Does new housing for the rich benefit the poor?

On trickle-down effects of new homes*

Gabriella Kindström[#]

Che-Yuan Liang[&]

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Abstract: We use microdata on the Swedish population and housing stock (1990–2017) to investigate how building new homes affects the housing distribution across income groups. While primarily rich people move into new homes, poor people are well represented among in-movers to vacated homes. As homes age and deteriorate, they filter down to poor people; it takes approximately 30 years for new homes to reach an even income distribution. We also find that in municipalities with higher construction rates, every income group gets better access to newer housing and housing space. Overall, we conclude that new homes, even those initially primarily inhabited by rich people, lead to substantial trickle-down effects that also benefit the poor.

Keywords: housing supply, housing inequality, moving chains, filtering, trickle-down effects

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Institute for Housing and Urban Research (IBF) at Uppsala University; e-mail: gabriella.kindstrom@ibf.uu.se.

& Institute for Housing and Urban Research (IBF), Urban Lab, Uppsala Center for Fiscal Studies (UCFS), and Department of Economics at Uppsala University. e-mail: che-yuan.liang@nek.uu.se.

1. Introduction

Most OECD countries have experienced a decrease in housing affordability over time (OECD, 2021). Not only is housing the item that families spend the most money on, but families' budget share spent on housing has also increased significantly. This trend has spurred political interest in potential policy interventions to increase the availability of adequate housing for the poor. Widely used interventions targeting the poor include housing vouchers, rent control, social housing, and inclusionary zoning requiring that a certain share of new housing units must be affordable. Alternatively, governments could stimulate the supply of new market-rate homes, e.g., by relaxing land-use regulations or by providing tax credits for constructing such homes (Glaeser and Gyourko, 2018; Been et al., 2018).

There are several related arguments for why an expansion of the housing stock might lead to trickle-down effects that also benefit the poor even when new homes are not affordable for them: First, as rich individuals move into new residences, they generate vacancies in the existing stock triggering ripple effects with moving chains involving homes that might be affordable for the poor. Second, as new residences age and deteriorate, they could become available for those with lower incomes and thus filter down to them. Third, a larger housing stock should relax the market and lower prices and rents, which benefits every income group. While the arguments are backed up by convincing theoretical models (Muth, 1973; Sweeney, 1974b; Ohls, 1975; Bruckner, 1977; Baer and Williamson, 1988; Chase, 1991; Arnot and Braid, 1997), solid empirical evidence is scant. It has also been argued that the housing market might be segmented (Anenberg and Kung, 2020; Piazessi et al., 2020); if that is the case, additional homes for one income group might almost exclusively benefit them and have minor ripple effects on other income groups.

A major obstacle to investigating how housing supply affects the distribution of homes across income groups has been the lack of high-quality microdata. Whereas one needs to observe a large number of housing units and residents to identify moving chains, it is essential to follow the same housing units over time to study filtering. Using address-level data on moves, Mast (2021) recently found that one new housing unit frees up half an existing unit in below-median income areas in the U.S. Bratu et al. (2023) used the same moving-chain method and found ripple effects of the same magnitude in Helsinki, Finland.[1] The seminal paper by Rosenthal (2014) used the American Housing Surveys 1985–2011 to study filtering and he showed that an in-mover to a 50-year-old home will have 60% lower income than the first occupant of the same home.[2]

In this study, we use rich data covering the entire Swedish population and every residential building each year for the period 1990–2017. In part of the analysis, we also employ housing-unit level data for the years 2014–2017. Our data allow us to better investigate whether new housing units lead to trickle-down effects by providing a uniquely comprehensive picture of supply effects on housing inequality in an entire country over a long time. We can capture moving chain and filtering effects that play out across the entire housing stock and population

[1] Other empirical moving-chain studies include the ones by Ferchiou (1982), Magnusson Turner (2008), and Magnusson Turner and Wessel (2019). Magnusson Turner (2008) found that new homes on average induce 3.7 families to move in Stockholm during 2000–2002.

[2] Liu et al. (2020) found similar results, and they are, together with Rosenthal (2014), the only ones providing direct empirical evidence of filtering so far. Several studies estimate the price or rent depreciation of homes over time, e.g., the studies by Chinloy (1979), Margolis (1982), Coulson and Bond (1990), Galster (1996), Sommerville and Holmes (2001), Smith (2004), Skaburskis (2006), Wilhelmson (2008), and Weicher et al. (2016). While they tend to find low depreciation rates, often around 0.5% per year, Rosenthal (2014) found that a small change in price is sufficient for creating substantial filtering as lower-income families are willing to spend substantially higher shares of their income on housing, which amplifies trickle-down effects.

both in the short run and in the long run. For instance, we can account for indirect effects due to how the supply of new homes affects moving chains and filtering in the existing housing stock. Moreover, filtering can occur through residents with negative income development deciding not to move, something previous studies focusing on moving individuals miss. In addition to studying moving chains and filtering, we also provide a novel analysis of the effects of varying the municipal construction rate on the distribution of housing units of different ages and sizes across different income groups. This analysis provides a more direct analysis of housing supply effects on the poor in terms of access to newer or larger housing units that they otherwise would not have lived in.[3] It also addresses the main limitation of previously used moving-chain and filtering methods, which is that they do not account for how moving patterns would have looked in counterfactual situations with other different construction rates in the city. Moreover, our analysis accounts for the fact that moving-chain and filtering effects per new home could vary with housing supply.

Sweden has an institutional setting that could offer many policy lessons of broad interest. After the government-driven “Million-Homes Program” 1964–1975, during which about 1 million housing units were built, the construction rate plunged. Figure 1 shows the number of individuals living in residential buildings with different construction years in 2017. We report the distribution across construction years separately for individuals with disposable incomes below and above the median income in 2017, respectively. We see that most residents live in homes constructed between 1960 and 1980. The figure also shows that homes constructed after 1975 have proportionally more rich than poor residents and the other way around for homes with earlier construction years. Hence, newer housing units are disproportionately inhabited by high-income people. This pattern would be amplified if one compared the poorest vs. richest income quartiles. The pattern of a decreasing construction rate and new homes more often occupied by richer residents has created a public perception that we have a housing shortage in Sweden and the need for cheaper new homes accessible to the poor.

One possible measure of housing quality for a group of residents is the mean construction year of their homes. In Figure 1, the difference in the mean construction year of the homes belonging to the high- and low-income groups is approximately two years. To get a simple indication of the total effects of housing constructions, moving chains, and filtering over time, we calculate the mean construction year for below- and above-median income residents for each year during our sample period (1990–2017). Figure 2 plots the increase in housing quality since 1990 over time. During these 27 years, the high-income residents got 5 years of newer housing, whereas the corresponding number is 7 years for the low-income residents. Thus, although rich residents more often occupied newer homes (as we saw in Figure 1), poor residents also got newer homes. Furthermore, poor residents got newer homes to a greater extent than rich residents. This provides our first piece of evidence showing that new housing leads to trickle-down effects beneficial for the poor.

We provide a detailed analysis of the trickle-down effect observed in Figure 2. First, we show that in the short run, individuals from the poorest income quartile are almost proportionally represented already among in-moving residents to the homes vacated by people moving into new homes. Thus, not only do moving chains geographically connect homes in low- and high-income areas as shown by Mast (2021) and Bratu et al. (2023), but moving chains also connect homes in which rich and poor people live.

[3] Nathanson (2019) calibrates a structural model and provides simulation evidence of trickle-down effects of new housing.

