique catchment areas. Although demographic forecasts are generally generated at the city level and provide valuable insights, they fail to account for the varying population growth rates across neighborhoods due to structural differences in sociodemographic composition, housing supply, and real estate market trends. In some neighborhoods, the housing stock is primarily composed of multifamily residences accommodating a diverse range of age groups and household configurations. In contrast, other areas might be predominantly occupied by single-family homes, which are less prone to frequent relocation but often exhibit significant under-use of space within each dwelling and inherently have a large potential for inner densification, depending on relocation behavior (Schmid & Schläpfer, 2023). To account for variability at the neighborhood scale, an improved spatial resolution of demographic forecasts is desirable.

Previous studies by the FSO (2024) and Fister et al. (2025) have found that moving behavior tends to vary by age: younger people typically move more frequently than older individuals. Younger individuals are more likely to relocate to urban areas, often into shared households, and are generally more sensitive to affordable rental prices. Educational opportunities and employment prospects are often significant drivers of their mobility. This also manifests in a higher moving quota in urban areas than in rural regions. In contrast, older individuals tend to move less frequently, as they often have well-established social networks within their communities and benefit from lower long-term rental costs Fister et al. (2025). For this age group, factors such as access to retirement homes or other suitable housing options within their neighborhoods, personal health, the affordability of alternative living arrangements, and the overall financial feasibility of relocation become increasingly important determinants of their residential decisions. The importance of social networks and communities is further reflected in relocation distances. 70% of relocations occur within a radius of 10 km (FSO, 2024) and most newly constructed buildings are initially populated by people from within the same agglomeration (Hermann et al., 2025).

With the rising urbanization of the Swiss population, substantial population growth is evident in urban areas and their agglomerations, with a continuous need to allocate resources for infrastructure appropriately, whereas more rural regions often experience population decline. As rural populations decrease, educational facilities and essential infrastructure are shut down, diminishing accessibility and potentially reinforcing ongoing demographic patterns that can lead to problematic situations for rural municipalities. Consequently, small-scale demographic projections can become a crucial planning tool for both growing and declining municipalities. Addressing the spatial mismatch between planning activities and demographic projections can improve the planning of schools, healthcare services, transport networks, and water, waste, and electricity infrastructure. This study aims to improve the understanding of relocation behavior by quantifying the effects of different variables on relocation rates and creating a model using machine learning techniques to predict relocations at the household level.

These demographic issues are intrinsically linked to the United Nations' Sustainable Development Goals (SDGs), particularly Goals 4 and 11. Goal 4 prioritizes inclusive and quality education, with Target 4a stressing the importance of creating safe, inclusive, and well-equipped educational settings. In Switzerland, where the cost of educational infrastructure is high, efficient strategic planning is crucial for optimal resource utilization. Goal 11 is centered on building inclusive, safe, and sustainable urban areas. Objectives 11.2 and 11.3 promote accessible transportation and efficient urban planning. Tackling these objectives is critical in the context of rapid urbanization and changing demographics, highlighting the necessity of data-driven infrastructure planning (UN, 2015).

2.2 Swiss demographic landscape

This section outlines the Swiss demographic context.

2.2.1 Fertility

Fertility, understood as the actual reproductive output of a population, is generally measured by indicators like the crude birth rate, general fertility rate, and total fertility rate. The total fertility rate, in particular, estimates the average number of children a woman would have throughout her life under current age-specific fertility conditions. Fertility is influenced by more than just biological fertility; it also depends on a complex mix of cultural, socioeconomic, and institutional factors, such as family formation norms, contraceptive access, women's education, and policy measures, making fertility difficult to predict. Despite these complexities, the fertility rate exhibits minimal spatial variation. Historical trends demonstrate steady declines in fertility during the demographic transition, marking shifts from agricultural to industrial and post-industrial production systems and changing family and gender dynamics (Bongaarts, 1994). The wartime and postwar baby boom in Switzerland is evident in birth rate data. Since the 1970s, Switzerland's fertility rate has been decreasing, with the current average at 1.3 children per woman (FSO, 2018b, 2025a). To sustain the population size without considering migration, a rate of 2.1 children per woman is needed. The baby boom and subsequent birth rate decline are also reflected in the age population pyramid (fig.1), illustrating the gradual aging of the Swiss population (FSO, 2018b, 2022b)

2.2.2 Mortality

Mortality constitutes the second major component of demographic change, encompassing the study of death rates, life expectancy, and survival patterns across populations. Standard indicators include the crude death rate (CDR), infant mortality rate (IMR), and life expectancy at birth, while more detailed analyses employ age-specific mortality rates to capture variations across cohorts. The long-term decline in mortality observed since the late nineteenth century has been strongly linked to advances in public health, medical technology, and improvements in nutrition and sanitation. The epidemiological transition framework emphasizes the shift from infectious disease-dominated mortality to one increasingly shaped by chronic and degenerative conditions, a transformation that underpins much of contemporary demographic change (Omram, 2001). In Switzerland, this trend is evident in the decreased mortality rate. In 1970, the annual death rate was 1,200 men and 800 women per 100,000 people, while in 2023 it decreased to 470 men and 333 women (FSO, 2022b,d).

2.2.3 Migration

Migration describes the movement of individuals across spatial boundaries and is the most volatile and context-dependent component of demographic change. Unlike fertility and mortality, which are biologically constrained, migration reflects economic opportunities, political circumstances, environmental pressures, and social networks. Demographers differentiate between internal migration, which refers to movement within a country's borders, and international migration, which involves movement between different nation-states. Both forms exert profound effects on the size, composition, and spatial distribution of populations, shaping labor markets, urbanization patterns, and cultural dynamics. Migration flows are also inherently selective, as migrants often differ systematically from non-migrants in age, education, and socioeconomic status, thereby generating feedback effects on both sending and receiving regions (Massey et al., 1993). Since 2015, there has been an increase in the emigration rate of individuals over 60 years old, which contributes to a reduction in the aging of the population. Overall, Swiss citizens have a negative migration balance, more Swiss citizens leave the country than move to it. Among foreign nationalities, immigration exceeds emigration in Switzerland (FSO, 2022b)

2.2.4 Population Structure

Beyond the three key processes, demographic analysis focuses on population structure, particularly the age and sex distribution of individuals. This structure is often depicted using population pyramids, which indicate wether a society is experiencing growth, stability, or decline. Indicators such as the dependency ratio, which measures the share of dependents compared to the working-age population, are crucial. They have significant implications for economic sustainability and social welfare. Additionally, population momentum is an important concept that describes continued population growth despite reduced fertility rates, driven by a substantial cohort of young people reaching reproductive age. These structural dynamics demonstrate that population change is influenced not only by current fertility or mortality rates but also by past demographic patterns. Although the Swiss population is consistently aging, this trend is projected to weaken by the mid-21st century (Bongaarts, 1994; Lutz et al., 2008; FSO, 2022b).

Migration significantly affects the age composition of the population in Switzerland. Individuals aged 20 to 39 make up the largest cohort among migrants, thereby boosting the working-age demographic. Nearly 60% of immigrants and 50% of emigrants fall within this age range. This group's high mobility leads to a continual renewal of its population. Since 2015, there has also been an increase in the number of emigrants aged 60 and above. As a result, migration is currently the primary driver of population rejuvenation. Nonetheless, this impact is expected to diminish over time. In the long run, migration flows will decline as Europe's population ages. The demographic aging observed across Europe plays a role in reducing the migration balance, as the competition for attracting skilled workers between Switzerland and these countries is predicted to become more intense (FSO, 2022b).

In 2016, 1.5 million people aged 65 and older lived in Switzerland. According to the scenarios of the FSO, this age group is expected to comprise more than 2.7 million people by 2045. As a result, the proportion of seniors in the total population is expected to rise from 18% (2016) to 27% within 30 years. Numerous sectors, including housing, will have to adapt to the needs of this population group. Currently, 96% of older people live at home, and only 4% of seniors live in a retirement, nursing home, or hospital facility. In nine out of ten cases, they live alone (32%) or in couple households (56%). The proportion of those living alone increases with age due to the mortality of their partners. For comparison: Nearly half (47%) of 25 to 64-year-olds live in couple households with children, 26% live in couple households without children, and 17% live alone. Older women are more exposed to the risk of widowhood and the consequences of a potential loss of autonomy than men. In addition, they are more likely to live alone or in an institution compared to men of the same age. This can be explained by the fact that women's life expectancy is higher than that of men, and that women in couples are often a few years younger than their husbands or partners. (FSO, 2018a, 2022b).

2.2.5 Marriage and Divorce

In 2020, 16,200 divorces were registered. This represents an increase of 23% compared to 1990 (13,600). Divorce is especially common in young marriages. Most divorces in 2020 occurred after eight years of marriage (769 or 4.7% of all divorces). Over the past decade, the frequency of divorces after 20 or more years of marriage has increased significantly. Couples who divorce after 20 or more years of marriage accounted for 32% of all divorces pronounced in 2020, compared to 22% in 1990.

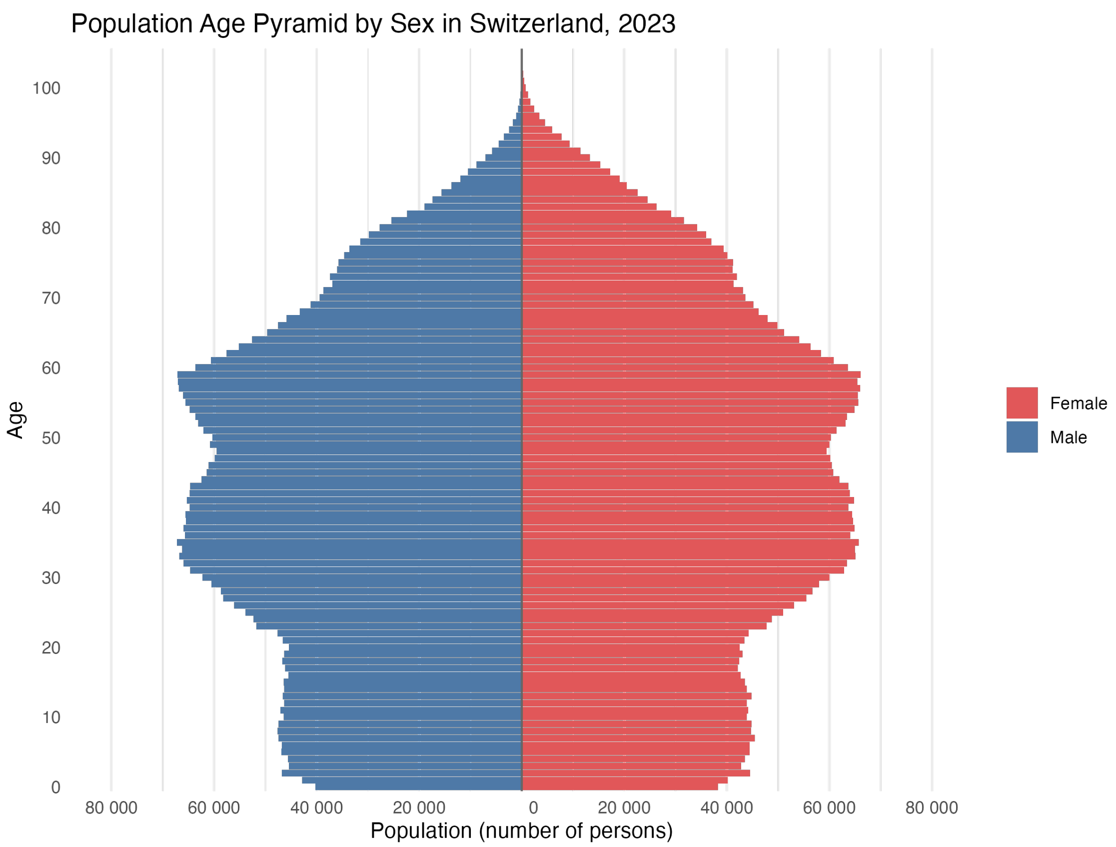


Figure 1: Age pyramid of Swiss population in 2023.

They now represent the largest group of divorced individuals. In 2020 the average duration of marriage was 15.6 years, compared with 11.9 years in 1990. The average age at the divorce has risen by seven years from 1990 to today: for men from 42.0 to 49.1 years and for women from 38.4 to 45.4 years (FSO, 2022b).

2.3 Demographic predictions for Switzerland

FSO's forecasts suggest that the long-term development of Switzerland's population will rely significantly on the intensity and nature of migration, as natural population growth is anticipated to remain low or nearly stagnant in the future. Population growth in Switzerland is expected to occur mainly in urban centers and agglomerations. The demographic shifts highlight pronounced regional disparities, reflecting Switzerland's economic geography and settlement patterns (Hermann et al., 2025; FSO, 2025b).

The population distribution across municipalities from 2013 to 2023 (fig. 2) indicates a marked concentration of growth in urban and peri-urban areas, contrasting with stagnation or decline in many peripheral and alpine regions. The major metropolitan areas, especially Zurich, Zug, Basel, Lausanne, and Geneva saw the most significant population increases, with growth of up to 20%, driven by robust labor markets, international migration, residential expansion, and densification. This trend indicates continued urbanization and increasing density, supported by housing demand and transportation links along the central plateau corridor. This trend has led to very low vacancy rates and increasing rent prices in many urban regions in Switzerland. In contrast, many rural municipalities experienced demographic declines of 10-20% during the same period. These regions, predominantly in the Jura arc, Valais, Grison and parts of Ticino, face structural challenges, limited economic diversity, and youth out-migration intensifying the population growth in the economic centers of Switzerland. The combined impact of aging and negative net migration fuels a reinforcing cycle of depopulation and reduced service provision in rural regions(FSO, 2025b).

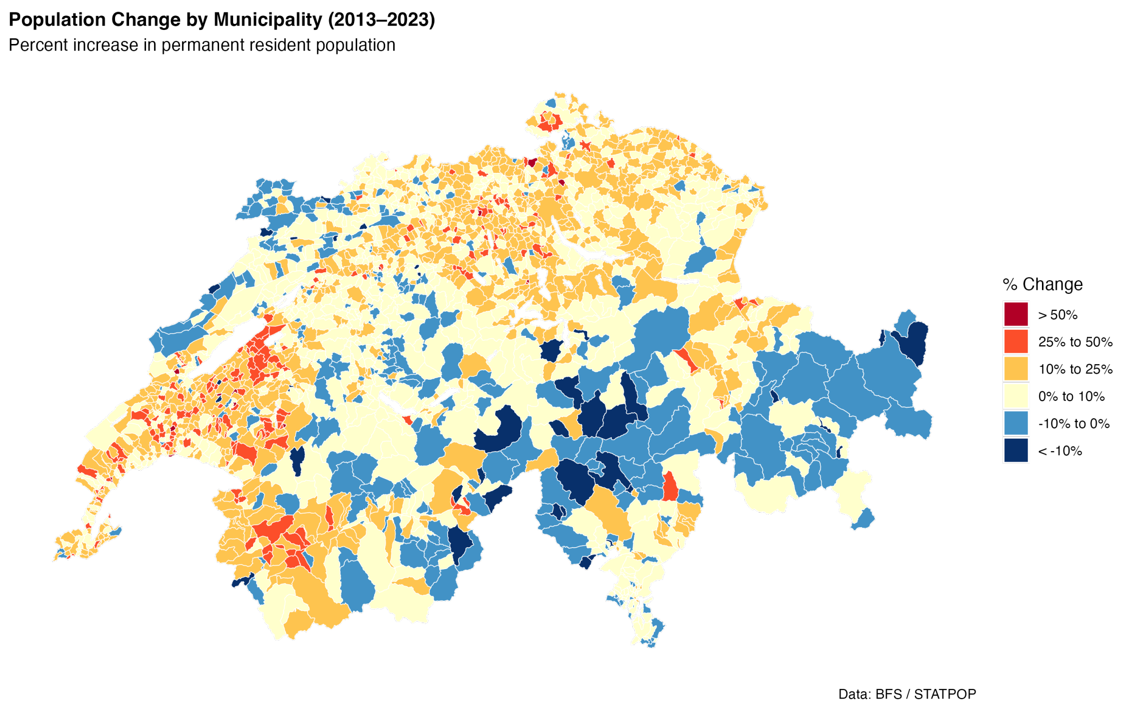


Figure 2: Population change per municipality during the 10-year period from 2013 to 2023. Data: BFS / STATPOP

2.4 Building Stock in Switzerland

In the year 2020, the FSO undertook an extensive and detailed examination of Switzerland's building inventory, utilizing data derived from the national building and dwelling statistics FSO (2022a). This meticulous analysis offers insights into the patterns of population distribution relative to various categories of housing types, the status of property ownership, and the spatial variations within the housing inventory. Throughout this study, single-family homes (SFH) and multi-family homes (MFH) are used as standard abbreviations.

At the end of 2020, there were approximately 1.8 million residential buildings in Switzerland, 7% more than in 2010. The total housing stock in Switzerland comprised around 4.6 million apartments, 14% more than in 2010. Of the full building stock more than half (55%) are apartments with 3 or 4 rooms. The average apartment size was 99 m^2. The average size of apartments has remained stable since 2000 (97 m^2). However, newer buildings have larger apartments. At the end of 2020, 2.3 million households (60%) in Switzerland lived in rental apartments. 57% of buildings used for residential purposes are single-family houses, where 27% of the population lives. In 2024 29.7% of buildings in Switzerland were built before 1946 and 18.5% were built after 2001. (FSO, 2022a).

Swiss households are more often renters than owners. At the end of 2020, Switzerland had 2.3 million renter households and 1.4 million households living in their own homes, corresponding to a homeownership rate of 36.2%. This rate has increased since 1970 (28.5%). Generally urban regions have lower ownership rates, where as ownership rates in rural regions are significantly higher. The cantons of Appenzell Innerrhoden (58%), Valais (54.3%), and Jura (49.3%) have the highest home ownership rates, while the urban cantons of Basel-Stadt (15.4%) and Geneva (18%) have the lowest (FSO, 2022a).

The prevalence of home ownership significantly varies between different household compositions. There is a clear connection between living together as a couple and acquiring home ownership. Couples, irrespective of whether they have children, demonstrate considerably higher home ownership rates (47%). In stark contrast, single-person households exhibit a markedly lower home ownership rate of 22.4%. Similarly, single-parent households, which include one or more children, also have reduced home ownership rates, reported at 27.1%. This disparity highlights the impact of household structure on relocation behavior (FSO, 2022a).

2.5 Densification Potential

Densification of urban areas has positive sustainability effects, as it mitigates urban sprawl and reduces C02 emissions from mobility and energy. In addition, densification projects increase the supply of housing, which in turn can help with affordability of housing, but may also lead to gentrification processes. The process of densification can enhance urban diversity and contribute to socioeconomic diversity in a neighborhood. This change not only alters the demographic composition of an area, but may also require adjustments in local services such as daycare centers, playgrounds, schools, health, and traffic infrastructure (Wicki et al., 2022; Schmid & Schläpfer, 2023; FSO, 2024).

In Switzerland, more than a third of households are inhabited by a single person. The proportion of individuals living alone in the permanent resident population is 17%. In another third of the households, two people reside. This corresponds to 30% of the permanent resident population. In 2020, a household comprises an average of 2.20 people, compared to 2.33 in 1990, indicating an overall less dense utilization of living spaces. Between 1990 and 2020, the proportion of larger households has slowly declined, while that of one- and two-person households has increased. In more than three-quarters of the buildings, there are 1 or 2 apartments. These buildings are inhabited by around 40% of the population. In only about 5% of the buildings there are 10 or more apartments. These buildings are inhabited by around a quarter of the population (FSO, 2022a).

In Switzerland, there are currently 1.1 million SFH, which make up more than half of the building stock (57%). However, SFH only accommodate 27% of the Swiss population with 47% of households consisting of a maximum of two people. With SFH residents using 25% more living area per person and significantly higher land use than residents of MFH there is a large potential for housing densification. If the densification process is activated, it could impact local demographics. The prerequisites for unlocking this potential include (1) the willingness of homeowners to move or allow transformation of their property, (2) the availability of suitable housing, (3) the financial feasibility and attractiveness of moving from a SFH to a rental or condominium and (4) the appropriate framework provided by authorities to enable suitable conditions to ensure that sufficient housing of the desired quality is built in appropriate locations (FSO, 2022a; Schmid & Schläpfer, 2023).

In 2016, nearly one in three elderly persons (31%) lived in a SFH. This proportion changes with the age of the person. Among those aged 30 and over, it steadily increases, reaching 35% for those around 50 years old. During retirement (people aged 60 to 64 years), the number of people in single-family homes decreases, while an increase is observed among those in apartments. For seniors aged 85 and over, just over a quarter (27%) still live in a SFH. This situation partly reflects the difficulties that may arise from deteriorating health and limitations in daily activities. As age increases, a multi-story house can be a burden regarding mobility (stairs, unsuitable bathrooms) and maintenance (surroundings, financial expenses) (FSO, 2018a).

Seniors live in apartments with an average of 4 rooms, which is comparable to the rest of the population (4.1 rooms). However, 90% of older people live alone or as a couple in their apartment, while half of those aged 25 to 64 live with at least two other people. If only those living alone and couples are considered, older people more often live in an apartment with four or more rooms than those aged 25 to 64. This difference exists because they have had more time to progress along their housing career ladder. The housing career ladder describes the progression of households through different housing types over the life course, driven by changes in income, household composition, and housing needs (FSO, 2018a; Lehner et al., 2023).

Seniors rarely adjust the size of their apartments to their household structure. It can be assumed that most of today's seniors moved into their apartments when their household included more people or was expected to grow. After children move out or a partner passes away, many older people remain in their apartments for practical, financial (e.g., lower rent), or social reasons (e.g., neighborhood). From a certain age, many people are reluctant to leave the place where they have spent much of their lives (Lehner et al., 2023; Hermann et al., 2025). This situation is favored by the fact that older people live longer and healthier lives than before and, thanks to outpatient care services, can stay in their apartments longer. Moreover, the housing market often does not allow older people to move even if they wish to. Finding an apartment at a reasonable price in the nearby area is often difficult. For these and other reasons, many older people live in apartments that are considered family-friendly. In this context, it is worth examining the proportion of older people living in particularly large or particularly small apartments in relation to their household size. Here, apartments with four or more rooms for singles and with five or more rooms for couples are considered particularly large. Particularly small apartments are those with one room for singles and two rooms for two or more people. 32% of people aged 65 and over live in particularly large apartments, and 4% in particularly small ones. For comparison, only 11% of people aged 25 to 64 live in a particularly large apartment, whereas 6% live in particularly high density conditions.(FSO, 2018a).

2.6 Influence of Housing Market

Rapid population growth and a housing shortage are exerting pressure on the housing markets in urban areas. A tight supply of new housing and low vacancy rates have pushed rent and land prices to high levels. Rising housing prices lead to a stronger locked-in effect: more people remain in their apartments, causing price pressure to increase on the apartments that do become available (Hermann et al., 2025). As of 2025, the average vacancy rate in Switzerland is approximately 1%. A housing shortage is generally assumed when the vacancy rate falls below 1%. Urban regions tend to show considerably lower values: Zurich currently records a vacancy rate of 0.1%, Geneva 0.34%, and Bern 0.4%, indicating a particularly tight housing market situation (FSO, 2022a).

Newly built apartments are frequently occupied by younger individuals and young families. They often look for a new apartment because of a change in their professional or educational situation, because they want to move out of their parents' home, or because they are expanding their household. In the large metropolitan areas, young adults and families often live in newly built apartments, while older residents remain in existing housing and benefit from lower rents (Hermann et al., 2025).

In the medium and long term, the change in population in Switzerland is shaped mainly by positive migration patterns, which are currently the largest contributors to population growth. These patterns affect future housing development, which can be restricted by the availability of housing development opportunities. Relevant variables include the availability of building land and the rate of densification. Together, these indicators capture the latent capacity of a neighborhood to accommodate additional population growth over time. Beyond physical housing capacity, economic factors in the housing market also shape demographic patterns. Recent studies have shown that almost 45% of the population would like to move, but the actual relocation rate is at 10% . This intention gap might partially be the result of a housing shortage and the lack of financial resources to move freely in a housing market with increasing rent prices (Lehner et al., 2023).

Rent levels and income distributions can determine who can remain in or move into areas. For example, gentrification processes, which are often driven by rising rents in desirable urban centers, can displace lower-income households from central neighborhoods to more affordable, peripheral regions. Such movements affect population densities and shape the sociodemographic composition of both gentrifying and receiving areas, as displaced households, on average, earn 4,800 CHF less per month than the average household. Foreign populations and single parents are disproportionately affected by displacement. With more than 70% of movements occurring within a radius of 10 km, displacement can alter the sociodemographic compositions of neighborhoods over time (Kaufmann et al., 2023; Hermann et al., 2025)

The attractiveness of a neighborhood influences rent levels. This attractiveness can be captured through micro- and macro-location ratings of real estate, reflecting factors such as accessibility, environmental quality, and proximity to amenities. In addition, household characteristics, including the age of residents, income class, household composition (e.g., single-person households versus families), and the overall demographic makeup of the neighborhood, provide further context for understanding how population structures evolve. Together, these elements might offer valuable insights into the mechanisms driving demographic change at fine spatial scales, complementing traditional macro-level models based on fertility, mortality, and migration (Schmid & Schläpfer, 2023)

2.6.1 Silver Tsunami

As in most other countries in the Global North, Switzerland is facing an aging population, with the baby boomer generation starting to move into retirement age, the so-called "Silver Tsunami". In the Swiss context, this phenomenon has raised concerns that the progressive aging of homeowners might trigger a wave of property sales and thus destabilize the housing market. However, recent evidence from Raiffeisen Schweiz (2025) regarding the “Silver Tsunami” phenomenon challenges this assumption. Drawing on comprehensive market and demographic data, the study concludes that a rapid sale of owner-occupied homes by elderly households is unlikely. Most homeowners aged 65 years and older demonstrate a strong desire to age in place, maintaining their established living arrangements rather than downsizing or relocating. This preference reflects high residential satisfaction, emotional attachment to one's home, and the financial security associated with long-term ownership among their age group (Lehner et al., 2023). Consequently, the expected “flood” of houses entering the market has not materialized and is not going to. Instead, the study characterizes the Silver Tsunami as a slow structural transformation rather than a sudden demographic shock. Complementary findings further indicate that the aging of property owners will gradually reshape market liquidity and the spatial distribution of available housing. As elderly homeowners continue to occupy large, often under-used dwellings, the effective supply of family housing remains constrained. At the same time, the growing cohort of retirees increases the demand for centrally located, accessible, and age-appropriate dwellings. This dual dynamic of limited release of existing stock and rising demand for barrier-free units reinforces long-term pressure in urban and peri-urban housing markets. In peripheral regions, by contrast, weaker demand from younger buyers can cause stagnation in aging-related housing, with a higher share of inherited or vacant properties that are slow to be re-absorbed into the active market (Raiffeisen Schweiz, 2025).

The intergenerational implications of the Silver Tsunami extend beyond market liquidity to patterns of relocation behavior among younger cohorts. As the baby boomer generation remains in place longer, opportunities for younger households to move into ownership, often through intergenerational transfer or inheritance, are delayed. This postponement can reinforce dependence on rental housing and prolong the tenure of younger households in smaller or less suitable dwellings. When ownership transfer eventually occurs, it often coincides with life-course milestones such as family formation or mid-career consolidation, producing spatial reallocation effects: inherited homes in peripheral areas may be sold, while recipients relocate toward urban employment centers. Thus, the Silver Tsunami indirectly shapes the mobility patterns of the next generation, influencing both the timing and geography of their housing transitions (Raiffeisen Schweiz, 2025).

2.7 Demographic forecasting – State of the Art

The modeling of demographic change has been a central topic in population research for over a century. One of the earliest and most influential approaches are the cohort component model (CCM), which was applied early on in demography by Cannan (1895); Bowley (1924) and Whelpton (1936). The CCM remains the classical foundation for population forecasting at both national and regional scales. The fundamental principle of the cohort component approach is to project population changes by age, sex, and fertility over time. The population is divided into cohorts, each representing individuals of the same age. Every cohort is assigned age-specific fertility, mortality, and migration rates. Over successive periods, cohorts advance in age, deaths are subtracted according to survival probabilities, and births are added by applying fertility rates to women of childbearing age. Migration is treated as a separate factor to capture its variability and dependence on external drivers. The CCM forms the methodological basis of nearly all contemporary population projections, including those produced by Eurostat, the United Nations, and the Swiss Federal Statistical Office (Whelpton, 1936; Bowley, 1924; Cannan, 1895; Smith et al., 2013; United Nations & Social Affairs, 2024; Eurostat, 2024; FSO, 2025b).

2.7.1 Bayesian Hierarchical Modelling

The cohort component model (CCM) has long been the standard method for forecasting population change. In recent years, this approach has been expanded with probabilistic and stochastic frameworks that explicitly represent uncertainty. These newer models use time-series techniques to quantify uncertainty around fertility, mortality, and migration rates. Bayesian hierarchical modelling (BHM) builds on these ideas by allowing uncertainty to be carried through every step of the projection process. Instead of producing a single forecast, the model generates a range of possible outcomes with associated probabilities. In a Bayesian framework, model parameters such as fertility or mortality rates therefore are treated as quantities that are not fixed but have probability distributions. These distributions are informed both by prior knowledge, such as past demographic trends or expert judgment, and by the observed data. As new data become available, the model updates its estimates, gradually narrowing the uncertainty around the most likely outcomes (Lutz & Goldstein, 2004; Raftery et al., 2012, 2014).

The United Nations adopted Bayesian hierarchical models in 2012 for its World Population Prospects (WPP) to produce probabilistic population projections. These models yield complete probability distributions for future population sizes and age structures, allowing the presentation of credible intervals (for example, 80 % or 95 %) rather than a single deterministic path in the CCM. This provides a more transparent picture of forecast uncertainty and supports more robust decision-making. For smaller populations, Bayesian models have proven especially valuable because they can share information between similar regions or demographic groups, improving estimates where data are sparse. For instance, fertility or migration patterns from neighboring cantons can inform forecasts in municipalities with limited observations. The Bayesian framework also makes it possible to include explanatory variables such as economic conditions, education levels, or policy indicators, thereby offering a richer and more flexible way to understand and project demographic change (Raftery et al., 2014; Bijak & Bryant, 2016; Eurostat, 2024).

2.7.2 Micro simulation & Agent-based Models

While Bayesian models primarily address uncertainty in demographic rates, micro simulation models focus on the heterogeneity of demographic behavior at the individual or household level. These models replicate the life trajectories of individual agents, each possessing characteristics like age, gender, education, and employment, utilizing transition probabilities derived from empirical data. They allow for detailed modeling of interactions between demographic, economic, and behavioral processes over time. Micro simulation and agent-based models (ABMs) have become notable for their capability to replicate individual life histories and interactions. Micro simulation models utilize extensive population datasets to assign attributes such as age, gender, education, and family structure, simulating transitions like births, deaths, migration, and partnership formation using empirical transition probabilities. These models can depict complex interdependencies, such as the influence of education or the housing market on fertility, as well as spatial interactions among individuals and regions. Agent-based models further this concept by integrating behavioral rules and feedback loops, enabling the simulation of policy interventions or environmental changes and their effects on demographics. The strength of micro simulation lies in its ability to capture non-linear and feedback effects, for instance how educational attainment influences fertility timing, or how aging and retirement affect labor supply. However, such models are data-intensive and computationally demanding. Calibration requires longitudinal micro data (e.g., population registers, surveys, or census-linked datasets), and validation depends on replicating observed aggregate statistics. When adequately parameterized, micro simulation can achieve high fidelity in reproducing both demographic and socioeconomic patterns, making it an increasingly powerful tool for policy-oriented demographic modeling. Micro simulation models often demand substantial computational resources and become challenging to interpret as they grow more complex. As these models increase in complexity, it becomes harder to grasp their operations and evaluate their predictive capabilities.(Van Imhoff & Post, 1998; Billari & Prskawetz, 2003; Spielauer, 2011; Grow & van Bavel, 2017).

2.7.3 Spatial Techniques in Demographic Modeling

Recent methodological advances in demographic modeling have moved beyond the traditional cohort-component framework, integrating probabilistic reasoning, micro simulation, and spatial analysis into unified modeling environments. These new approaches enhance the capacity to represent uncertainty, heterogeneity, and interdependencies within demographic systems, while also improving the explanatory power of projections for policy analysis and planning.

While Bayesian hierarchical models address uncertainty in demographic parameters, recent methodological developments have also focused on incorporating the spatial dimension of population change. Spatial demographic modeling acknowledges that demographic processes such as fertility, mortality, and migration are not evenly distributed across space but are shaped by regional context and spatial interdependencies. Neighboring regions often share similar social, economic, or environmental conditions, leading to spatial clustering of demographic outcomes. Ignoring these dependencies can result in biased estimates and misleading inferences, particularly in regional or subnational analyzes. Early spatial demographic studies primarily used descriptive mapping and correlation techniques to explore regional differences in population trends. With advances in spatial statistics and computational power, more sophisticated approaches such as spatial regression, geographically weighted regression (GWR), and multilevel spatial models have emerged. These methods explicitly account for spatial dependence and heterogeneity by allowing relationships between demographic variables to vary across space. For example, spatial lag and spatial error models incorporate the influence of neighboring regions in the estimation process, capturing diffusion effects or regional spill-overs in demographic behavior. Spatially explicit methods also extend the traditional cohort-component framework by enabling population projections for multiple interconnected regions. Multi regional and multi area models consider migration flows between areas, while geostatistical and spatial interaction models describe how demographic processes evolve within continuous space. Such models are particularly relevant in contexts where population change is driven by urbanization and internal migration, producing strong spatial gradients in growth and decline. Recent advances in data availability and geographic information systems (GIS) have further strengthened spatial demography as a field. The increasing accessibility of high-resolution spatial data allows the integration of demographic, environmental, and socioeconomic variables. This integration improves small-area estimation, enables spatial forecasting, and supports policy applications such as urban planning or regional service provision. As Matthews and Parker (2013) note, demography is inherently spatial, and contemporary modeling efforts are moving toward approaches that combine spatial and probabilistic reasoning to capture the complex, interconnected nature of population dynamics (De Castro, 2007; Chi & Zhu, 2008; Matthews & Parker, 2013; Gu et al., 2020; Uhryn et al., 2023).

2.7.4 Machine Learning and Hybrid Approaches

In recent years, machine learning (ML) and hybrid models have been explored as complementary tools to improve demographic forecasting for data sparse regions. Further ML methods are applied to deepen the understanding of cohort specific determinants, for example, to deepen the understanding of divorce determinants in Germany, mortality for under-5-year olds in Ethiopia, or to analyze health characteristics (Arpino et al., 2018; Hamad et al., 2019; Bitew et al., 2020).

3 Related Work

Residential location choice is widely recognized as a key contributor to overall quality of life. Over the past decade, numerous studies have examined the determinants of housing location choice in context of residential self-selection. Residential self-selection assumes that residents do not only adapt to their built environments, but also choose their residential location based on personal preferences and act on these preferences. Much of the literature has therefore focused on patterns of residential relocation and the commuting behavior associated with preferred modes of transportation, following the idea that individuals aim to optimize their mobility preferences through their housing choices. These insights are particularly useful when governments participate in efforts to provide attractive and affordable housing to alleviate overpopulation issues Adhikari et al. (2020). Existing research highlights a range of significant factors including the built environment surrounding the dwelling, major life-course events, commuting distances, individual and household socio-demogrpahic characteristics, and travel-related preferences (Van Acker et al., 2014; Ibrahim, 2017; Yu et al., 2017; Fatmi & Habib, 2017; Kroesen, 2019; Wolday et al., 2019; Adhikari et al., 2020; Xue & Yao, 2022).

Studies by Ibrahim (2017); Kroesen (2019); Wolday et al. (2019) examined the effects of built environment characteristics, such as population density, intersection density, land use mix, and distance to points of interest, such as the city center or public transport stops on residential self-selection. Important life events such as marriage, separation, and family formation were analyzed by Van Acker et al. (2014); Fatmi & Habib (2017); Yu et al. (2017); Adhikari et al. (2020). Sociodemographic factors at the personal and household level, such as gender, age, level of education, marital status, economic strength, and household composition, have been studied by Ibrahim (2017); Yu et al. (2017); Ardeshiri & Vij (2019); Kroesen (2019). Xue & Yao (2022) developed a residential relocation behavior model based and found that the built environment factors had the greatest impact on relocation behavior.

According to the FSO, the annual moving rate in Switzerland has ranged between 9.3% and 10.3%, with a gradual decline observed in recent years. Although approximately 769,000 people moved in 2020, this number fell to 695,000 by 2023. Among those who relocated, nearly 75% remained within the same canton, and 37% stayed within their municipality of origin. Only about 2% of the movers crossed language borders. The FSO found that in 2023, young adults aged 20 to 36 years had the highest mobility rate of 19.3%, followed by children under the age of two at 15.3%. In contrast, the rate of moving for people under 60 years of age declined by nearly 10% over the past decade, while the rate for people over 60 years of age increased by 2%, suggesting a modest shift in relocation behavior among older adults (FSO, 2023).

The clear age dependence of relocation suggests that different factors shape relocation behavior at different stages of life. Recent research has shown that relocation behavior in Switzerland is shaped by a complex combination and interplay of life-course, socioeconomic, and spatial factors. Studies by the FSO (2024), Die Schweizerische Post (2023) and Fister et al. (2025) demonstrate that moving behavior varies markedly across age groups and declines with age. Lehner et al. (2023) conducted qualitative and survey-based research with more than 1,000 individuals from various age groups and backgrounds. Their findings also show that residential moves are primarily motivated by life-course transitions such as partnership formation, separation, or the establishment of new households. These factors are followed by housing-market and affordability considerations, including the desire for a better residential environment or lower housing costs. Younger individuals relocate more frequently than older cohorts, are more likely to move to urban areas and shared households, and are particularly sensitive to rental affordability. Educational opportunities and employment prospects are also major drivers of their mobility, reflected in higher relocation rates in urban regions compared with rural ones.

Young families often relocate due to childbirth and the resulting need for additional living space. In contrast, older adults move less frequently because they have established social networks, benefit from stable long-term rental contracts, and exhibit a stronger attachment to place. A slight increase in relocation activity is observed around the age of 65, corresponding to the statutory retirement age in Switzerland. After retirement, relocation often occurs in favor of age-appropriate housing or because independent living becomes difficult due to deteriorating health. For this group, relocation decisions increasingly depend on the availability of suitable housing options such as retirement homes or accessible dwellings within their neighborhood, as well as on health status and financial feasibility (FSO, 2023; Die Schweizerische Post, 2023; Fister et al., 2025).

The willingness to move declines not only with age but also with increasing personal and financial commitments, such as childbearing or home ownership. Overall, 45%

of respondents expressed a willingness to move, 25% were open to the idea but had no immediate plans, and 30% were entirely settled. This distribution points to a high general openness to relocation but also reveals a clear intention–behavior gap: many who express a willingness to move ultimately do not do so. This gap is attributed to status quo bias, decision complexity, and the uncertainty associated with change (Xue & Yao, 2022; Lehner et al., 2023).

Individuals who are not planning to relocate tend to be further along in their housing careers, characterized by larger living spaces, higher home ownership rates, and greater residential satisfaction. Attachment to both the social and spatial environment also plays a decisive role: 88% of non-moving respondents reported satisfaction with their current location, and 73% cited positive relationships with neighbors as a main reason for staying. Even among those who express a willingness to move, relocation is a deliberate and lengthy process, with most individuals taking more than two years to find a suitable dwelling. Overall, residential satisfaction across the Swiss population is high, and 43% of respondents wish to remain permanently in their current or future home, underscoring the enduring value placed on stability and home ownership within the Swiss housing context (Lehner et al., 2023).

Taken together, these findings suggest that the probability of relocation in Switzerland is determined not only by structural variables such as age, household composition, and tenure status, but also by behavioral and motivational factors, including satisfaction, inertia, and perceived control over change. From a modeling perspective, these findings suggest that relocation probability should be conceptualized as a function of both individual characteristics such as age, household composition, home ownership, income, and contextual factors, including housing-market conditions and neighborhood quality. Variables capturing life-course events, housing adequacy (e.g., dwelling size per person), and financial constraints should be included to represent triggers for relocation (Lehner et al., 2023)

Younger households and renters, who are more exposed to changes in employment, education, and affordability, are expected to exhibit a higher probability of relocation. In contrast, older and more established households are likely to remain more stable, especially when there is a strong social and financial attachment to the place. Furthermore, because relocation in Switzerland tends to be a slow and intentional process, models should incorporate temporal dependencies, for example, through lagged variables or cumulative relocation pressures. Integrating these behavioral and structural insights enables a more realistic and context-sensitive estimation of household relocation probabilities within the Swiss housing market (Lehner et al., 2023).

3.1 Modeling Relocation Behavior

Xue & Yao (2022) developed a residential relocation behavior model based on an Random Forest (RF) approach, using survey data from 900 households in Beijing. The model incorporated variables related to the built environment, commuting distance, housing prices, dwelling size, and a range of socioeconomic and demographic characteristics of households. It found that the built environment factors had the greatest impact on relocation behavior, accounting for over 70% of variable importance, with distance to the city center accounting for over 50% of the relative variable importance.

Bostanara et al. (2024) develop a dynamic, forward-looking model of residential relocation using longitudinal HILDA panel data for households in the Sydney metropolitan area. Their dynamic discrete choice framework jointly models relocation timing and destination choice by allowing households to decide whether to stay or move while accounting for expected future utilities, life-course events, housing affordability, neighborhood characteristics, and labor market conditions. Job-related mobility is modeled separately using a time-varying hazard framework, with the resulting job relocation probabilities incorporated into the residential choice model. This integration explicitly links employment and housing decisions and is argued to provide a more behaviorally realistic representation of residential mobility than static or purely hazard-based approaches, as it treats relocation as an intertemporal decision process.

3.2 Research Gap

While Lehner et al. (2023) provides a detailed descriptive analysis of relocation behavior, the quantitative contributions and relative importance of individual explanatory variables to relocation rates remain unclear. This study addresses this gap by explicitly estimating both the direction and magnitude of key sociodemographic and building stock effects on relocation behavior, with a particular focus on differences across age groups. In contrast to much of the existing literature, which predominantly analyzes individual-level moves, this study considers relocation decisions at both the individual and household levels, thereby capturing complete household relocations alongside single-person movements. Furthermore, a complete population dataset covering all of Switzerland is used, allowing for a comprehensive perspective on residential relocations rather than relying on a limited number of households to train models. Many existing modeling approaches are instead confined to specific urban contexts, such as Sydney or Beijing, and may not be directly transferable, as cultural, institutional, and housing market differences can influence how explanatory variables are weighted in relocation behavior in Switzerland. Ultimately, this study aims to contribute to a deeper understanding of relocation behavior in Switzerland and to support the further development of demographic models and quantitative approaches to modeling residential mobility.

4 Method

This study analyzes the influence of a broad set of variables on relocation behavior in Switzerland. The first step follows the methodology of the Swiss Federal Statistical Office, which calculates relocation rates at the person level. In this framework, each individual who changes residence is counted as one relocation. A household of four persons, therefore, represents four relocations, whereas moves occurring within the same building are not counted. Based on these individual level movements, complete household relocations are derived by aggregating persons into household units and testing whether all members relocate within the same year. All relevant individual, household, dwelling, and municipality level characteristics are then consolidated at the household level, enabling the analysis to reflect household level decision making processes rather than isolated individual movements. All data processing was carried out using R. The procedure for data processing is outlined in Chapter 5.

For each explanatory variable, relocation rates are subsequently assessed by stratifying the variable by average household age and building category, thereby linking it to associated demographic, socioeconomic, life-course, and spatial characteristics. This involves categorizing or transforming variables, computing relocation rates within these categories, and examining how variations in each characteristic correspond to different levels of relocation activity. This exploratory procedure provides an initial understanding of variable specific patterns and highlights potential determinants of residential mobility. It also informs the subsequent modeling stage by revealing differences in relocation behavior across household types and contexts, ensuring that the model captures important sources of variation in the data.

To obtain a comprehensive representation of the drivers of relocation, a Light Gradient Boosting Machine (LightGBM) model is trained using a logistic objective function, which is well suited for binary outcomes such as relocation versus non relocation. LightGBM, introduced by Ke et al. (2017), is a modern and highly effective supervised learning model that builds on the gradient boosting framework and incorporates several algorithmic innovations designed to optimize computational efficiency for large datasets. The data is trained using three-fold cross-validation to ensure robustness and to mitigate overfitting.

A key innovation of LightGBM is gradient based one side sampling (GOSS), which accelerates training by retaining all samples with large gradients while randomly sampling from those with small gradients. Since large gradient instances contribute the most to improving the model, this selective sampling reduces computational costs without sacrificing predictive accuracy. LightGBM also employs exclusive feature bundling (EFB), a method that reduces dimensionality by combining mutually exclusive sparse features into a single representation. This technique is particularly effective for high dimensional data structures. The model's success further stems from its leaf wise, best first tree growth strategy. In contrast to traditional gradient boosting algorithms that grow trees level wise, LightGBM expands the leaf that offers the largest reduction in loss. This creates deeper and more specialized trees that capture complex interactions and nonlinear relationships more effectively. Although such trees may risk overfitting, LightGBM mitigates this by integrating L1 and L2 regularization. In addition, LightGBM uses histogram based learning, in which continuous variables are discretized into bins. Operating on histograms rather than raw values significantly reduces memory consumption and accelerates split finding, making the algorithm highly efficient for large scale and high dimensional data (Ke et al., 2017).

These advantages make LightGBM particularly suitable for analyzing relocation behavior in Switzerland, where the full dataset of household level relocation comprises more than thirty million observations and where the number of non moving households greatly exceeds the number of relocations. Its ability to model nonlinear effects, interaction terms, and complex variable structures without extensive manual feature engineering allows the model to uncover nuanced patterns that would remain hidden in simpler models. Alternative methods were evaluated prior to selecting LightGBM. Generalized Linear Models could not be estimated on the full data set due to memory constraints and did not capture the complex relationships present in the data. Random Forest models are a suitable alternative, but the LightGBM framework was preferred for its capability of handling missing values and computational efficiency. XGBoost was tested on smaller subsets but was unable to scale to the full data volume. LightGBM therefore provided the best combination of scalability, predictive power, and interpretability.

Model performance is evaluated using standard classification metrics, including the confusion matrix, balanced accuracy, the area under the ROC curve (AUC), receiver operating characteristic (ROC) analysis, and Cohen's kappa. Model interpretability is obtained by applying Shapley Additive exPlanations (SHAP). SHAP provides a theoretically grounded framework derived from cooperative game theory, allowing each prediction to be decomposed into additive feature contributions.

This facilitates a nuanced evaluation of how individual variables influence relocation probability across the entire population. Global SHAP summaries, based on mean absolute SHAP values, provide an overview of overall variable relevance, while SHAP dependence plots reveal nonlinear relationships, variable specific thresholds, and interaction effects that would not be detectable using standard feature importance measures. Continuous features (e.g., dwelling area and household size) are analyzed in their numeric form, whereas categorical attributes (e.g., building type, marital status) are modeled as factor variables. This interpretability framework enables a detailed and transparent understanding of the structural, demographic, spatial, and behavioral drivers of relocation probability through the applied modeling process.

In summary, this methodological approach combines descriptive relocation rate analysis with a robust and scalable machine learning framework. The integration of LightGBM with SHAP based interpretation makes it possible to identify both well established determinants of relocation and more subtle behavioral patterns, thereby offering a comprehensive empirical basis for analyzing residential mobility in Switzerland.

Spatial dependence in the model residuals was evaluated using Moran's I, a standard measure of global spatial autocorrelation. The analysis was conducted on the test dataset, where each observation represents an apartment linked to the centroid coordinates of its building. A sparse k-nearest neighbor ($k = 8$) spatial weights matrix was constructed using the *knearneigh* function from the `spdep` package. Because of the large sample size the computation of a full pairwise distance matrix would have been computationally prohibitive. Therefore, the spatial autocorrelation was computed on a subsample of 100'000 data points. Since equal coordinates are not allowed and multiple apartments have the same building coordinates, a jitter was added to each coordinate.

The spatial weights were row-standardized to ensure comparability across observations, regardless of local point density. Global Moran's I statistics were then computed to quantify the overall degree of spatial clustering in the residuals and to assess whether the model adequately captured the spatial structure in the data. To examine how spatial dependence changes across broader distances, a spatial correlogram was estimated by calculating Moran's I for successive neighbor orders.

4.1 Validation

To assess the robustness and temporal generalizability of the model, an out-of-year validation strategy is applied. In this approach, the LightGBM model is trained exclusively on data from the year 2020, which serves as the reference year for parameter estimation. The trained model is then used to predict relocation outcomes for households in other years of the observation period. By comparing predictive performance across multiple years, it is possible to evaluate whether the model captures structural and behavioral patterns that remain stable over time, rather than simply fitting year-specific characteristics.

Model performance is evaluated using standard classification metrics, including the area under the receiver operating characteristic curve (AUC), precision, recall, balanced accuracy, and Cohen's kappa. These metrics are computed separately for the training year and for each validation year. Consistent performance across years indicates that the model is able to generalize beyond the data on which it was trained, whereas marked deviations would suggest either temporal instability in relocation dynamics or overfitting to the training year.

Since relocation behavior may vary due to macroeconomic conditions, demographic shifts, or changes in housing supply, out-of-year validation provides an important test of temporal robustness. This validation framework ensures that the model not only fits past data well but also maintains predictive accuracy when applied to other years. It therefore offers a more rigorous assessment of model reliability for real-world applications, where predictions must remain valid under evolving conditions.

5 Data

This research is based on datasets from the Federal Statistical Office (FSO) and Wüest Partner AG. From the FSO, anonymized individual data from the Building and Dwelling Statistics (GWS)[1] and the Population and Household Statistics (STATPOP)[2] are employed. The STATPOP and GWS datasets can be linked through the dwelling and building identifiers, along with the corresponding reference year. The combined data provide a wide range of key sociodemographic characteristics and detailed information on the building stock. By merging these datasets, we can examine how relocation behavior and buildings interact with individuals and household structures, and untangle the underlying spatial connections. Within these datasets, each person can be uniquely identified by the building ID, dwelling ID, person ID, and data year; therefore, this dataset is subject to strict data privacy policies due to the sensitive nature of the data, and any results can only be published in aggregated form. Wüest Partners supplied comprehensive real estate market indicators, including micro- and macro-location assessments of properties, vacancy statistics, and advertised residential rental and sale prices. These data were integrated into the analysis to quantify and interpret how housing market conditions influence relocation behavior.

5.1 STATPOP

The Population and Households Statistics (STATPOP) are part of the Swiss Federal Population Census and provide annual information on the size, demographic structure, and changes in the permanent resident population. Together with the structural survey, STATPOP also forms the basis of Swiss household statistics. The STATPOP dataset used in this study was accessed and processed within the secured analytics environment of Wüest Partner AG. Table 1 lists all STATPOP variables used in the analysis.

[1] https://www.bfs.admin.ch/bfs/en/home/statistics/construction-housing/surveys/gws2009.html

[2] https://www.bfs.admin.ch/bfs/en/home/statistics/population/surveys/statpop.html

The complete dataset covers the period from 2013 through 2023. The dataset was filtered to include only the resident population ($populationtype = 1$). This yielded approximately 94 million data points for the full time span. By comparing individuals' places of residence across consecutive years, relocation events were detected, including instances of emigration. Using this approach, relocation directions, distances, and changes in building categories can be tracked. Although these factors were not relevant for this study's results, they proved to be useful information in detecting relocations, differentiating false from true relocations, and verifying results.

From the original STATPOP variables, new variables are computed. Firstly, households with a child up to the age of 5 years were detected and classified with binary values. The time since separation and marriage are extracted by comparing the date of separation or marriage to the data year and storing the years since the event. To define the time passed since a divorce or marriage, the mid-year point of the data year is used and compared to the event date. If no divorce or marriage occurred, the value -1 is used. Registered partnerships are included in marriages. Separation through the death of the partner is computed separately, as this type of separation is a different life course event that typically occurs in households with a higher average age and different household structures. For the LightGBM model, both the time elapsed since the life-course event and an additional binary indicator capturing whether the event occurred in the given year were included.

5.1.1 Compute Relocations

The identification of residential moves in this study follows the conceptual framework of the Federal Statistical Office (FSO), but several adaptations were necessary. The following section describes the full procedure used to detect relocations at the individual and household levels and explicitly outlines where this implementation differs from the official FSO methodology (FSO, 2022c).

In the first step, the relocation of individuals is identified. This was achieved by grouping the data by person ID and comparing the building ID and the dwelling ID with those of the previous year. If the building ID changed, the entry was marked as a relocation. In line with the FSO definition, relocations within the same building are not counted in this study. Due to the annual structure of STATPOP, each individual can experience at most one observable relocation per year, which is sufficient for the analytical objectives. The analysis is restricted to the permanent resident population.

A change in building ID generally corresponds to a genuine relocation. However, in some cases, the building ID changes for administrative reasons, even if the individuals have not physically moved. Such cases are referred to as “false moves”. False moves typically occur under the following circumstances:

1. Building ID Mergers: Multiple terraced houses, each previously assigned their own building ID, are administratively merged into a single building ID.
2. Building ID Splits (Separation): A building previously recorded under a single building ID is divided into several separate building IDs.
3. Reassignment of Residents Between Related Buildings: When residents are mistakenly assigned to the wrong building, the error is corrected by swapping their assignments to the correct one.

In all three situations, individuals remain in the same physical location, even though their building ID changes. Most false moves result from building ID mergers or splits. To ensure accurate mobility statistics, such cases must be identified and excluded from the count of actual moves. Given the large number of moves, this identification must be automated using deterministic rules that distinguish between true and false relocations.

The conceptual framework set by the FSO to distinguish between true and false moves is based on the following five identification criteria:

- A) Migration distance between 0 and 50 meters.
- B) Presence of both origin and destination buildings at the beginning and end of the year within the stock of residential buildings.
- C) Construction of the destination building during the previous year.
- D) Presence of both origin and destination buildings at the beginning and end of the year within the non-residential building stock.
- E) The share of moving persons in the origin or destination building exceeds 30%.

The migration distance (Rule A) is calculated as the straight-line (Euclidean) distance between the geographic coordinates of the origin and destination buildings. Most false moves are characterized by very small distances (typically less than 50 meters). Rule B considers whether the origin and destination buildings exist in the residential building registry at both the start and the end of the year. In the case of a building ID merger, the origin building no longer appears in the register at year’s end. In contrast, in an ID split for the building, the destination building does not

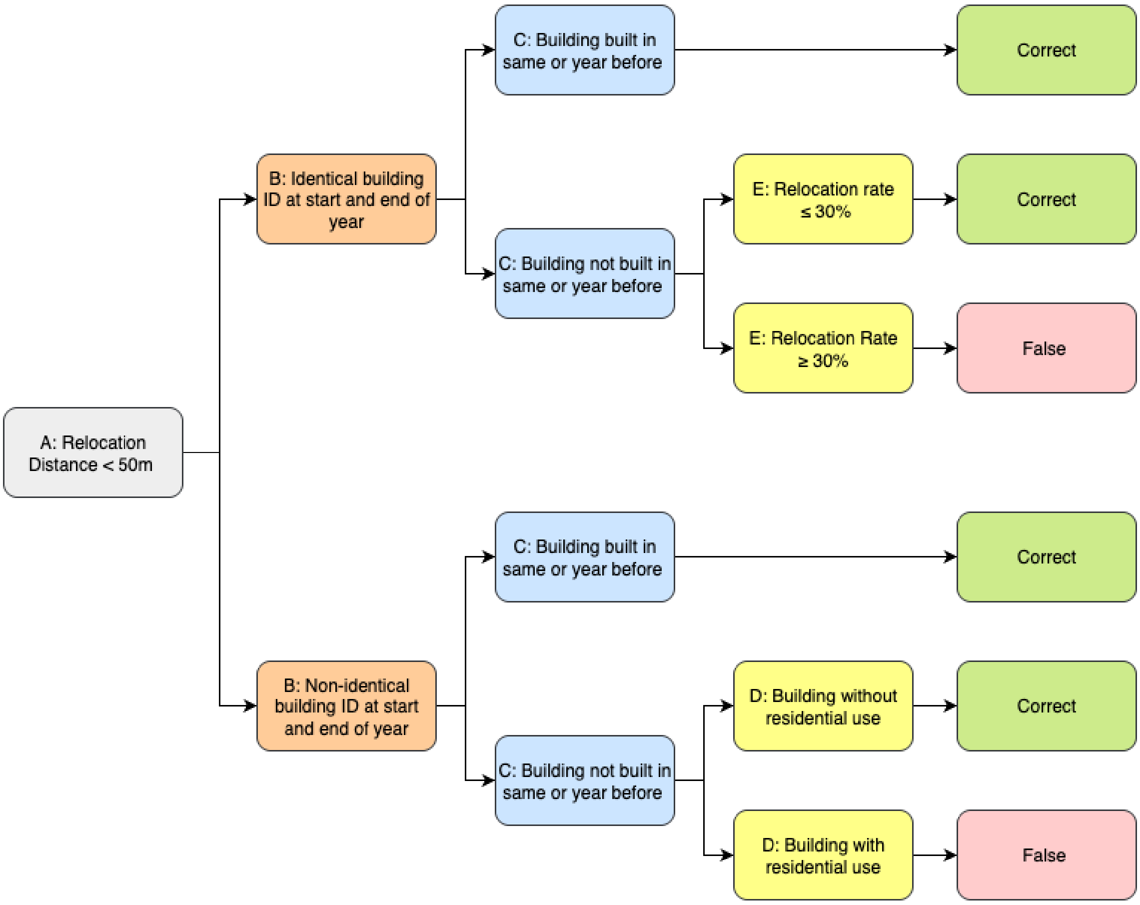


Figure 3: FSO Processing framework to remove administrative errors in relocations, source: FSO

yet appear at the beginning of the year. Rule C provides a correction mechanism: if the destination building was newly constructed during the current or previous year, the assumption of a false move (fusion or split) is rejected. Rule D further refines this classification: a supposed building ID split can be excluded if the destination building was already recorded as non-residential at the start of the year. Similarly, a proposed merger of building identification can be excluded if the origin building was listed as non-residential at year's end. Finally, Rule E examines the proportion of residents who moved between the origin and destination buildings. If at least 30% of residents of either building are involved in the move, this strongly suggests an administrative building ID change rather than a physical relocation.

The relocation-detection procedure implemented in this study builds on the conceptual framework of the Federal Statistical Office (FSO) but adapts several steps to the structure of the available STATPOP data. Individual annual trajectories were reconstructed by ordering all persons by their pseudonymized ID and year and attaching previous-year information on building ID, dwelling ID, and geographic coordinates. A change in building ID between consecutive years was interpreted as a potential residential move. The corresponding Euclidean migration distance was calculated from the coordinates. This step fully reflects the FSO's definition of arrival- and departure-year relocations.

To avoid missing relocations when individuals disappear from the register for one or more years, missing-year gaps were treated as exits from Switzerland. These exits were added to the set of relocations unless the individual later reappeared in exactly the same building, in which case the event was classified as a non-move. This reproduces FSO logic, which distinguishes emigration from temporary register inconsistencies.

The FSO further distinguishes true relocations from administrative changes in building identifiers ("false moves") through a set of rules based on migration distance, building existence in the registry, building-use type, and the share of residents affected by the change. To compensate for missing data elements the study implements deterministic approximations of these criteria. Moves of less than 50 m were flagged as potential false relocations when the destination building was not newly recorded and household sizes before and after the move differed by no more than ±30%. Although moves within the same building were not classified as relocations, some recorded relocations still involved travel distances of only a few meters. Therefore, movements of less than 10 m were automatically classified as false moves, as they were assumed to represent changes within the same building, or a relocation resulting from an ID split or merger. This second threshold is an extension of the FSO procedure and compensates for the lack of information on non-residential building conversions or administrative building updates. As a consequence, relocation rates in this study remain slightly higher than the official FSO statistics but follow the same underlying logic.

After removing all identified false moves, the relocation indicator was aggregated from individuals to households by grouping records by building, dwelling, and year. A complete household relocation was recorded only when all household members were classified as movers in the same year. This allows the computation of both individual- and household-level relocation rates for all years except 2013, where incomplete arrival information prevents the construction of full household transitions.

5.2 Building and Dwelling Statistics (GWS)

The Building and Dwelling Statistics offer information on all buildings in Switzerland. This dataset is linked to the STATPOP data using the data year, building, and dwelling ID. It details the building type, age, number of apartments, apartment sizes, number of rooms in each apartment, and household structure information. It also includes the municipality and coordinates for each building.

5.2.1 Building Category

The classification of buildings is divided into four principal categories. The first category, Single-Family Houses (SFH), refers to dwellings that encompass a single apartment. Occasionally, SFH may be terraced houses that share a sidewall with another SFH yet are identified by a unique federal building identifier alongside two dwelling identifiers. Under such circumstances, these structures are still considered SFHs. The second category, Multi-Family Houses (MFH), encompasses buildings containing a minimum of two apartments. The third classification, Residential + Auxiliary Use, refers to structures predominantly utilized for residential purposes, with auxiliary functions, such as commercial spaces, playing a secondary role. The fourth category, Partially Residential Buildings, comprises structures that integrate residential spaces where the dominant utilization is for business purposes. Given the comparable characteristics of categories 2 through 4, they were consolidated into category 2, which contains MFH.

5.2.2 Dwelling ID

The dwelling ID is a unique identifier for each apartment within a building and is indexed starting at 1. For the modeling process, entries with dwelling ID -9 or 999 were removed. -9 is a place holder used when the dwelling of a person is unknown. 999 is used when a person lives in a collective household, such as a foster home or an elderly home. Buildings with dwelling ID 999 cant be disassembled into single households and therefore were omitted in the calculation of household relocations. Collective households were not omitted in the computation of person level relocation rates.

5.2.3 Coordinates

Each building has a point coordinate. This allows for matching with spatial variables such as the micro location rating, which is provided at the address level in raster form and added to the point data via spatial join. The coordinates are used to compute relocation distances, which are applied in the process of identifying false relocations and evaluating spatial autocorrelation.

5.3 Municipality Typology

The FSO categorizes municipalities into 9 and 25 different groups, ranging from urban to rural (Figure 4) . This system is intended to assist in distinguishing the variations in relocation patterns between rural and urban environments and to account for spatial autocorrelation in the modeling process. The classification of municipalities of Switzerland are made according to defined criteria by the FSO. These classifications are based on population and employment density, structural connections, minimum number of residents, commuter flows, accessibility, number of overnight stays in hotels, and economic structure. The municipality types are intended to capture some of the spatial variability between urban and rural regions. This study concentrated on the nine-category classification of municipality types, since more fine-grained groupings did not yield any added value.

5.4 Vacancy Rate

The vacancy rate can be indicative of the possibility of relocation. Many relocations happen within very small distances ($< 10km$), since people often prefer to remain close to their social surroundings. If there is no available housing within the municipality, the willingness to relocate can be lowered, as low vacancy rates limit the choice of housing and influence rent prices. The data is provided year wise by the FSO as absolute counts of vacant spaces per municipality. The total number of apartments is extracted from the building and dwelling statistics. Then the year wise vacancy rates are computed.

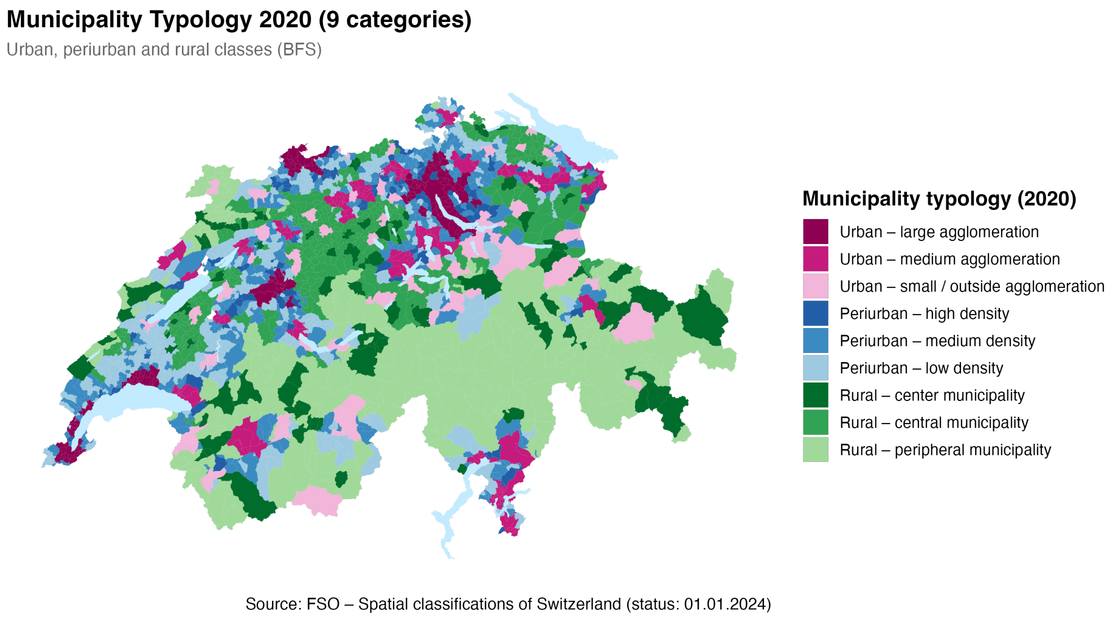


Figure 4: Map showing the muncipality typology 2020 by the Swiss FSO.

5.5 Micro Location Rating

The micro location rating is a model developed by Wüest Partner that outputs a 25-meter resolution raster. This rating evaluates the quality of residential locations within a municipality by examining factors such as topography, infrastructure, emissions, population density, and proximity to recreational areas. Ideally, individuals or households in highly rated zones may be less inclined to relocate due to the superior advantages of their location. Nevertheless, preferences can change with age. Younger individuals might seek more vibrant areas, while families may favor quieter neighborhoods. Older adults require locations with convenient access to shopping, public transportation, and healthcare facilities.

5.6 Macro Location Rating

The macro location rating provides information at the municipality level regarding location quality. The rating is provided yearly at the municipality level, with values ranging from 1 (lowest) to 5 (highest) by Wüest Partner AG. The rating is computed using variables such as accessibility, infrastructure quality, demographic traits, municipality typology, number of workplaces, municipality level tax burden, housing infrastructure and real estate market descriptors such as asking prices of residential spaces, transaction indices and vacancy risk.

5.7 Asking Prices

Rent asking prices were provided by Wüest Partner and are available for each year of observation. The data report asking rents per municipality, building type, and year, and are derived from publicly listed rental advertisements combined with historical price trends. Asking prices are categorized by building type and number of rooms and are provided as quantiles. Monthly rents are calculated based on average dwelling sizes corresponding to the number of rooms. For this study, asking prices were matched to individual dwellings based on building type and number of rooms, using the 0.1, 0.5, and 0.9 quantiles. Together with the vacancy rate, this variable serves as a proxy for housing affordability, which is assumed to act as a constraining factor on household relocation decisions.

5.8 Relocation Data Set Overview

The processed dataset utilized to train the LightGBM model contains the variables listed in Table 1. The variables are arranged according to their source or the source from which they were computed. An overview of the processing workflow is provided in Figure 5.

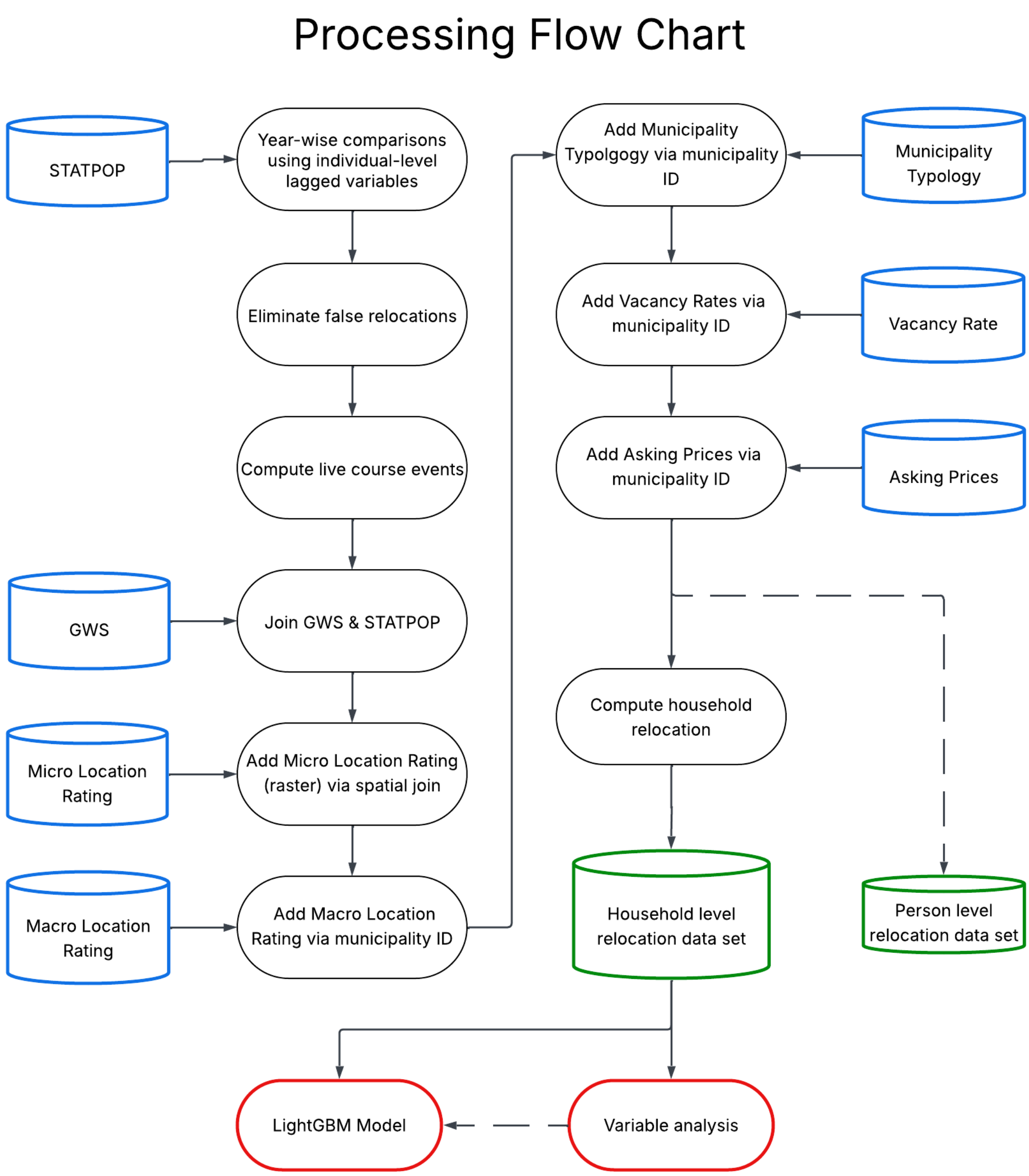


Figure 5: Data processing workflow overview. Blue boxes represent input data, black boxes processing steps, green boxes output data sets and red boxes represent processes displayed in the result section.

Variable	Values	Description
1. Building and Dwelling Statistics (GWS)		
is_sfh	categorical	Building type: 1 = Single-family house (SFH) 0 = Multifamily housing (MFH)
building_period	categorical	5-year construction period class
n_rooms	integer	Number of rooms
size_m2	numeric	Dwelling size (m^2)
hh_structure_25	categorical	Household age composition: 1 = all members <25 2 = all members 25–65 3 = all members >65 4 = mix: <25 + 25–65 5 = mix: <25 + >65 6 = mix: 25–65 + >65 7 = all three groups
hh_nation_tot	categorical	Household nationality: 1 = Swiss household 2 = Mixed Swiss/foreign 3 = Foreign household
2. Household Characteristics (STATPOP)		
avg_age_hh	integer	Average age of household members
n_person_hh	integer	Number of household members
has_baby	binary	Household contains a child under age 5
years_since_marriage	integer	Time since last marriage event
marriage	binary	Marriage within data year
years_since_separation	integer	Time since last divorce event
separation	binary	separation event within data year
years_since_widow	integer	Time since widowhood
widow	binary	widow event within data year
years_since_pension	integer	Time since Pension
pension	binary	Indicator: average household age 64 – 66
3. Real Estate Market Variables (Wüest Partner		
pr_10	numeric	Asking price (10th percentile)
pr_50	numeric	Asking price (median)
pr_90	numeric	Asking price (90th percentile)
rating_sfh	numeric	Micro Location Rating SFH (address level)
rating_mfh	numeric	Micro Location Rating MFH (address level)
macro_rating_sfh	numeric	Macro Location rating SFH (municipality level)
macro_rating_mfh	numeric	Macro Location rating MFH (municipality level)
vacancy_rate	numeric	Vacancy rate in the municipality
4. Spatial Context Variables (FSO Typology)		

Continued on next page

Variable	Values	Description
mun_type_9	categorical	FSO 9-class municipality typology (2020): 1 = Urban municipality, large agglomeration 2 = Urban municipality, medium agglomeration 3 = Urban municipality, small agglomeration 4 = Peri-urban municipality, high density 5 = Peri-urban municipality, medium density 6 = Peri-urban municipality, low density 7 = Rural center municipality 8 = Centrally located rural municipality 9 = Peripheral rural municipality
5. Target Variable		
complete_relocation	binary	Indicator for complete household relocation

Table 1: Variable Inputs for LightGBM, grouped by data source

5.8.1 Outliers

Households with more than 10 inhabitants are treated as outliers and omitted from the dataset, as there are only very few families of that size, and the relocation of complete households with 10 or more people is rather rare and might have different motivations than can be shown with the current data.

Households with an average age below five years were excluded from the dataset as lower average household ages are implausible. The household average ages below this threshold can only occur in highly specific and extremely rare cases, such as very young single parent households with one or more children. For example, even a single-parent household in which a 20-year-old mother is raising three children aged one, two, and three would have an average household age of 6.5 years, which represents an unusually young household composition. In addition, observations were classified as outliers if, for a given dwelling, the difference between the number of rooms and the number of household members plus one exceeded five or was smaller than minus ten.

6 Results

The results are presented in three main sections: (1) Section 6.1 - Relocation Rate, (2) Section 6.2 - Variable Analysis, and (3) Section 6.3 - Modeling Results. Section (1) is a high level review of countrywide relocation rates; section (2) displays the relocation rate broken down into several key variables, and section (3) presents the model built from the key variables described in section (2).

6.1 Relocation Rate

This study examined data from 2013 to 2023 and yielded results similar to the FSO. Compared to FSO data, this study overestimates relocation rates by 0.7%. The relocation rates from the FSO are not available for every year (Table 6.1), whereas this study provides relocation rates of individuals for the full time span of 2014 to 2023. This study further focuses on the relocation rates of complete households, as suggested by Xue & Yao (2022).

Year	FSO (%)	This Study (%)	This Study complete relocations (%)	Difference FSO - This Study (%)
2014	NA	10.7	8.9	–
2015	NA	10.6	8.8	–
2016	NA	10.7	8.9	–
2017	NA	10.8	9.0	–
2018	10.3	10.9	9.2	0.6
2019	NA	11.0	9.3	–
2020	10.3	11.0	9.3	0.7
2021	10.1	10.8	9.3	0.7
2022	9.5	10.2	8.8	0.7
2023	9.3	10.0	8.7	0.7

Table 1: **Comparison of relocation rates:** own calculations (person and household relocations) and official BFS values.

The relocation rate of households is not published by the FSO. This study found the relocation rate of households for 2023 to be 8.7%. For the study period the average difference between person and household level relocation is 1.65%. From 2014 to 2020, the gap relative to the person-level relocation rate was between 1.7% and 1.8%. Between 2020 and 2023, the difference between person-level and household relocation rates decreased to an average of 1.4%. A possible reason for this shift could be an overall tightening housing market and the onset of the COVID-19 pandemic. Over the study period, the mean relocation rate is 3.57% for SFH and 10.5% for MFH. Relocation rates by building type follow the same temporal patterns, with no evidence of systematic shifts in relocation behavior between single-family and multi-family housing.

6.2 Variable Analysis

This section presents an overview of different variables and corresponding relocation rates. First, the sociodemographic variables are presented, followed by variables describing building and apartment-specific characteristics and their impact on the relocation rate of households. In the third section, the influence of real estate market descriptors are presented. All relocation rates were filtered to include average household ages from 5 to 100 and households with 10 or less persons. Resulting tables with values averaged across household age and data years are provided in the Appendix .1.

6.2.1 Sociodemographic Variables

This section presents findings on the impact of sociodemographic variables on household relocation behavior.

6.2.1.1 Age

The average household age is the most influential factor shaping relocation rates. The form of the relocation curve is largely determined by the relocation rate of MFH. At an average household age of 25, the relocation rate for MFH is 16.5%, and for SFH, it is 3.6%. This study separates the relocation rate into 3 phases according to distinct relocation behavior based on average household age (Figure 6). These phases are visible in the relocation rate of MFH. The first phase is titled the "family formation phase" and includes households with average ages of up to

40 years. Typically, households in the family formation phase consist of families where the children still live with their parents, young couples, or shared apartments. Households that fall into the family formation phase are typically more mobile, live in an MFH, or have moved into an SFH. In contrast, households residing in SFHs exhibit significantly lower relocation rates, as SFHs are commonly regarded as the final stage of the housing career and are associated with higher homeownership rates.

The second phase is the settling phase, during which household relocation rates continue to decline. This phase is characterized by a dip in the number of households, which primarily reflects the underlying demographic structure, specifically the relatively smaller cohort of Generation X, situated between the baby boomers and their children. This demographic effect is further intensified by household composition changes, as children moving out lead to a sharp increase in average household age skipping the intermediate household age. Together, these dynamics create a visible gap between the family formation and retirement phases, which is particularly pronounced in the age distribution of households residing in SFHs. As mobility decreases with age while moving towards the statutory retirement age, households become increasingly stable. At this stage, households have typically settled: they have established social networks, are less likely to change jobs, and do not expect additional children that would require more living space. Consequently, they have progressed along the housing ladder, tend to occupy larger dwellings, and are increasingly able to afford living in an SFH. Relocation rates among households living in SFHs remain low across all age groups in the settling phase, while the relocation rate in MFH falls to 5.5%.

A peak in relocations occurs around the statutory pension age of 65, marking the start of the retirement phase. This is followed by a renewed decline in average relocation rates, underscoring retirement as a major life-course transition. The peak in retirement-related residential mobility is most pronounced among foreign households residing in MFHs. The absence of this peak among SFH suggests comparatively higher residential stability among SFH households during the transition into retirement. At very high household ages, relocation rates increase sharply, reflecting moves into assisted living, transitions following widowhood, or relocations associated with end-of-life circumstances.

6.2.1.2 Number of Persons in Household

As the number of persons in a household increases, the relocation rate falls. SFH with one inhabitant show a significantly higher average relocation rate (8.49%) than

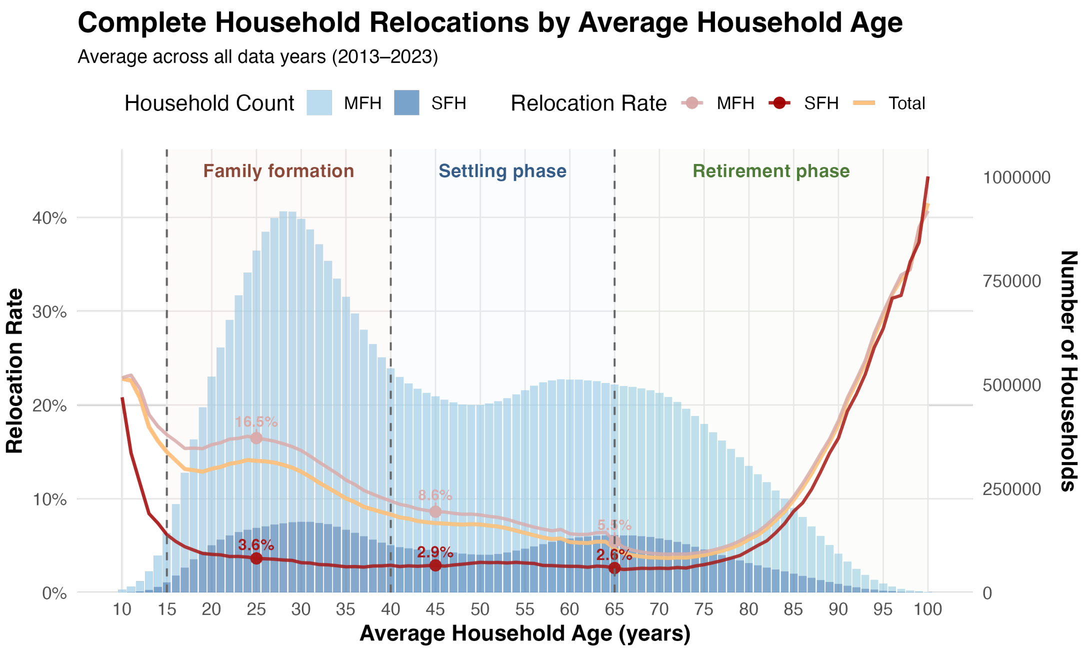
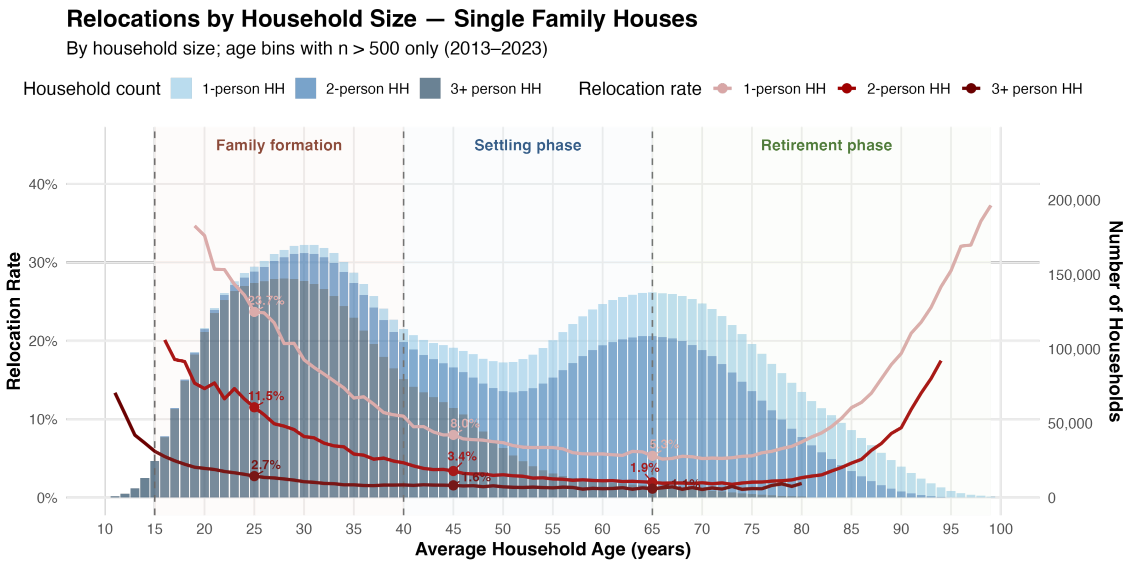


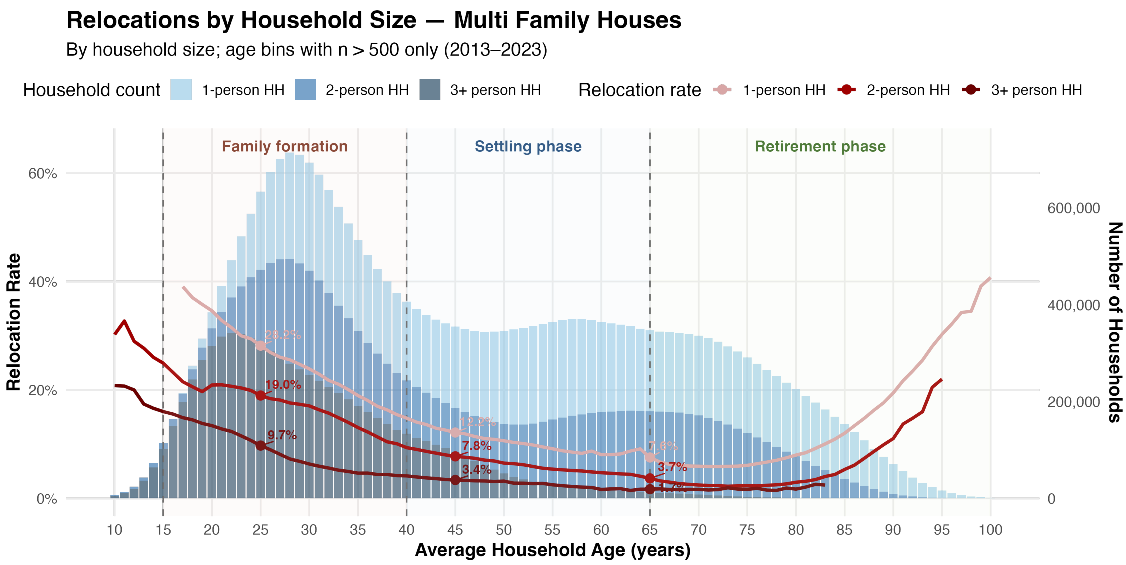
Figure 6: Relocation rate of households by age group for Switzerland, defined as household move-outs, including emigration. Data: GWS – STATPOP, 2023

households with 2 or more people (2.57%). Households in SFH with 3 or more people show average relocation rates lower than 3%. The relocation rate of households with only one person is 2 to 2.8 times higher than the relocation rate of households with two persons, depending on the average household age.

In MFH, the difference in relocation rates between one person and two person households ranges from a factor of 1.5 to 2. Generally, the decline in the relocation rate with increasing household size is comparable to SFH. Compared to SFH, there are more households in the family formation phase. Moreover, single-person households are more prevalent in MFH in all age groups, and in both SFH and MFH these one-person households exhibit the highest relocation rates across all ages, underscoring the greater mobility of individuals who live alone. Along with the average age of household members, household size has the greatest impact on relocation behavior.



(a) Single-family houses (SFH)



(b) Multi-family houses (MFH)

Figure 7: Relocation rates by household size and average household age in Switzerland.

6.2.1.3 Household Structure

Households where all members are younger than 25 have the highest likelihood of relocation (28.75% in MFH and 23.68% in SFH). These households are either very young families, single parents, or mixed households. This age group occurs rarely in SFH, with fewer than 17'000 observations across 10 data years. Households where all members are between 25 and 65 are the most common household structure in

MFH, with a relocation rate of 13.06% and a relocation rate of 4.39% in SFH.

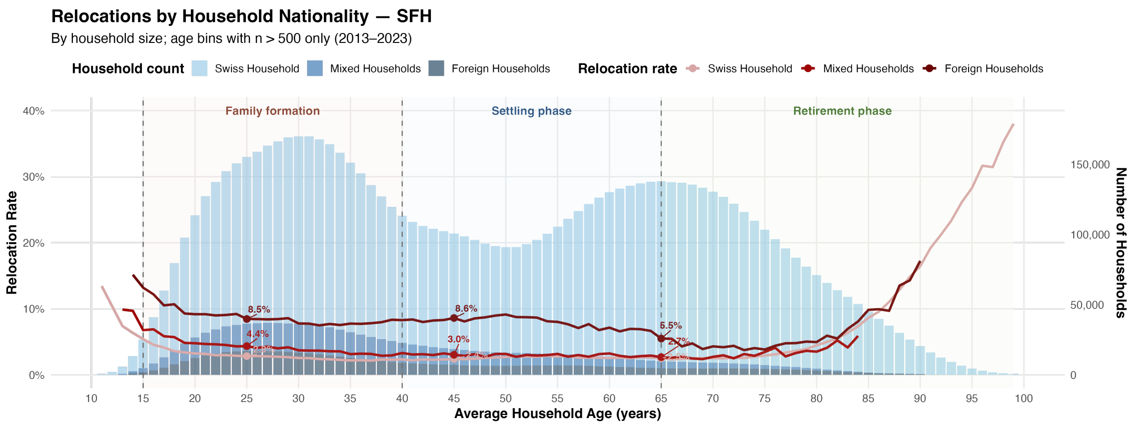
Mixed households in which people younger than 25 and those between 25 and 65 live together mainly consist of families. This class shows a high relocation rate in MFH (10.02%), but a comparably low relocation rate for SFH (2.67%). The underlying causes of the higher relocation rate in this household structure group were not examined in more detail. It is, however, hypothesized that families residing in MFH are more mobile because they are looking for larger apartments and are more vulnerable to rent price increases. On the other hand, families living in SFH have little inclination to move, as they typically have larger living spaces and tend to be more financially stable, in part because they are more likely to own rather than rent their home.

Other household forms, such as intergenerational households where all age classes are present, or households where no person between the ages of 25 and 65 is present, occur rarely and can be considered edge cases. The relocation rate of these groups is typically low as they have at least 3 members.

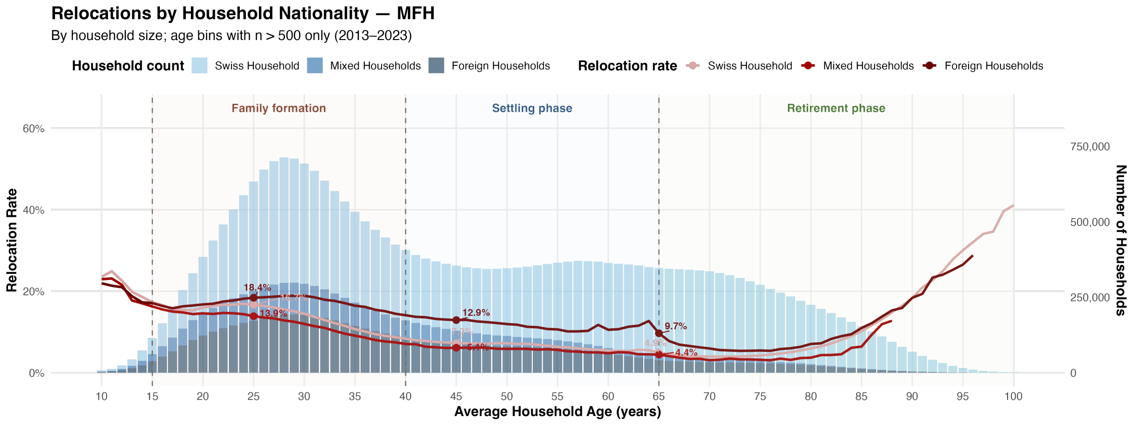
6.2.1.4 Household Nationality

Household nationality is categorized into three groups: (1) Swiss nationality, (2) mixed nationality, and (3) foreign nationality, without differentiating by country of origin. Households of foreign nationality are more likely to reside in MFHs and exhibit higher relocation rates in both MFHs (14.68%) and SFHs (7.96%) compared to Swiss households, whose relocation rates are 9.38% in MFHs and 3.22% in SFHs. The proportion of mixed and foreign nationality households relative to Swiss households is significantly lower in SFHs than in MFHs.

Across all household phases, foreign households display consistently higher relocation rates, with the difference being particularly pronounced in SFHs. Moreover, the relocation peak marking the onset of the retirement phase occurs earlier among foreign households and is followed by a sharp decline in relocation rates at the beginning of retirement. This earlier peak may reflect a higher incidence of earlier retirement among foreign households and may also coincide with increased emigration. In contrast, mixed and Swiss households exhibit little to no relocation increase around retirement age.



(a) Single-family houses (SFH)



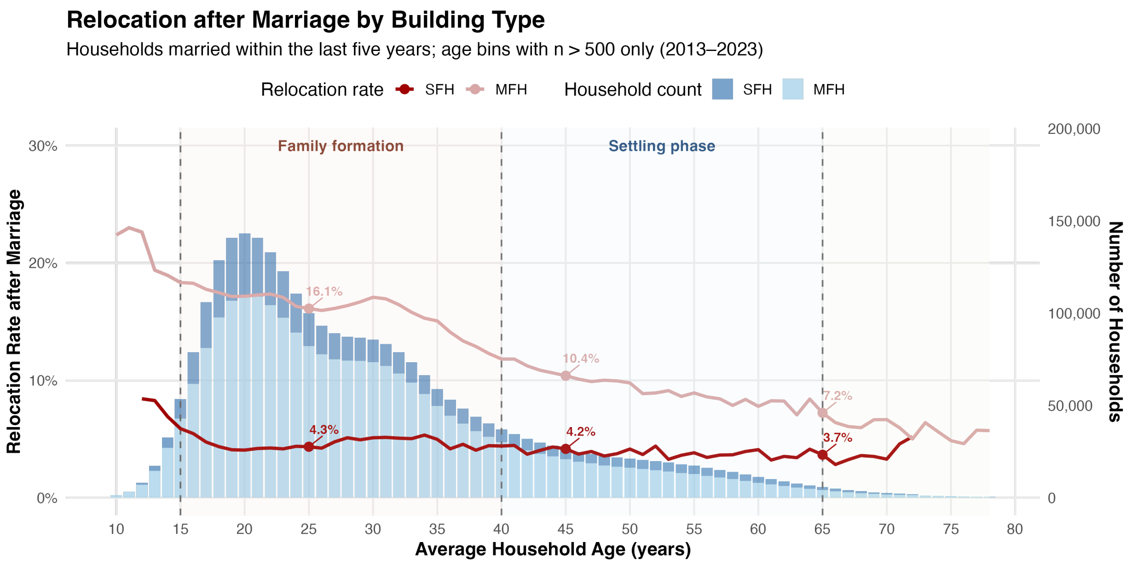
(b) Multi-family houses (MFH)

Figure 8: Relocation rates by household nationality and average household age in Switzerland.

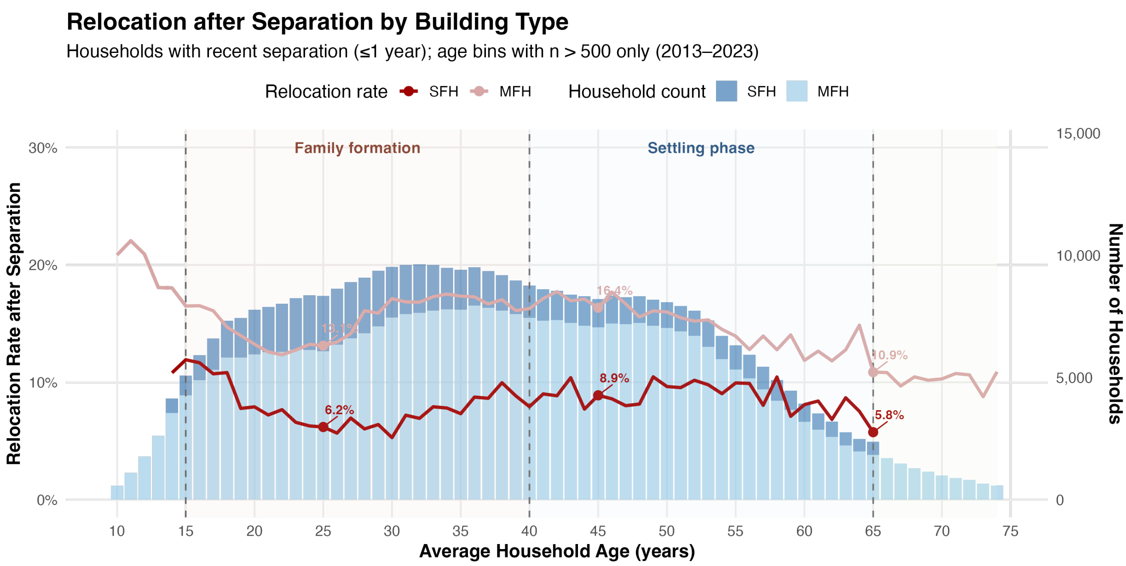
6.2.1.5 Marriage, Divorce & Widowhood

In the year of marriage, both MFH and SFH show higher than average building specific relocation rates of 18.04% and 5.70% per household. Further, being married for a period of more than 10 years coincides with a reduction in the household's relocation rate compared to average building type specific relocation rates.

If a divorce occurs, there is an increased probability of relocation for the entire household. The relocation most often happens within one year after the separation. For MFH, the share of households that relocate within the first year after a divorce is 16.36%, compared to 8.4% for SFH. These relocation rates refer to households in which every member moves. However, when examining relocation after a separation, this perspective may not fully capture the dynamics of relocation processes during separations. It is likely that only a fraction of cases results in the entire household moving at the same time. It is likely that only some household members relocate, which is not captured in these results.



(a) After recent marriage



(b) After recent divorce

Figure 9: Relocation rates by building category and average household age following recent partnership events.

For young divorces ($average household age < 30$), the relocation rate for both SFH and MFH is lower than that for divorces among higher average household ages. The presence of children could explain the lower relocation rate for young separations. Additional qualitative studies on post-separation relocation behavior of individuals and households with and without children could offer explanations for the observed differences between age groups and building categories.

When entering widowhood, an increased relocation rate for MFH (14.08%) and SFH (6.38%) is observed.

6.2.1.6 Family formation

The presence of a young child ($age < 5$) increases the relocation rate for MFH to 13.65%, while for SFH, only a slight increase in relocations to 3.85% is observed (Table .1).Overall, households living in MFH with an average age below 25 exhibit higher relocation rates; beyond this age, the relocation rate shows a continuous stagnation (Fig. 10).

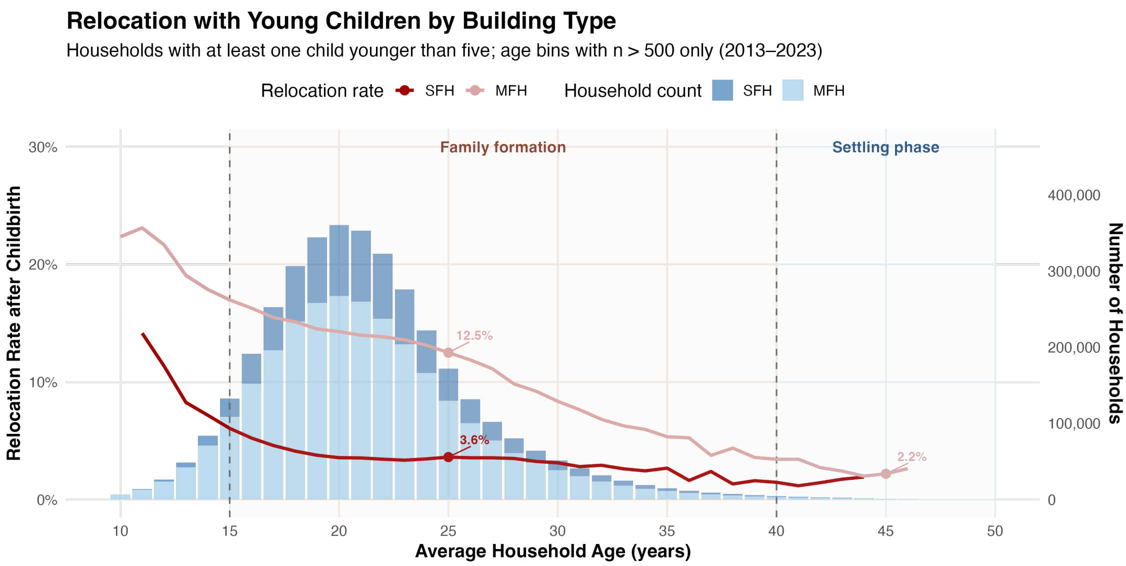


Figure 10: Relocation rate of households by age group for Switzerland. Data: GWS - Statpop, 2023

6.2.2 Building Variables

6.2.2.1 Building Category

The relocation rate for SFH significantly deviates from the observed relocation rate of MFH (Figure 6). The difference in the relocation rate has multiple reasons. First, in SFH, the ownership rate is higher than that for other building categories. Ownership implies that a person or household has achieved a high level in their housing career, as it is seen as the most desirable level of the housing career by many. Once the level of ownership is reached, there often remains little incentive to relocate. These findings match the observations of Lehner et al. (2023).

6.2.2.2 Building Period

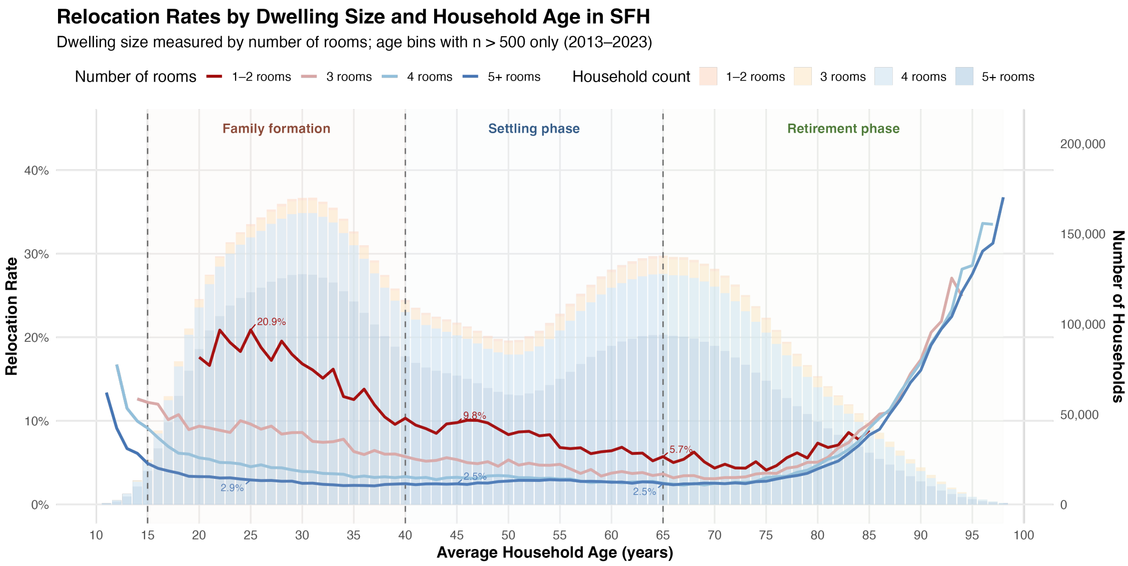
The lowest relocation rate is observed for buildings constructed approximately 20 years ago, at 5.7%. In contrast, relocation rates are substantially higher in new buildings (up to 29.7%) and tend to increase again for older structures, reaching 10.8% for buildings constructed before 1919. The elevated relocation rates in newly constructed buildings are difficult to fully disentangle with the available data, but several mechanisms may contribute. First, newly built dwellings often exhibit higher prices and rents, which may lead some early occupants to relocate after a short period as they reassess affordability or adjust to financial constraints. Second, new developments can attract households in transitional life stages, who might subsequently relocate as their household composition, income, or housing needs change. Third, there may be initial mismatches between housing expectations and reality (e.g., neighborhood dynamics, accessibility, or construction quality) that result in higher early turnover. This trend is also observed for SFH, but with an overall lower level of relocations.

In contrast, buildings around 20 years old may represent a period of relative equilibrium: the housing stock is modern enough to remain attractive and energy-efficient, and prices and rents are lower than those offered on the market. The building's age allows tenants to benefit from the generally lower rents available to long-term residents, leaving them with little incentive to relocate. After 20 years, the relocation rate starts to increase again. This may be connected to a rise in renovation projects, which frequently result in people having to move. Lastly, older properties may seem less appealing than residing in a newer house or apartment.

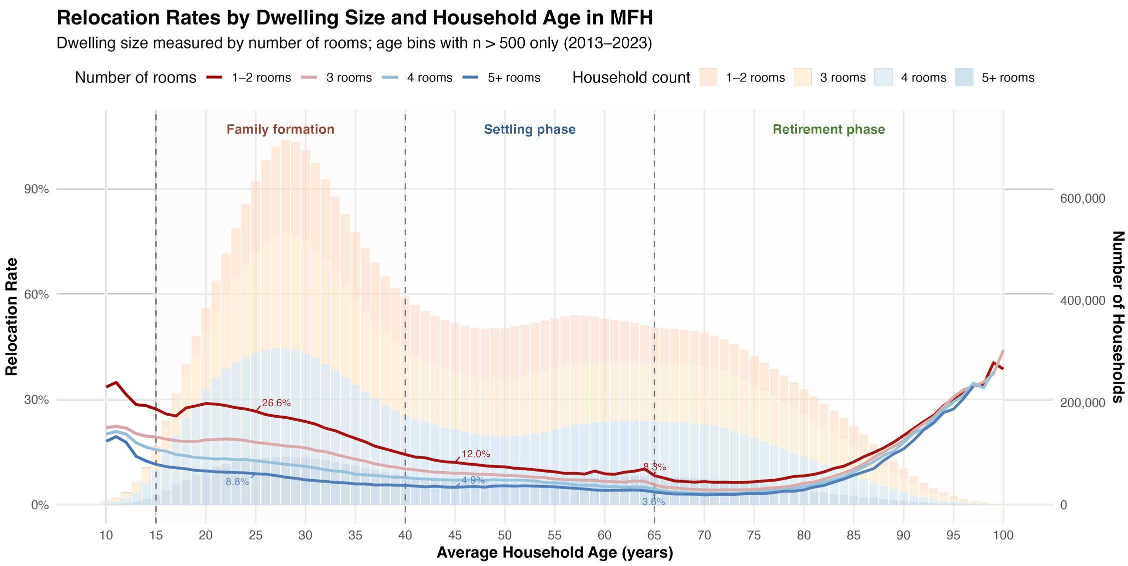
6.2.2.3 Number of Rooms

Households with fewer rooms exhibit a higher relocation rate, as these typically accommodate fewer people, and households with fewer people have a higher relocation rate. In MFH dwellings, units with 1 room have a relocation rate of 19.01%, and those with 2 rooms show a rate of 14.31%. Dwellings with 3 rooms have an average relocation rate of 11.13%. Only a very small number of SFH have so few rooms, but the relocation rate for small SFH (fewer than 3 rooms) is 6.61%, which is clearly above the average. Whereas in MFH an increasing number of rooms consistently corresponds to a lower relocation rate, SFH with more than 6 rooms show an increasing relocation rate.

Households with fewer rooms typically accommodate fewer people in both SFH and MFH; therefore, fewer rooms in a household show a higher average relocation rate. Larger housing space is seen as favorable and can indicate that a household has progressed further within the housing career ladder, leading to fewer relocations (Figure 11).



(a) Single-family houses (SFH)

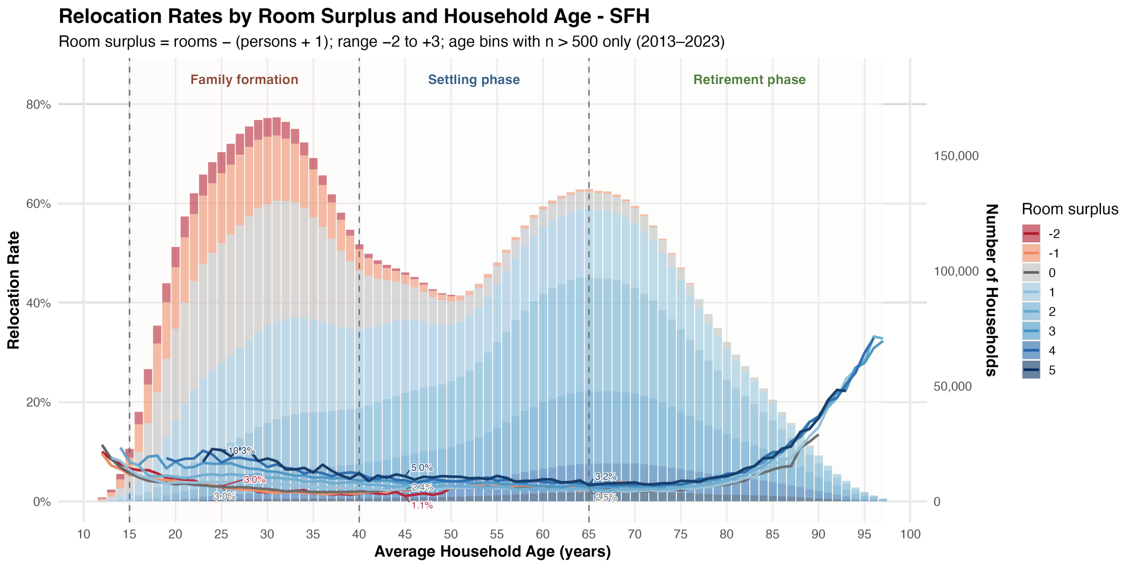


(b) Multi-family houses (MFH)

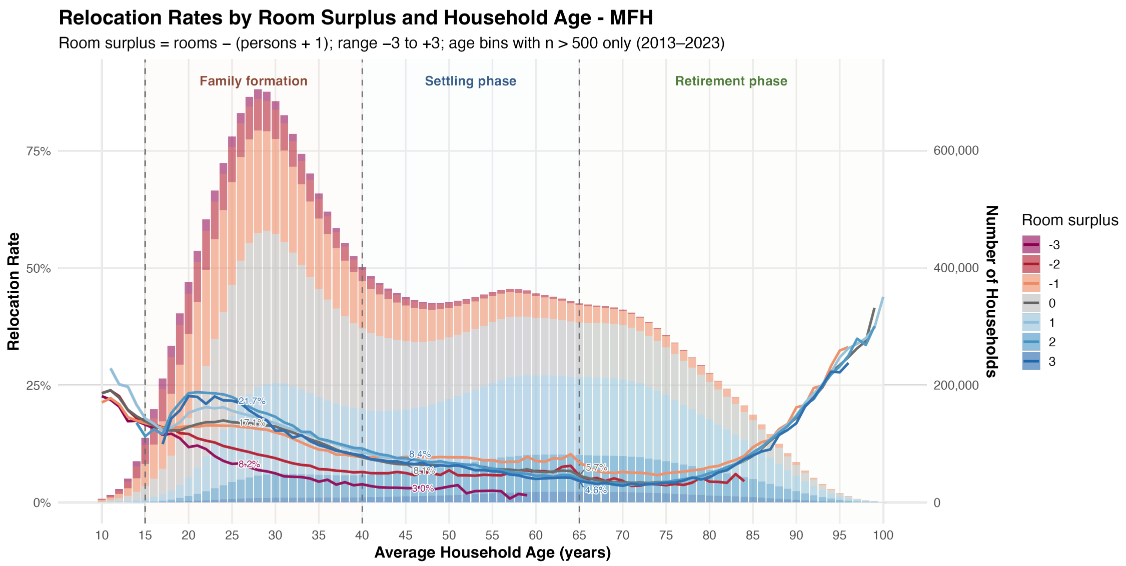
Figure 11: Relocation rates by dwelling size (number of rooms) and average household age in Switzerland.

6.2.2.4 Room Surplus

The surplus of rooms is calculated by making an assumption of ideal utilization of a dwelling which = $n\_rooms - (n\_person + 1)$. This formula is based on the assumption that the optimal usage is one room per person, plus one extra room designated as a living room. Under this assumption, we find that dwellings with an overutilization of rooms (negative values) have lower relocation rates during the family formation phase. In SFH, the number of overutilized dwellings is considerably lower in the settlement phase and nearly 0 when entering the retirement phase. In MFH, this pattern is true as well, although the overutilization rate does not drop as low as for SFH with increasing household age. The pattern suggests that young households, which often are families, are most prone to live in overutilized spaces. It should be considered that sharing rooms for children occurs frequently, which can skew the overutilization towards younger households. While households in the family formation phase tend to relocate more often with increasing underutilization of space, this trend inverts during the settlement phase. This means that older households are more likely to hold on to their larger dwellings. The peak in the relocation rate at the beginning of the retirement phase is larger for smaller dwellings. The Figure 12 shows that households with a high overutilization have the lowest relocation rates, indicating that these might be financially weak family households that cannot afford to relocate into a dwelling with more rooms.



(a) Single-family houses (SFH)

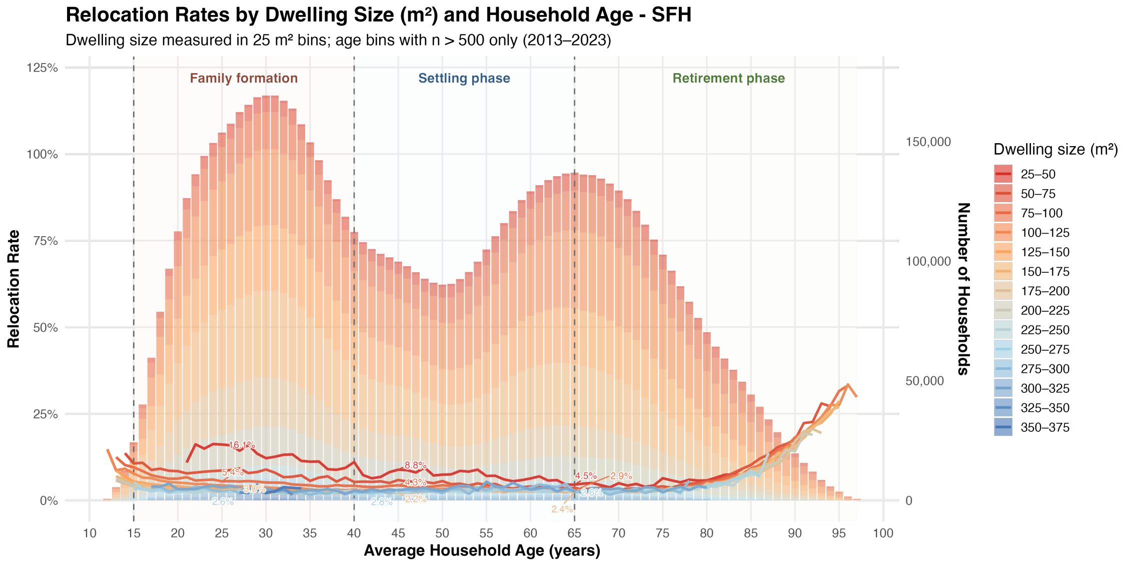


(b) Multi-family houses (MFH)

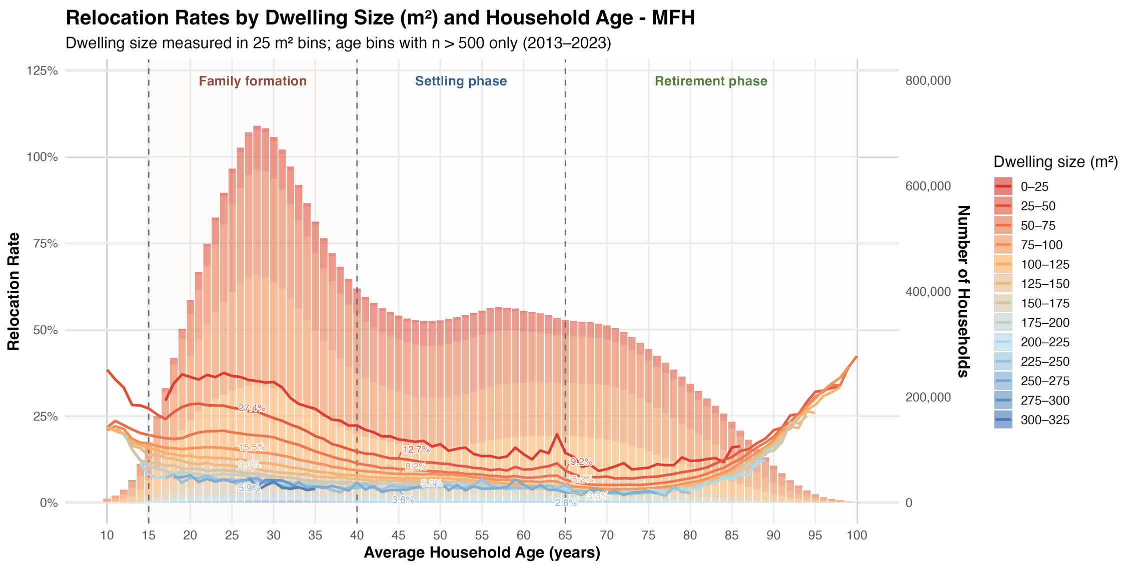
Figure 12: Relocation rates by room surplus (rooms minus household size plus one) and average household age in Switzerland. Results are shown only for age–room-surplus cells with more than 500 observations. Data: GWS, STATPOP (2013–2023).

6.2.2.5 Size of housing (m^2)

The smaller a dwelling is, the higher the relocation rate. While apartments sized 75-99m^2 show an average relocation rate for MFH (10.12%), larger dwellings show below average relocation rates. For SFH, the turning point is at sizes from 125-149m^2. This indicates an equilibrium point in the housing career ladder, where dwelling size is met by affordability. For small dwellings a higher relocation rate is observed. This result is expected, as smaller dwellings typically have fewer household members, which in turn makes them more mobile. In the smallest MFH dwellings ($0 - 25m^2$), a distinct peak at pension age can be observed. The group living in the smallest dwellings tends to relocate disproportionately often at their pension age compared to other dwelling sizes, indicating a possible relationship to renting foreign households.



(a) Single-family houses (SFH)

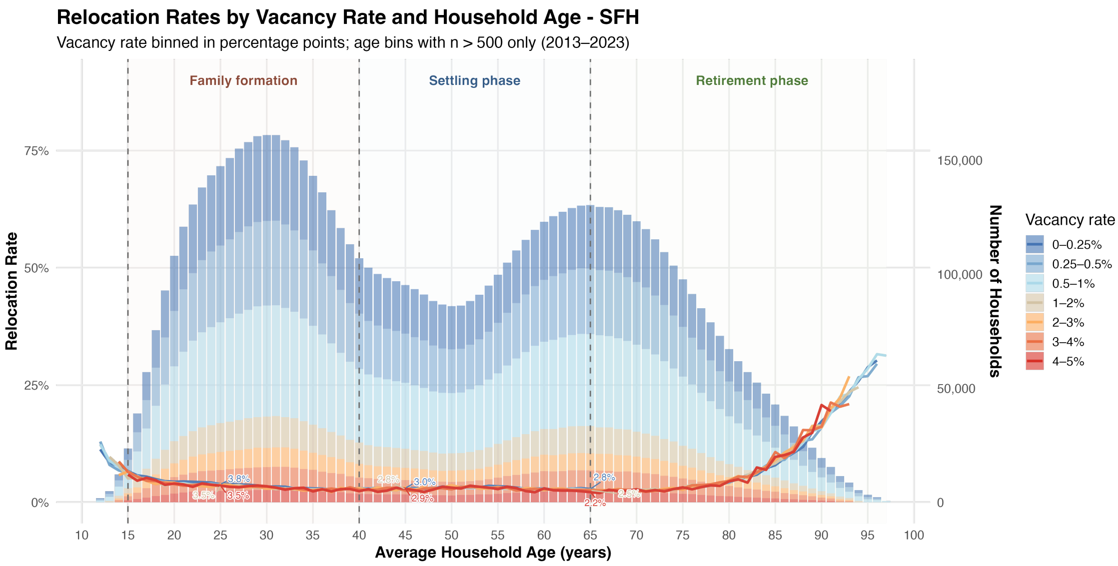


(b) Multi-family houses (MFH)

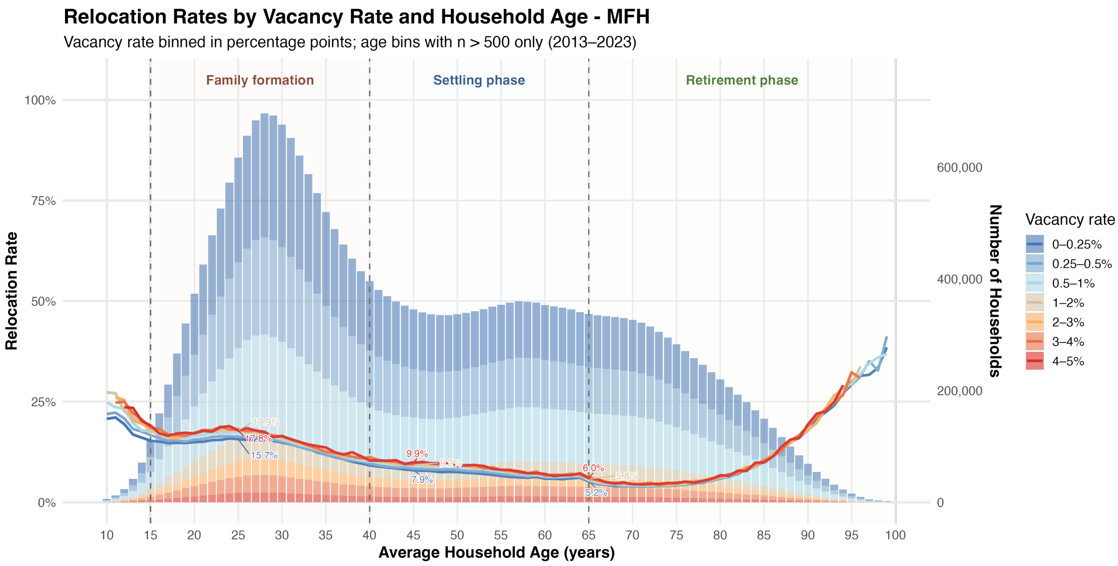
Figure 13: Relocation rates by dwelling size (floor area in 25 m^2 bins) and average household age in Switzerland.

6.2.3 Real Estate Market

6.2.3.1 Vacancy Rate



(a) Single-family houses (SFH)

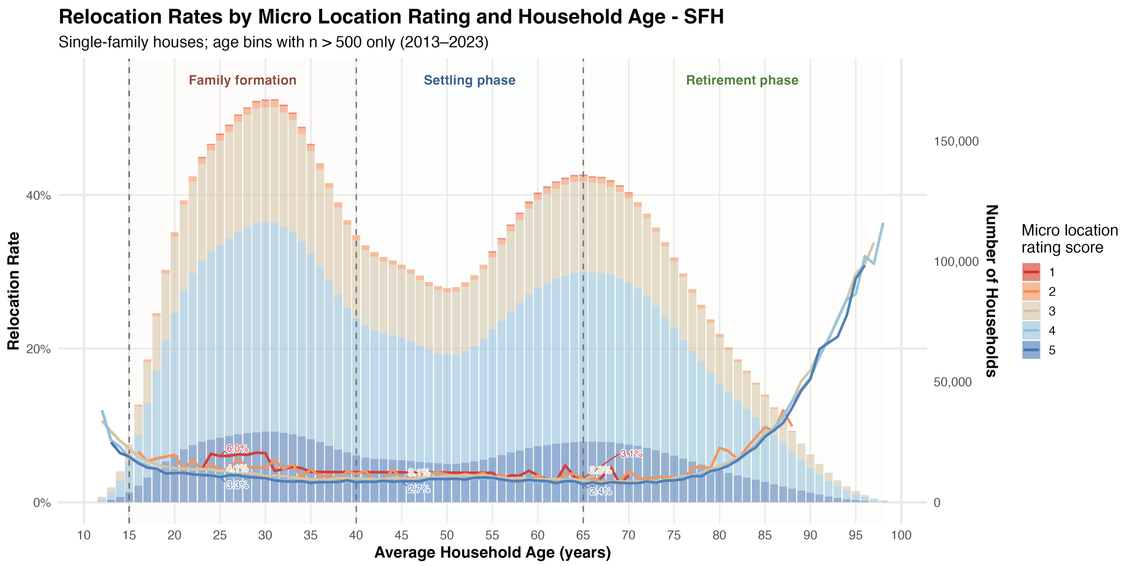


(b) Multi-family houses (MFH)

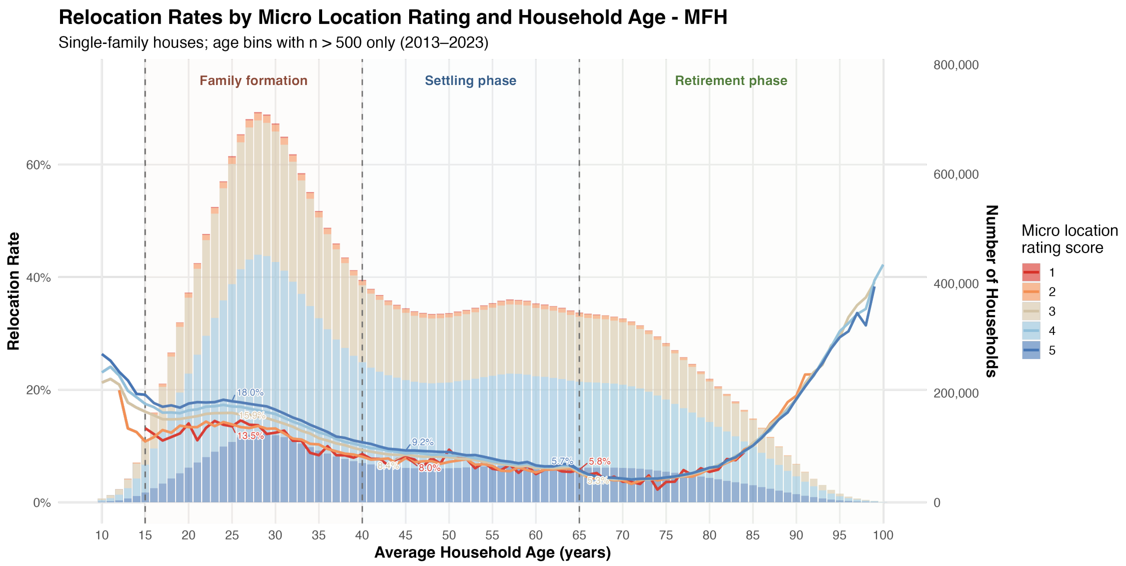
Figure 14: Relocation rates by local housing vacancy rate and average household age in Switzerland. Vacancy rates are discretized into bins.

Low vacancy rates negatively impact the relocation rates of MFH. This relationship remains consistent across household age groups, indicating that the vacancy rate exerts a more structural influence. A vacancy rate of 0.01-0.02% on average corresponds to a relocation rate of 10.88% for MFH. While relocation rates in SFHs vary slightly across municipal vacancy-rate classes, the magnitude of these differences is small. Across the full range from fully constrained to moderately slack markets (0–5% vacancy), relocation rates remain tightly clustered around 3.5% for SFH, with a total spread below 0.4%.

6.2.3.2 Micro and Macro Location Rating



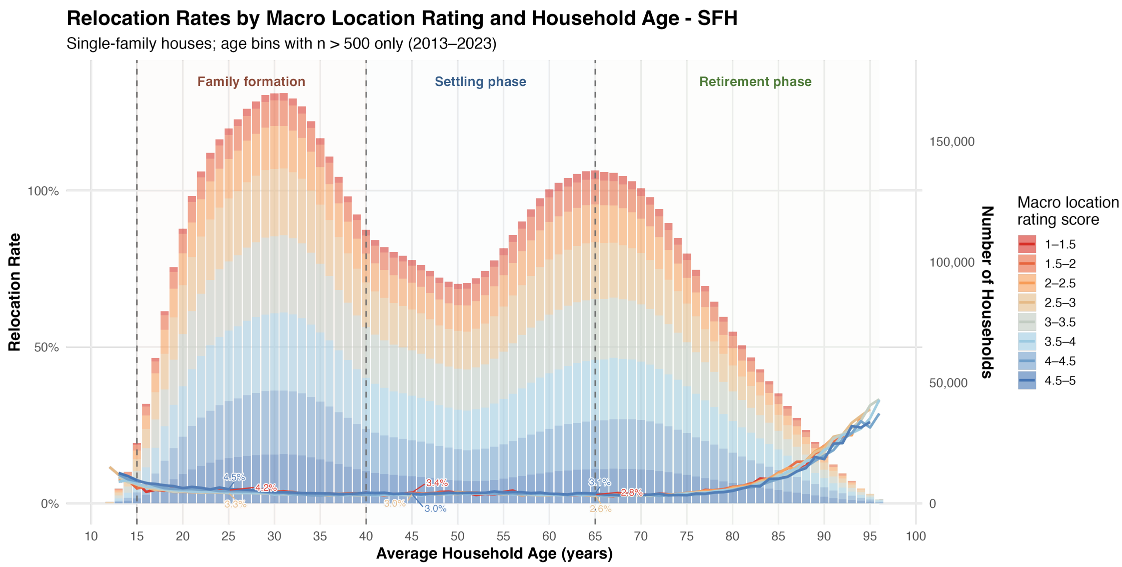
(a) Single-family houses (SFH)



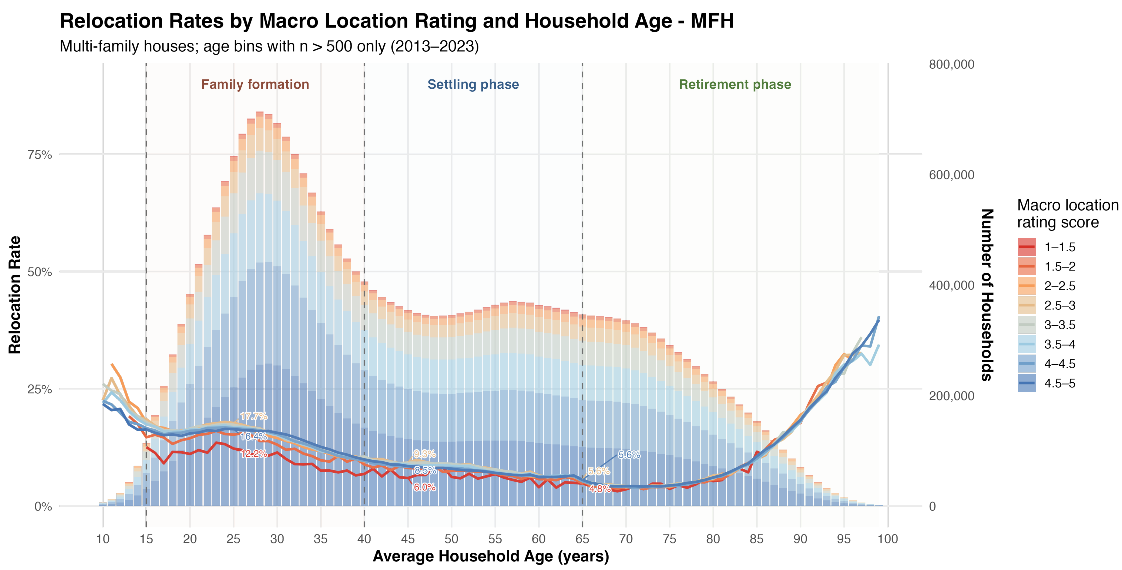
(b) Multi-family houses (MFH)

Figure 15: Relocation rates by micro location rating score and average household age in Switzerland.

For MFHs, relocation rates increase with both micro- and macro location quality. In MFHs, the lowest micro-location rating (score 1) is associated with an average relocation rate of 9.00%, whereas the highest rating (score 5) corresponds to a higher rate of 11.22%. A similar pattern is observed for macro-location ratings, where relocation rates rise from 7.58% in the lowest-rated regions to 10.95% in the highest-rated regions.



(a) Single-family houses (SFH)



(b) Multi-family houses (MFH)

Figure 16: Relocation rates by macro location rating score and average household age in Switzerland.

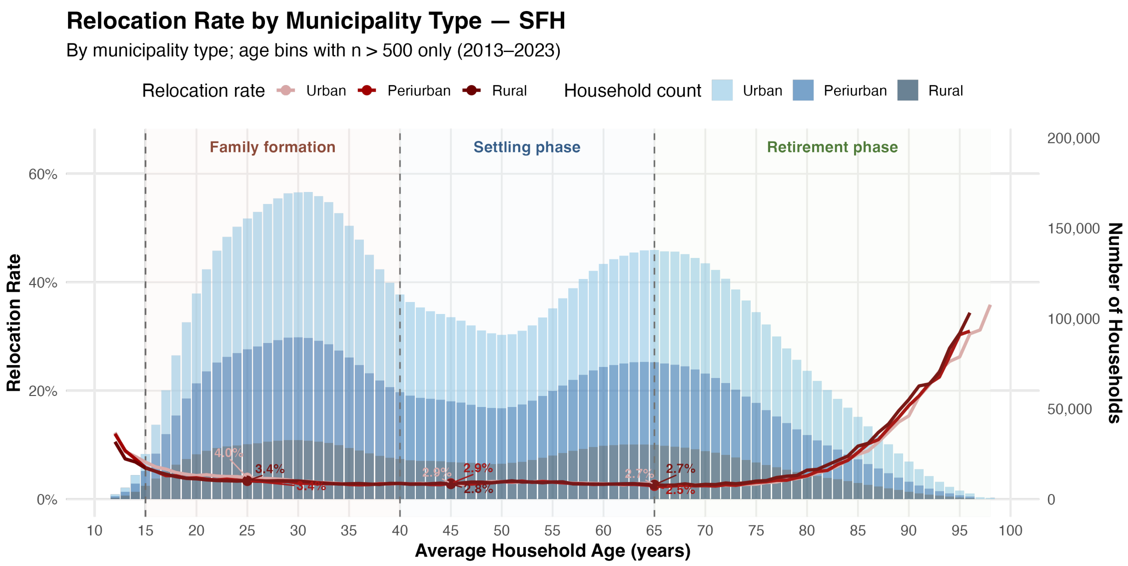
In contrast, the relationship is reversed for SFHs at the micro-location level. Lower-rated micro locations exhibit higher relocation rates, with households in the lowest-rated areas showing an average relocation rate of 4.79%, compared to 3.44% in the highest-rated locations. For macro-location ratings, however, SFHs display higher relocation rates in better-rated regions, reaching a maximum of 4.20% in the top-scoring areas.

6.2.3.3 Asking Prices

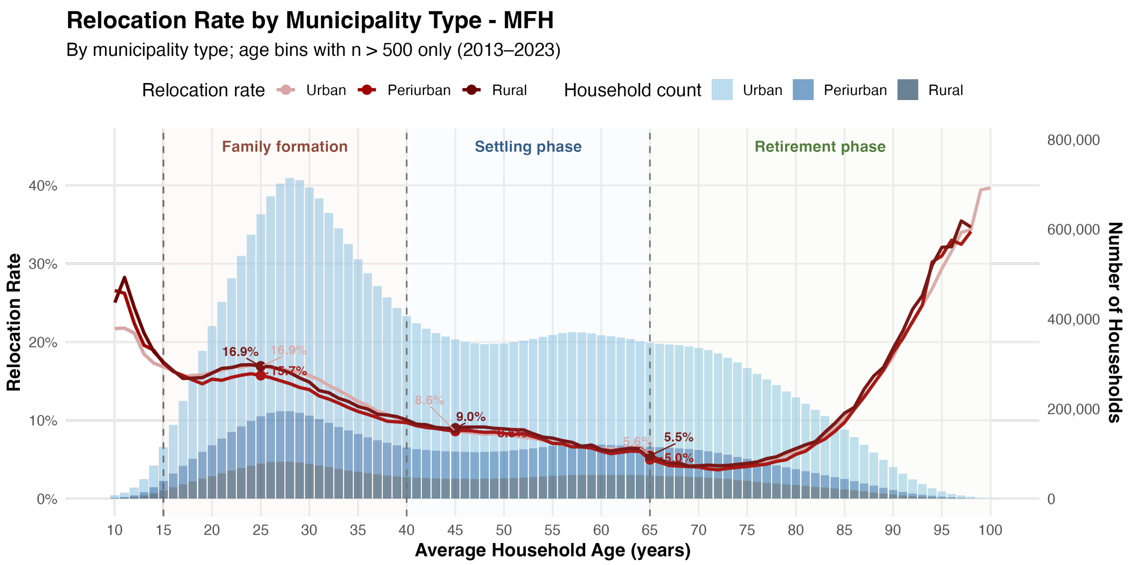
The asking prices reflect the prices of residential properties on the market in CHF per month. We can see that, on average, regions with high asking prices display lower relocation rates, whereas relocations occur more often when space is inexpensive. High asking prices for living space reduce the relocation rate in SFH.

6.2.3.4 Municipality Type

To account for regional heterogeneity across the rural–urban spectrum, relocation rates are examined using nine distinct municipality-type classifications. Across Switzerland, no large differences were found on the basis of different municipality types, although a difference was expected. This result shows that there might be differences between various agglomerations. While urban regions typically have higher relocation rates, this effect might be compensated for by other urban regions. Furthermore, the municipality typology might not be suited to capture urban-rural differences in terms of relocation.



(a) Single-family houses (SFH)



(b) Multi-family houses (MFH)

Figure 17: Relocation rates by grouped municipality types (urban, periurban, and rural) and average household age in Switzerland.

6.3 Modeling Results

A LightGBM model was trained to predict relocation probabilities at the household level. Model performance was evaluated using standard predictive metrics. Plots of the mentioned metrics are provided in the appendix.

6.3.0.1 Classification performance

When evaluated as a binary classification task, the model achieved an overall accuracy of 0.864; however, this performance must be interpreted in light of class imbalance. The positive class (relocation) had a prevalence of approximately 9.3%, resulting in a comparatively low sensitivity of 0.278 and a high specificity of 0.924. The balanced accuracy was 0.601, and Cohen's Kappa indicated modest agreement beyond chance ($\kappa = 0.199$). Precision–recall analysis further confirmed limited discriminative power for identifying relocation events, with an area under the precision–recall curve of 0.228. While the model is effective at identifying non-relocation cases, predictive power for rare relocation events remains constrained.

Model calibration diagnostics indicated a systematic relationship between predicted probabilities and residuals, with increasing dispersion at higher predicted probabilities. Temporal comparisons of prediction scores between 2016 and 2020 revealed no substantial score drift, suggesting that the model's predictive structure remains stable over time and is not driven by short-term temporal artifacts.

Spatial diagnostics revealed statistically significant spatial autocorrelation in model residuals. The global Moran's I statistic was positive ($I \approx 0.021$) and highly significant ($p < 2.2 \times 10^{-16}$), indicating residual clustering beyond random expectation. The average spatial autocorrelation of household-level LightGBM model residuals across increasing spatial distance classes. Positive autocorrelation is observed at short distances, indicating local clustering of residuals, while autocorrelation declines rapidly with distance and approaches zero at larger spatial lags. This suggests that the model captures most large-scale spatial patterns in relocation behavior, with the remaining spatial dependence confined to small-scale, local effects. The spatial correlation is possibly linked to relocations in MFH, where each apartment is connected to the same point geometry, explaining the very localized nature of the spatial autocorrelation. As a result, the remaining spatial dependence in relocation outcomes appears to be confined to localized effects rather than systematic regional patterns. The absence of spatial autocorrelation at larger distances indicates that municipality-type classifications, in combination with macro and micro location ratings of the real estate market, effectively capture the broad spatial structure of relocation behavior, particularly along the urban–rural gradient.

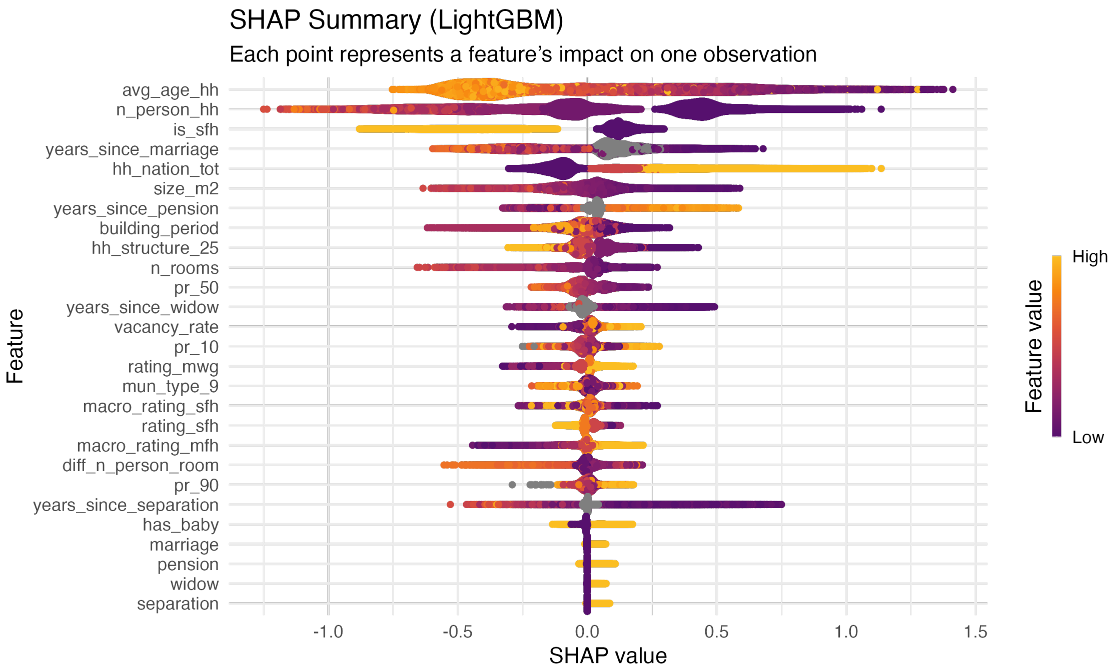


Figure 18: SHAP beeswarm visualisation of variable effect and direction.

Figure 18 presents SHAP-based feature attributions for the relocation model. The SHAP beeswarm plot illustrates both the direction and the strength of each variable's contribution to the predicted relocation probability, conditional on the variable's value. Each point represents an observation, where color indicates the feature value (with lighter colors corresponding to higher values) and the horizontal position reflects the SHAP value, indicating the variable's contribution to increasing or decreasing the predicted probability of relocation. The horizontal spread of points reflects how frequently similar SHAP values occur. Using average household age as an example, high age values (shown in orange to yellow) are predominantly associated with negative SHAP values, indicating that older households reduce the predicted likelihood of relocation. In contrast, low age values are mainly associated with positive SHAP values, implying that younger households contribute to higher predicted relocation probabilities. The vertical feature order indicates the overall order of importance within the LightGBM model. Therefore, the most influential predictor is the average household age. Household size (number of persons), and dwelling type (single-family versus multi-family housing) emerge as further key determinants. Larger households tend to exhibit lower relocation probabilities, consistent with higher coordination costs, while living in a single-family house is generally associated with reduced mobility relative to multi-family housing. These effects are asymmetric and heterogeneous, suggesting that household size and housing type jointly condition mobility decisions in complex ways across different household structures, rather than exerting uniform effects.

A prominent group of predictors relates to major life-course transitions, including years since marriage, separation, widowhood, retirement, and pension entry. These variables show concentrated SHAP impacts around zero years since the event, indicating that relocation rates spike shortly after major demographic transitions and gradually attenuate over time. In particular, separation and widowhood display strong positive SHAP contributions shortly after occurrence, reflecting the destabilizing effect of household dissolution. However, these only describe a minor percentage of total relocations. In contrast, years since retirement and pension entry show more muted but still systematic effects, consistent with slower, delayed mobility responses among older households.

Dwelling characteristics, such as floor area, number of rooms, building period, and room surplus, also play a substantial role. Larger dwellings and a higher room surplus tend to reduce relocation probabilities, while smaller or more constrained housing conditions increase predicted mobility within the model. The SHAP distributions for these variables are notably wide, underscoring the fact that housing characteristics interact with household composition and life-course stage rather than determining relocation independently.

Price-related variables, including asking price quantiles, contribute additional explanatory power but appear secondary relative to household structure and life-course variables. Their SHAP values are centered closer to zero, indicating that price effects are conditional and context-dependent, likely capturing affordability pressures that only become decisive for certain household types or at specific life stages.

Contextual and spatial variables, such as vacancy rates, micro- and macro-location ratings, and municipality typologies, exhibit comparatively smaller SHAP magnitudes. While these factors do influence relocation probabilities, their effects are generally weaker and more symmetric around zero. This pattern suggests that spatial context primarily modulates relocation behavior indirectly by shaping housing availability and market conditions. The relatively modest contribution of municipality type aligns with earlier findings that broad urban–rural classifications capture large-scale spatial structure but do not fully explain individual relocation decisions.

Finally, the bee swarm structure itself reveals substantial heterogeneity in household-level effects across nearly all predictors. For most variables, both positive and negative SHAP values are observed across the sample, indicating strong non-linearities and interaction effects. This heterogeneity confirms the suitability of a non-parametric, tree-based modeling approach and underscores that relocation behavior cannot be explained by single variables in isolation. Instead, it emerges from the interaction of household composition, housing characteristics, life-course timing, and local context.

By the resulting model metrics, this model captures some key elements and variable interactions determining relocation rates; however, it still fails to fully disentangle the interconnected effects of each variable on the relocation rate.

7 Discussion

This study combines large-scale administrative population data from the Federal Statistical Office (STATPOP and GWS) with proprietary real estate market indicators from Wüest Partner AG to analyze household relocation behavior in Switzerland. The integration of these data sources enables a uniquely detailed, longitudinal, and spatially explicit analysis of residential mobility at the household level. At the same time, the complexity and administrative nature of the data introduce several methodological challenges that must be carefully considered when interpreting the results.

A key strength of this study lies in the comprehensive coverage and longitudinal structure of the STATPOP and GWS datasets. With annual observations spanning 2013–2023 and near-complete coverage of the permanent resident population, the data allow for robust identification of relocation events and the analysis of relocation dynamics across the life course. The large sample size enables fine-grained stratification by age, household composition, dwelling characteristics, and the spatial context of variables.

The linkage of STATPOP with the Building and Dwelling Statistics (GWS) is another major advantage. This linkage allows household-level relocation behavior to be analyzed in direct relation to the physical characteristics of dwellings and buildings, such as building type, construction period, dwelling size, and number of rooms. As a result, the analysis goes beyond purely sociodemographic explanations and explicitly incorporates housing stock characteristics.

The integration of market indicators from Wüest Partner, including vacancy rates, asking prices, and micro- and macro-location ratings, further strengthens the analysis by embedding relocation decisions within their economic and spatial context. These variables capture aspects of housing availability, affordability, and location quality that are central to relocation decisions but typically unobservable in official population registers.

Finally, the aggregation of individual relocations to complete household relocations ensures conceptual consistency with the study's focus on household-level decision-making. This distinction is particularly important when analyzing life-course events and dwelling characteristics, as a live course event of one single member often has consequences on the household level.

Despite these strengths, several limitations arise from the structure and content of the data. First, relocation detection relies on annual observations, which implies that only one relocation per individual and year can be observed. Short-term relocations occurring within the same year or temporary moves that are reversed before the next observation remain unobserved. While this limitation is inherent to STATPOP, it may lead to an underestimation of highly mobile populations, particularly younger individuals.

Although extensive efforts were made to remove false moves, the classification of administrative versus true relocations cannot be perfect. The absence of complete information on non-residential building conversions, detailed construction timelines, and administrative correction events necessitated the use of deterministic thresholds (e.g. distance and household size changes). As a result, some false relocations may remain undetected, while a small number of true relocations, particularly very short-distance moves, may have been incorrectly excluded. This likely contributes to relocation rates that remain slightly higher than official FSO figures, even though overall patterns are consistent. Further, relocations within the same building are excluded to align with FSO definition of relocations, but might be relevant in some cases.

The analysis excludes collective households and households with extreme characteristics (very large households, and extreme under- or over-occupancy). While these exclusions are methodologically justified and affect only a small share of observations, they imply that the results primarily describe relocation behavior in conventional private households. Relocation dynamics in institutional settings or atypical living arrangements are therefore not captured and might show differing relocation patterns from those observed.

Several explanatory variables, particularly asking prices, vacancy rates, and location ratings, are measured at aggregated spatial scales (municipality or raster cells) and assigned uniformly to households within those units. This introduces potential measurement error, as households within the same municipality may face heterogeneous housing market conditions. Although micro-location ratings mitigate this issue to some extent, unobserved within-area variation may still attenuate estimated effects. While building type specific ratings are available, the vacancy rate was not disassembled into building types. While this may be less relevant for MFH households, a vacancy rate specific to SFHs could potentially improve the prediction of relocations among SFH households.

A further limitation concerns unobserved household preferences and constraints. Register data provide rich structural information but lack direct measures of subjective preferences, expectations, financial constraints, or informal social ties. As a result, some drivers of relocation behavior, such as individual tenure preferences, or anticipated life events, remain unobserved and may be absorbed indirectly by correlated variables such as age or household composition.

Finally, the use of municipality typologies and spatial variables reduces but does not fully eliminate the risk of residual spatial dependence. While later analyzes suggest limited spatial autocorrelation at larger distances, localized neighborhood effects or micro-scale amenities may still influence relocation decisions in ways not fully captured by the available spatial indicators.

7.1 Results

At an aggregate level, the relocation rates estimated in this study closely mirror official FSO statistics, with a stable upward deviation of approximately 0.7%. This difference is plausibly explained by methodological adaptations required to detect relocations in register data. Importantly, the consistency of temporal trends suggests that the implemented relocation-detection procedure is robust and captures genuine mobility patterns rather than artifacts.

A key contribution of this study is the explicit distinction between person-level and complete household relocations. The observed gap between these two measures confirms that individual mobility does not automatically translate into household mobility. The comparison between SFH and multi-family houses MFH further demonstrates that while relocation levels differ substantially by building type, their temporal evolution follows the same overarching patterns. Although the temporal dimension moves in similar directions, the relocation rate in SFH differs significantly from that of MFH households and should, when possible, always be viewed separately. A key factor that this research missed is the ownership status of apartments and houses. It is hypothesized that ownership of a residence dampens the relocation rate compared to renting across both MFH and SFH. Being able to own a residence also has socio-demographic implications that will influence relocation behavior.

Across all analyzes, average household age emerges as the dominant determinant of relocation behavior. The three-phase structure of family formation, settling, and retirement provides a clear life-course interpretation of residential mobility from the household perspective. High relocation rates among young households reflect educational transitions, labor-market entry, and household formation, while declining mobility in mid-life aligns with increased place attachment, stable employment, and established social networks. The modest retirement-age peak highlights retirement as a trigger for relocation, especially among households of foreign nationality. The subsequent decline underscores that later-life mobility remains selective and often constrained by health, ownership, and social ties. As households in the retirement phase are a subgroup which own SFH and typically have a lot of underutilized space, further analysis of the influence of this age group is particularly relevant. Examining relocation rates in relation to the availability of housing for older adults and retirement homes within individuals' social spheres could reveal additional distinct drivers of relocation. Relocations driven by health reasons were neither explicitly modeled nor captured using a proxy variable.

Household size and structure reinforce this life-course narrative. Larger households consistently exhibit lower relocation rates, which can be interpreted as the result of coordination costs, the increasing difficulty of aligning preferences, employment locations, schooling needs, and social networks across multiple household members. Single-person households, by contrast, face fewer constraints and therefore remain the most mobile group across all ages and building types.

Life events such as marriage, divorce, widowhood, and childbirth introduce sharp but temporary increases in relocation probabilities, confirming their role as mobility triggers rather than long-term determinants. Notably, separations show a strong association with relocation shortly after the event, particularly in MFH, while SFH households appear more resistant to relocation even after disruptive life events. This asymmetry highlights the stabilizing role of having reached an advanced stage in a household's housing career. While divorces are associated with higher household-level relocation rates, the effect is likely even stronger at the individual level, reflecting the fact that separations often involve individual moves that do not necessarily translate into full household relocations. At the same time, the number of observed life events is small relative to the total volume of relocations occurring each year, implying that life events exhibit strong explanatory power but account for only a limited share of overall relocation activity.

Building and dwelling characteristics systematically shape relocation behavior in ways that align with housing career theory. Smaller dwellings, fewer rooms, and higher room overutilization are all associated with higher relocation rates, especially during the family formation phase. These patterns suggest that relocations are frequently driven by mismatches between household needs and dwelling characteristics, such as space constraints following household growth. However, as the degree of overutilization increases further, relocation rates decline. This pattern likely reflects the situation of financially constrained households that, despite severe space mismatches, are unable to afford relocation and therefore remain in their dwellings. Further research could investigate the household structures and financial circumstances of households living in strongly overutilized dwellings to better understand these constraints and their implications for mobility.

Conversely, larger dwellings and underutilized space are associated with lower mobility, particularly among older households. The tendency of older households to remain in larger dwellings despite declining space needs points to strong place attachment, financial security, and limited incentives to downsize. The pronounced relocation peak in small MFH units at pension age could indicate that transitions into assisted living are concentrated among households already residing in smaller dwellings. Furthermore, a distinct relocation peak can be observed among foreign households shortly before the mandatory retirement age. This peak is likely to include a substantial share of emigrations.

While municipal level inner densification trends were analyzed, the results suggest that observed densification trends cannot be directly attributed to relocation rates within the scope of this study. Instead, densification appears to be more strongly associated with structural factors such as job availability and rising rent levels, particularly in urban regions where economic opportunities are concentrated. Increasing housing costs in these areas incentivize more efficient use of living space, contributing to higher residential densities without necessarily implying higher relocation activity. In contrast, peripheral regions dominated by single-family housing may experience indirect effects of urbanization, as households extend their residential search further from urban centers in response to affordability constraints.

The observed U-shaped relationship between building age and relocation rates reflects high mobility in new buildings, likely linked to transitional households and affordability reassessments, while increased mobility in very old buildings may be driven by renovation pressures or declining housing quality.

Real estate market variables exert a measurable but secondary influence on relocation behavior. Vacancy rates show a clear association with relocation in MFH, consistent with the idea that housing availability constrains mobility. Location ratings and asking prices reveal nuanced and sometimes counterintuitive patterns. Higher-rated locations are associated with higher relocation rates in MFH but lower rates in SFH. This divergence likely reflects tenure differences: high-quality locations in MFH may attract more mobile, higher-income renters, while SFH households in high-rated areas are more likely to be long-term renters or owners with strong incentives to remain. Similarly, high asking prices are associated with lower relocation rates, suggesting that affordability constraints suppress mobility rather than induce it.

The limited explanatory power of municipality typologies supports the conclusion that broad urban–rural classifications capture only part of the spatial structure of relocation behavior. While urban regions generally exhibit higher relocation rates, these differences appear to be driven primarily by household composition and housing stock characteristics rather than by location per se. One possible explanation is that the inclusion of the micro and macro location ratings captures key aspects of spatial attractiveness for residential living, thereby mitigating spatial autocorrelation and reducing the additional explanatory power of coarse municipality typologies. Further research could analyze individual urban agglomerations and compare them to assess whether all agglomerations respond similarly to housing market influences. Such heterogeneity across agglomerations may help explain the limited explanatory power of the municipality typology employed here.

The LightGBM model confirms and integrates the descriptive findings by demonstrating that household composition and life-course variables dominate the prediction of relocation probabilities. The strong non-linear effects captured by SHAP values, particularly for age, household size, and life events, underscore the complexity of relocation behavior and justify the use of a flexible, non-parametric modeling approach.

The modest classification performance reflects the inherent difficulty of predicting relatively rare events, such as household relocations. Nevertheless, the model provides well-calibrated probability estimates and captures meaningful interaction effects that are not easily observable in descriptive analyzes alone. The presence of localized spatial autocorrelation in residuals suggests that while large-scale spatial patterns are well captured, micro-scale neighborhood effects remain partially unobserved.

Importantly, within this thesis, the aggregation of household-level predictions to the municipal level was tested and found to yield interpretable patterns beyond individual prediction tasks. Although these results are not included in the present analysis, they indicate the model's potential for applications such as spatial planning and policy analysis, where aggregated mobility patterns are often more relevant than individual outcomes. Further improvements in model performance could enhance its suitability for this purpose.

Beyond cross-sectional prediction, this thesis also explores the model's capacity to anticipate future relocation events by aging the population and applying the trained LightGBM model to predict relocations. However, these exploratory tests, which are not reported in the results section, indicate that while the approach shows some promise, aging the population alone is insufficient to capture future relocation dynamics, and improvements in predictive performance are still required. In particular, key life course transitions such as educational trajectories, partnership formation, marriage, and childbearing, as well as their associated probabilities, need to be explicitly considered when aging the population. Given the strongly dynamic and path dependent nature of residential mobility, life course modeling approaches, particularly agent based models, may therefore be more suitable. Combining such frameworks with the proposed model could offer a more robust way to capture long term relocation dynamics and future mobility patterns.

Overall, the results suggest that relocation behavior is primarily a function of household life-course dynamics and housing characteristics, with market conditions and spatial context acting as enabling or constraining factors rather than primary drivers. Differences between urban and rural regions, as well as between building types, largely reflect compositional effects rather than fundamentally different mobility regimes.

These findings reinforce the importance of considering household structure and housing stock characteristics in housing policy and spatial planning. Policies aimed at increasing residential mobility, whether to improve labor-market matching or housing efficiency, must account for the strong stabilizing forces associated with ownership, household size, and life-course stage. At the same time, the limited explanatory power of broad spatial typologies suggests that more fine-grained, context-sensitive approaches are needed to understand and influence relocation behavior at the local level.

While the model captures many key determinants of relocation, the remaining unexplained variation highlights the role of unobserved preferences, expectations, and social ties. Future research could build on these findings by integrating qualitative insights or more detailed financial and tenure information to further disentangle the complex motivations underlying household mobility.

8 Conclusion

This study examined household relocation behavior in Switzerland between 2013 and 2023 by integrating large-scale register data from the Federal Statistical Office with detailed housing-market indicators provided by Wüest Partner AG. The STATPOP and GWS datasets offer a near-complete cross-section of the Swiss resident population and enable the identification of residential relocations on a year-to-year basis. By linking individuals, households, and dwellings across consecutive years, the data provide a robust empirical foundation for analyzing relocation dynamics at both the individual and household levels.

At the descriptive level, the estimated relocation rates closely align with official FSO statistics, confirming the validity of the implemented relocation-detection framework. Further, the household level relocation rates were computed and subsequently analyzed. The computed relocation rates varied markedly across average household age, the number of household members, and building category. Young households with few members living in rented apartments are the most mobile group. Overall, household composition, nationality, and life-course dynamics emerge as further drivers of relocation. Larger households and households living in single-family houses exhibit substantially lower mobility, reflecting higher coordination costs, stronger place attachment, and higher rates of ownership. Housing characteristics further condition relocation behavior. Smaller dwellings, fewer rooms, and households with few members are associated with higher mobility, particularly during the family formation phase, while larger and underutilized dwellings are linked to residential stability at later life stages. Market variables such as vacancy rates, asking prices, and location ratings influence relocation behavior, but their effects are comparatively modest and largely conditional on household characteristics. High prices and low vacancy rates tend to suppress mobility rather than induce it, suggesting that affordability and availability act primarily as constraints rather than direct triggers of relocation.

The LightGBM modeling results reinforce these conclusions. While predictive performance is constrained by class imbalance and the inherently complex nature of relocation decisions, the model successfully captures key non-linear relationships and interactions among predictors. Importantly, several predictors display heterogeneous effects across subpopulations, indicating that certain variables influence relocation behavior in different directions depending on household composition, age, or housing context.

Future research could build on this work by refining key explanatory variables, incorporating tenure information, longitudinal income dynamics, or qualitative insights into household decision-making. Nevertheless, the present study demonstrates the value of combining comprehensive administrative data with interpretable machine-learning methods to advance the understanding of residential mobility.

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Appendix

.1 Relocation Rate Results

Average Household Age	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
10	23.39% / 16.08%	42 317 / 2 978
15	16.72% / 5.89%	539 218 / 117 520
20	16.02% / 4.17%	2 016 233 / 545 012
25	16.56% / 3.74%	3 179 413 / 743 636
30	15.05% / 3.29%	3 760 640 / 873 922
35	12.21% / 2.81%	2 748 382 / 738 333
40	9.79% / 2.83%	2 250 427 / 610 379
45	8.69% / 2.86%	1 824 781 / 491 567
50	8.16% / 3.12%	1 873 663 / 486 071
55	7.34% / 3.16%	1 829 332 / 494 710
60	6.34% / 2.76%	1 994 527 / 686 879
65	5.66% / 2.71%	1 733 017 / 637 770
70	4.11% / 2.54%	1 827 847 / 699 291
75	4.46% / 3.02%	1 452 336 / 489 659
80	5.84% / 4.29%	1 227 915 / 386 006
85	10.20% / 8.39%	777 045 / 222 359
90	17.45% / 15.60%	382 784 / 111 188
95	28.03% / 26.55%	92 547 / 26 598
100	36.83% / 37.28%	9 173 / 2 591

Table 1: Relocation rates and household counts by average household age and building type (averaged across all data years)

Number of Persons	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
1	13.66% / 8.49%	12 099 744 / 1 416 838
2	8.71% / 2.86%	9 313 284 / 3 125 089
3	9.47% / 2.78%	3 666 012 / 1 315 380
4	7.54% / 2.04%	3 081 032 / 1 714 172
5	6.59% / 2.15%	995 039 / 600 757
6	5.48% / 2.46%	284 192 / 143 588
7	4.75% / 2.82%	81 354 / 33 576
8	3.58% / 2.98%	28 000 / 11 209

Table 2: Relocation rates and household counts by number of persons and building type (averaged across all data years)

Household Age Structure	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
All $<$25	28.75% / 23.68%	614 062 / 16 774
All 25–65	13.06% / 4.39%	12 310 751 / 2 108 076
All $>$65	6.76% / 4.79%	6 009 229 / 2 021 826
Mix: $<$25 + 25–65	10.02% / 2.67%	7 606 740 / 3 320 117
Mix: $<$25 + $>$65	4.78% / 2.69%	39 447 / 14 623
Mix: 25–65 + $>$65	3.52% / 1.91%	1 399 611 / 743 589
Mix: all ages	3.53% / 1.66%	268 228 / 141 512

Table 3: Relocation rates and household counts by household age structure and building type (averaged across all data years)

Nationality Type	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
Swiss Nationality	9.38% / 3.22%	18 862 867 / 7 108 245
Mixed Nationality	10.18% / 3.68%	2 971 318 / 696 301
Foreign Nationality	14.68% / 7.96%	6 418 780 / 564 160

Table 4: Relocation rates and household counts by number of persons and building type (averaged across all data years)

Years Since Marriage	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
0	18.04% / 5.70%	406 505 / 68 761
1	16.98% / 5.26%	408 792 / 78 977
2	15.78% / 4.70%	406 171 / 90 181
3	14.59% / 4.33%	402 911 / 100 936
4	13.31% / 3.97%	390 582 / 110 554
5	12.23% / 3.57%	377 790 / 117 709
6	11.18% / 3.39%	363 278 / 123 403
7	10.35% / 3.14%	347 209 / 127 168
8	9.59% / 2.95%	332 844 / 130 269
9	9.00% / 2.76%	319 746 / 132 506
10	8.50% / 2.68%	307 616 / 133 935
11	8.16% / 2.56%	295 743 / 133 864
12	7.67% / 2.51%	283 990 / 133 362
13	7.45% / 2.41%	274 660 / 134 204
14	7.07% / 2.38%	264 499 / 133 741
15	6.65% / 2.20%	254 275 / 132 887

Table 5: Relocation rates and household counts by years since marriage and building type (averaged across all data years)

Years Since Separation	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
0	16.36% / 8.30%	191 749 / 41 352
1	14.13% / 7.88%	152 712 / 33 292
2	12.74% / 7.05%	110 594 / 24 102
3	11.49% / 6.72%	79 437 / 17 166
4	10.62% / 6.39%	59 709 / 12 620
5	9.46% / 5.51%	46 667 / 9 677
6	8.98% / 4.68%	37 916 / 7 580
7	8.88% / 4.67%	31 753 / 6 271

Table 6: Relocation rates and household counts by years since divorce and building type (averaged across all data years)

Years Since Widowhood	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
0	14.08% / 6.38%	264 805 / 54 058
1	12.84% / 5.46%	257 110 / 52 813
2	11.79% / 5.13%	246 028 / 51 728
3	11.01% / 5.01%	241 688 / 51 506
4	10.42% / 4.70%	233 647 / 50 508
5	9.97% / 4.42%	226 695 / 49 497
6	9.66% / 4.34%	220 488 / 48 371
7	9.14% / 4.20%	214 801 / 47 632
8	8.81% / 4.26%	208 226 / 46 167
9	8.74% / 4.09%	199 326 / 44 230
10	8.40% / 3.99%	189 561 / 41 869

Table 7: Relocation rates and household counts by years since widowhood and building type

Child under 5 present	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
No	10.24% / 3.54%	26 564 236 / 7 468 439
Yes	13.65% / 3.85%	2 997 988 / 898 078

Table 8: Relocation rates and household counts by presence of young children and building type (averaged across all data years)

Building Type	Relocation Rate	Number of Households
MFH	10.59%	29 562 224
SFH	3.57%	8 366 517

Table 9: Relocation rates and household counts by building type (averaged across all data years)

Building Period	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
Period before 1919	11.69% / 5.11%	4 442 819 / 955 009
1919 to 1945	11.90% / 4.46%	2 478 201 / 832 633
1946 to 1960	11.74% / 4.50%	3 416 644 / 896 311
1961 to 1970	10.82% / 4.41%	4 444 398 / 753 513
1971 to 1980	9.74% / 3.36%	3 675 884 / 1 087 335
1981 to 1985	9.47% / 2.92%	1 268 975 / 568 268
1986 to 1990	9.56% / 3.06%	1 530 482 / 683 073
1991 to 1995	9.49% / 2.97%	1 355 385 / 453 215
1996 to 2000	8.18% / 2.47%	1 165 286 / 621 596
2001 to 2005	7.54% / 2.37%	881 891 / 538 599
2006 to 2010	9.60% / 2.48%	1 352 568 / 506 395
2011 to 2015	12.17% / 2.49%	1 474 444 / 347 728
2016 to 2020	12.11% / 2.22%	761 091 / 122 842

Table 10: Relocation rates and household counts by building period and building type (averaged across all data years)

Number of Rooms	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
1	19.01% / 11.89%	1 742 135 / 9 504
2	14.31% / 9.77%	4 645 360 / 71 979
3	11.13% / 6.03%	9 253 116 / 476 660
4	8.58% / 4.02%	8 636 938 / 1 919 747
5	6.68% / 3.14%	2 795 722 / 3 226 113
6	5.31% / 3.03%	784 478 / 1 734 180
7	4.57% / 3.21%	250 764 / 589 053
8	4.46% / 3.46%	90 036 / 214 278

Table 11: Relocation rates and household counts by number of rooms and building type (averaged across all data years)

Room Surplus	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
-5	5.25% / 3.41%	35 079 / 4 254
-4	7.15% / 3.75%	125 455 / 14 786
-3	9.15% / 3.57%	429 124 / 51 398
-2	11.01% / 3.24%	1 517 078 / 197 582
-1	12.87% / 2.77%	5 095 006 / 681 220
0	11.13% / 2.71%	8 732 904 / 1 440 363
1	9.84% / 3.09%	7 934 337 / 1 966 005
2	9.23% / 3.64%	3 199 803 / 2 048 618
3	8.11% / 4.62%	814 474 / 1 208 156
4	7.55% / 5.44%	217 903 / 453 838
5	7.57% / 6.09%	64 006 / 144 941

Table 12: Relocation rates and household counts by room surplus and building type (averaged across all data years)

Dwelling Size (m^2)	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
0–24	23.64% / 14.59%	293 494 / 2 276
25–49	16.49% / 8.78%	2 616 320 / 63 364
50–74	12.47% / 6.12%	7 688 102 / 366 782
75–99	10.12% / 4.82%	8 311 634 / 950 432
100–124	8.43% / 3.83%	5 417 358 / 1 806 607
125–149	7.22% / 3.27%	1 982 473 / 1 371 062
150–174	6.18% / 2.93%	1 045 206 / 1 610 589
175–199	5.71% / 2.77%	399 139 / 850 172
200–224	5.11% / 2.82%	258 685 / 662 093
225–249	5.02% / 2.75%	81 759 / 214 145
250–274	4.88% / 2.81%	53 184 / 166 529
275–299	4.97% / 3.02%	20 016 / 64 072
300–324	4.46% / 3.41%	19 308 / 66 384
325–349	4.18% / 3.06%	4 335 / 16 156

Table 13: Relocation rates and household counts by dwelling size (25 m^2 groups) and building type (averaged across all data years)

Vacancy Rate Class	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
0–0.25%	10.40% / 3.73%	426 5442 / 861 715
0.25–0.5%	9.96% / 3.62%	3 978 776 / 889 432
0.5–0.75%	10.33% / 3.58%	4 111 203 / 938 563
0.75–1%	10.55% / 3.55%	2 716 868 / 844 982
1–2%	10.88% / 3.53%	7 143 764 / 2 425 173
2–3%	11.22% / 3.52%	3 193 946 / 1 138 733
3–4%	11.35% / 3.54%	1 323 579 / 530 960
4–5%	11.49% / 3.46%	746 941 / 285 090

Table 14: Relocation rates and household counts by municipal vacancy rate class and building type (averaged across all data years)

Micro Location Rating	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
1	9.00% / 4.79%	106 699 / 33 865
2	9.12% / 4.35%	535 465 / 140 875
3	10.26% / 3.82%	9 690 641 / 2 329 560
4	10.85% / 3.44%	12 785 877 / 4 258 422
5	11.22% / 3.44%	5 079 243 / 1 478 331

Table 15: Relocation rates and household counts by micro location rating and building type (averaged across all data years)

Macro Location Rating	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
1.0	7.58% / 4.12%	35 156 / 75 669
1.5	8.69% / 3.81%	240 369 / 421 764
2.0	9.95% / 3.68%	667 266 / 774 314
2.5	10.69% / 3.44%	1 468 982 / 1 186 007
3.0	10.86% / 3.42%	2 669 721 / 1 494 408
3.5	10.76% / 3.43%	4 429 428 / 1 562 144
4.0	10.55% / 3.56%	6 390 944 / 1 393 788
4.5	10.60% / 3.70%	6 914 651 / 921 077
5.0	10.95% / 4.20%	5 382 032 / 412 343

Table 16: Relocation rates and household counts by macro location rating and building type (averaged across all data years)

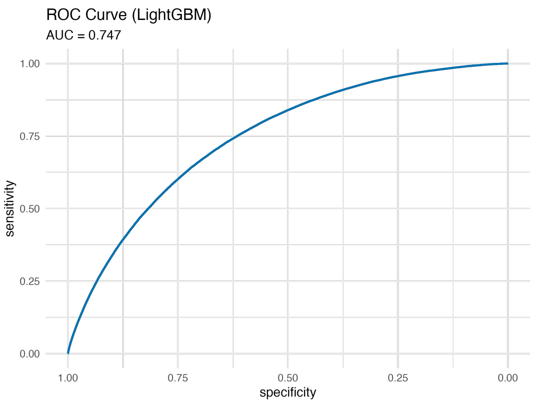
Median Asking Price (CHF/month)	Relocation Rate (MFH / SFH)	Number of Households (MFH / SFH)
0–499	21.13% / 10.01%	70 301 / 81 483
500–999	16.54% / 5.78%	3 895 496 / 98 255
1000–1499	11.30% / 4.20%	12 127 531 / 1 414 402
1500–1999	8.61% / 3.26%	8 244 239 / 2 563 741
2000–2499	7.17% / 3.17%	2 871 810 / 1 967 897
2500–2999	6.44% / 3.31%	729 367 / 1 050 625
3000–3499	6.52% / 3.48%	179 202 / 526 340
3500–3999	7.07% / 3.80%	67 483 / 265 839
4000–4499	7.80% / 4.12%	12 624 / 137 797
4500+	- / 4.15%	- / 76 572

Table 17: Relocation rates and household counts by asking price class and building type (averaged across all data years). The asking prices reflects monthly rent cost as function of dwelling size, data year and municipality.

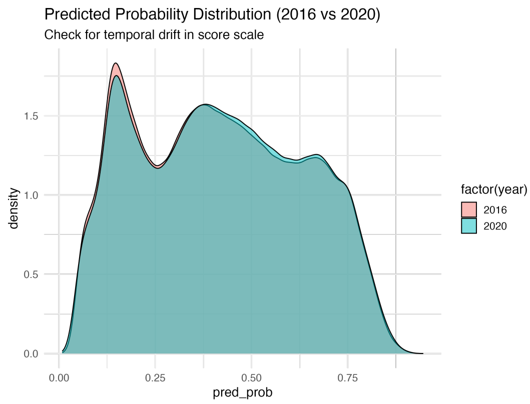
.2 Model Results

.2.1 Model Metrics

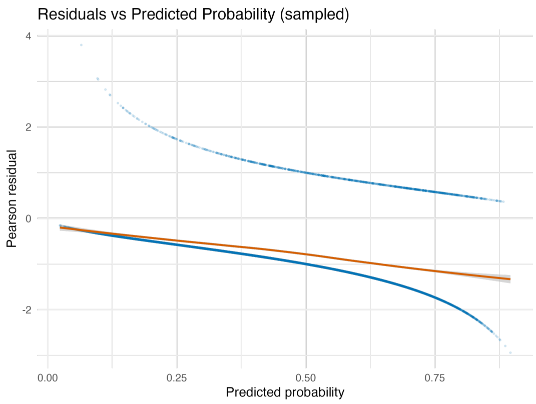
This section contains model metrics for the described LightGB model in Chapter 6.



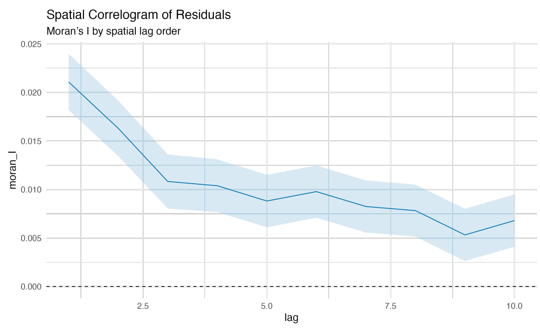
(a) Receiver Operating Characteristic (ROC) curve for the household-level relocation model.



(b) Score drift between training year (2020) and validation year (2016)



(c) Residuals versus predicted probabilities

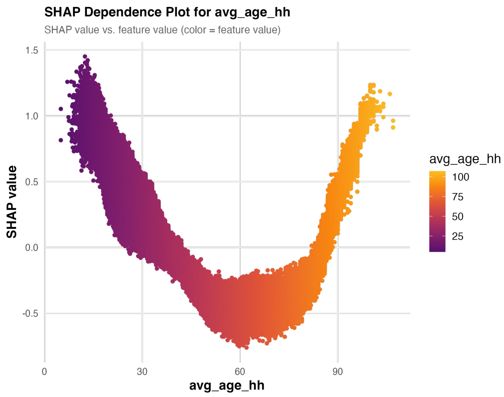


(d) Spatial correlogram of model residuals.

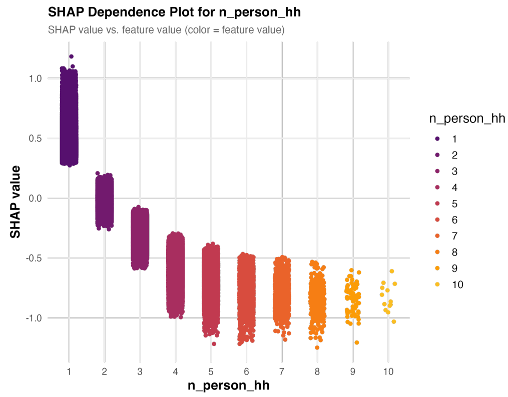
Figure 19: These plots contain metrics of the applied LightGBM model.

.2.2 SHAP Visualisations

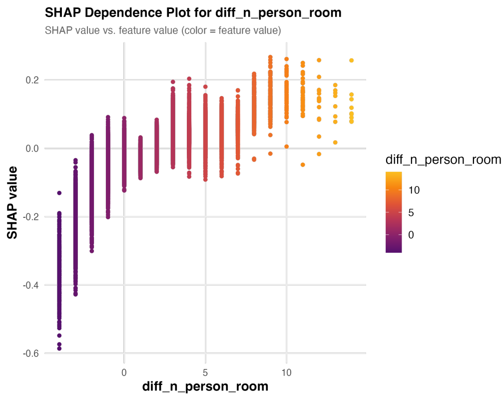
The following pages contain supplementary figures referenced in Chapter 6, providing additional visualisations of the results in terms of Mean Error Distance and Area Under the Curve.



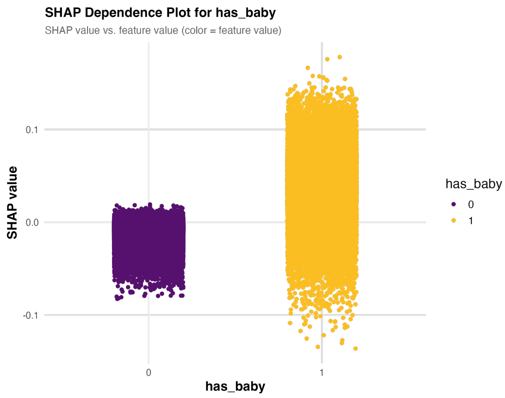
(a) Average household age



(b) Household size

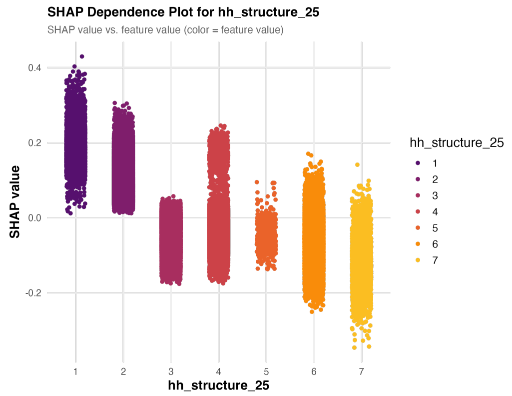


(c) Persons per room

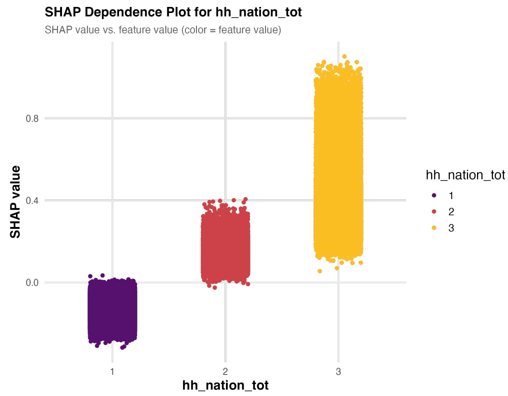


(d) Presence of a baby

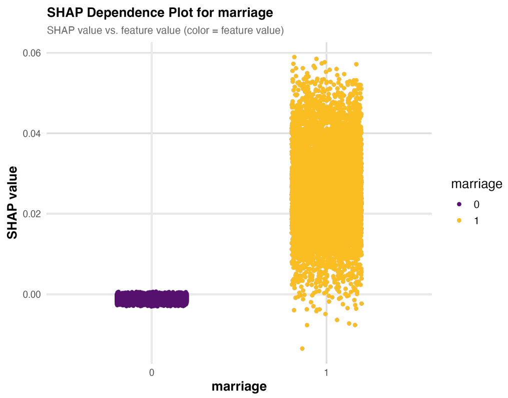
Figure 20: SHAP dependence plots for core household characteristics.



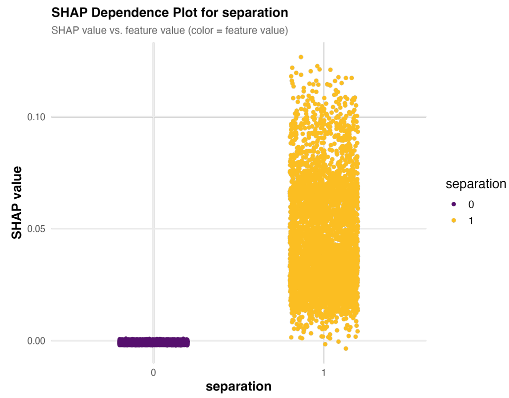
(a) Household age structure



(b) Household nationality

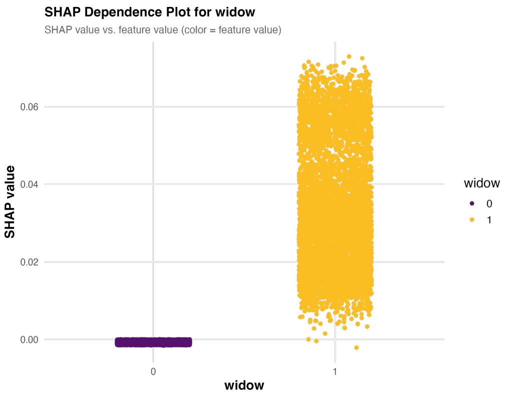


(c) Years since marriage

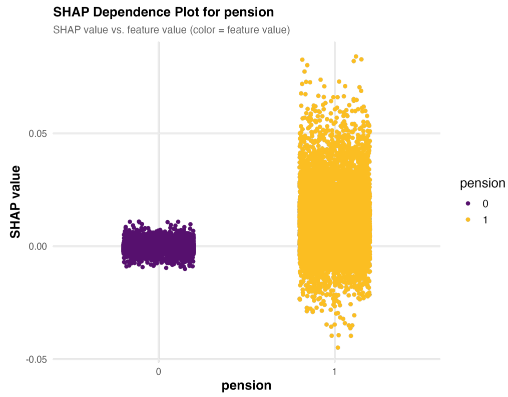


(d) Years since separation

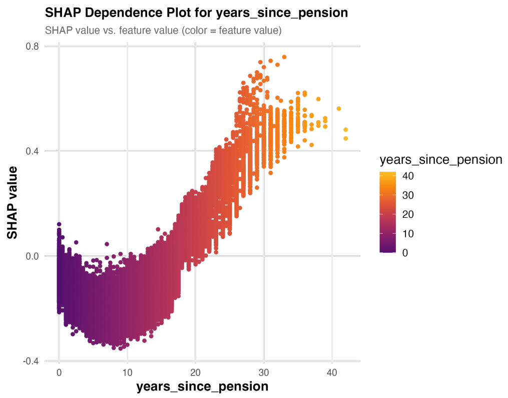
Figure 21: SHAP dependence plots for household composition and family events.



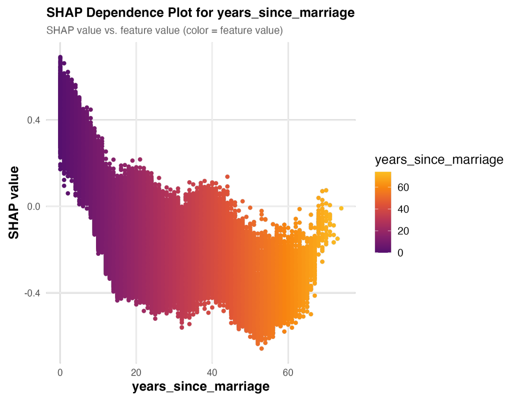
(a) Years since widowhood



(b) Pension indicator

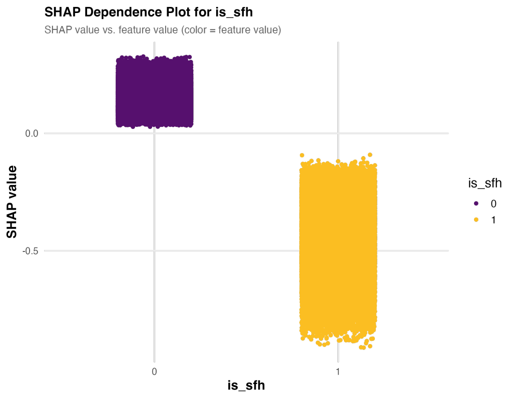


(c) Years since pension

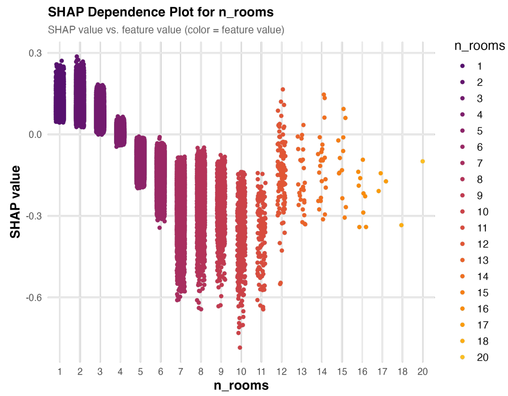


(d) Years since marriage (alternative)

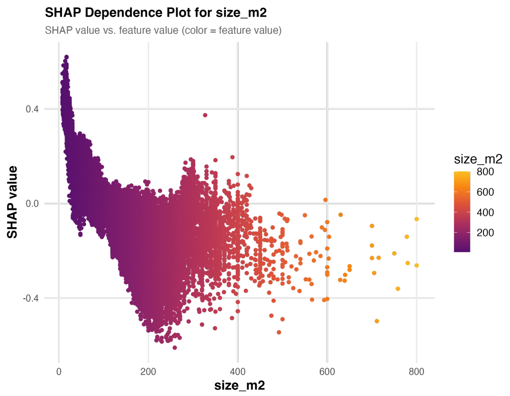
Figure 22: SHAP dependence plots for later life course events.



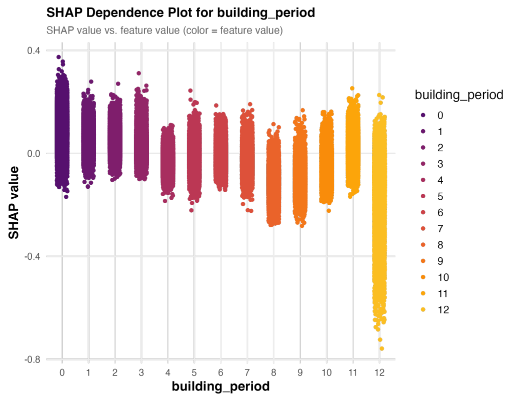
(a) Single-family house indicator



(b) Number of rooms

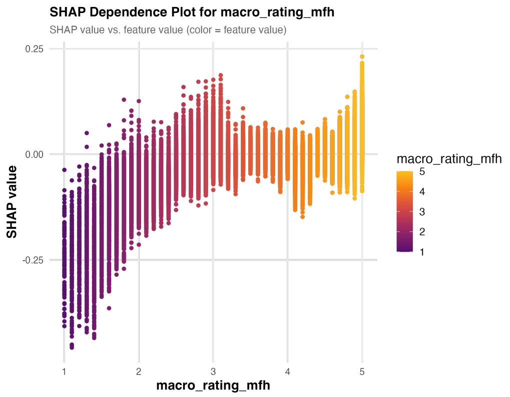


(c) Dwelling size (m^2)

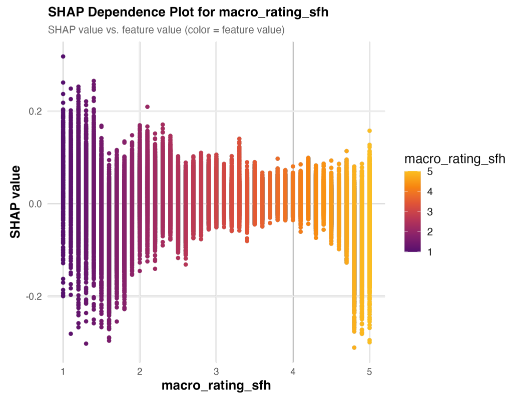


(d) Building construction period

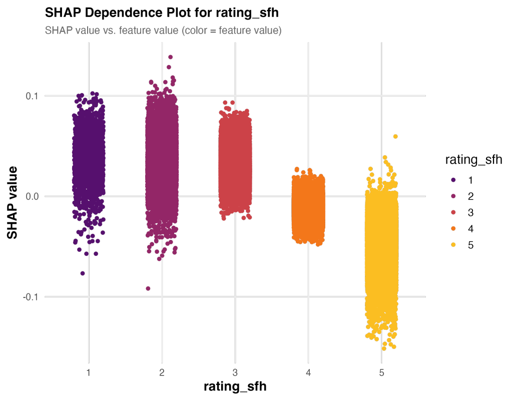
Figure 23: SHAP dependence plots for dwelling characteristics.



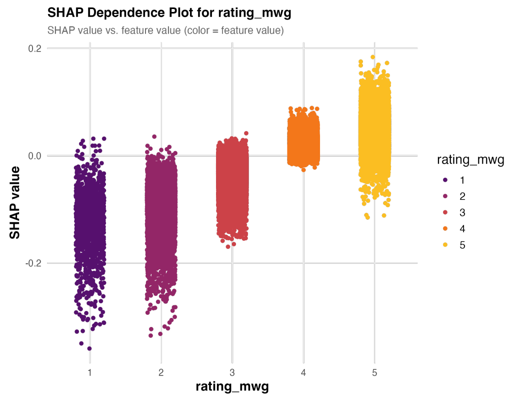
(a) MFH macro location rating indicator



(b) SFH macro location rating indicator

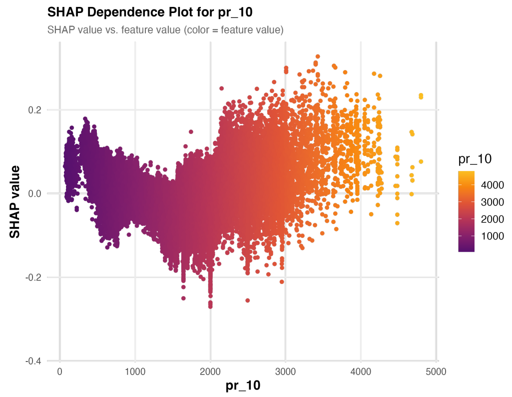


(c) SFH micro location rating indicator

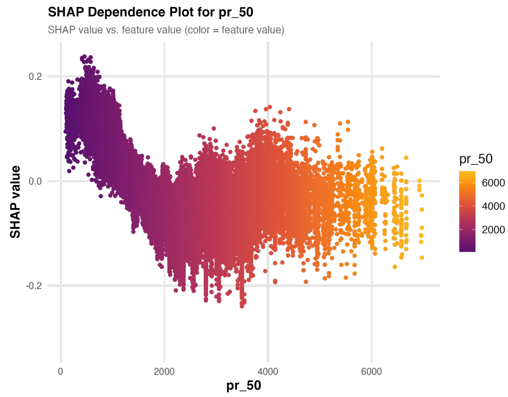


(d) MFH micro location rating indicator

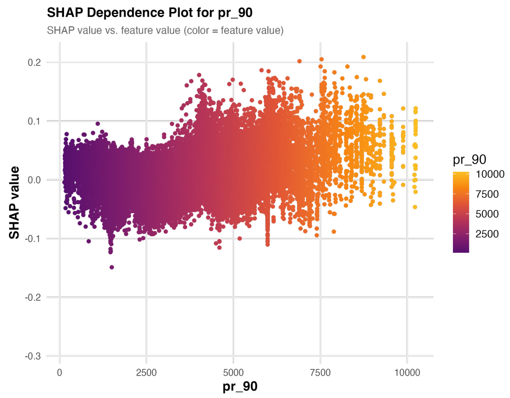
Figure 24: SHAP dependence plots for location rating indicators.



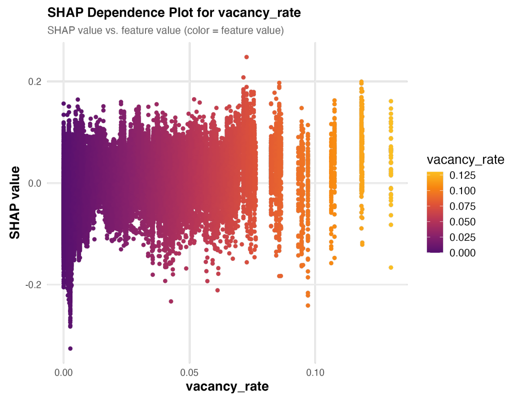
(a) Asking price (P10)



(b) Asking price (P50)

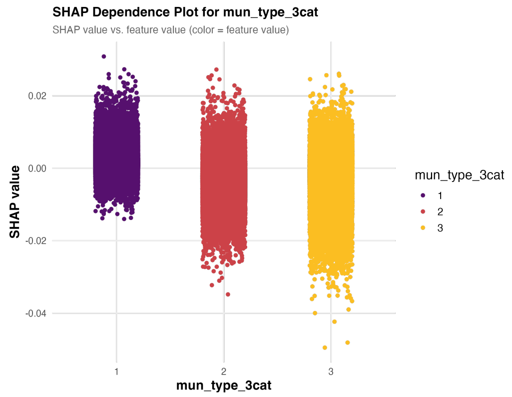


(c) Asking price (P90)

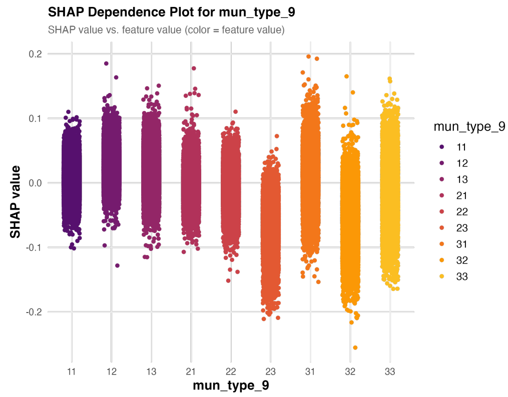


(d) Vacancy rate

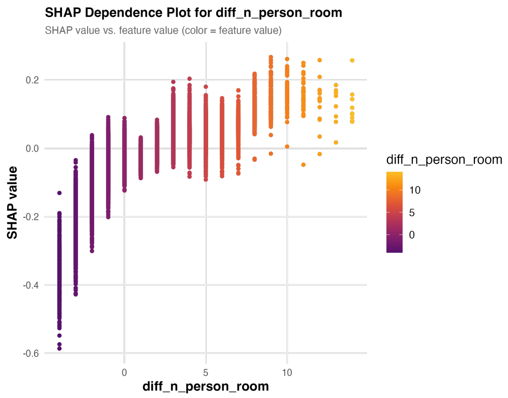
Figure 25: SHAP dependence plots for housing market conditions.



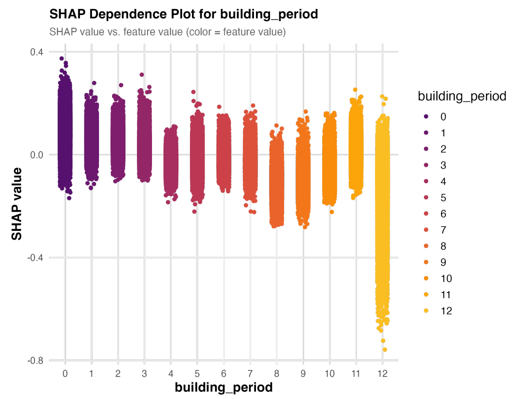
(a) Municipality type with 3 categories



(b) Municipality type with 9 categories



(c) Over- or underutilization of living spaces



(d) Building construction period

Figure 26: SHAP dependence plots for municipal and spatial characteristics.

Personal Declaration

I hereby declare that the submitted thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the thesis.

I further declare that I used ChatGPT and OverleafAI for rephrasing, translation, and grammar and style corrections. ChatGPT was used to create, improve, and format code. Nonetheless, I assume full responsibility for the content of this thesis.

Cyril Geistlich, 18.01.2026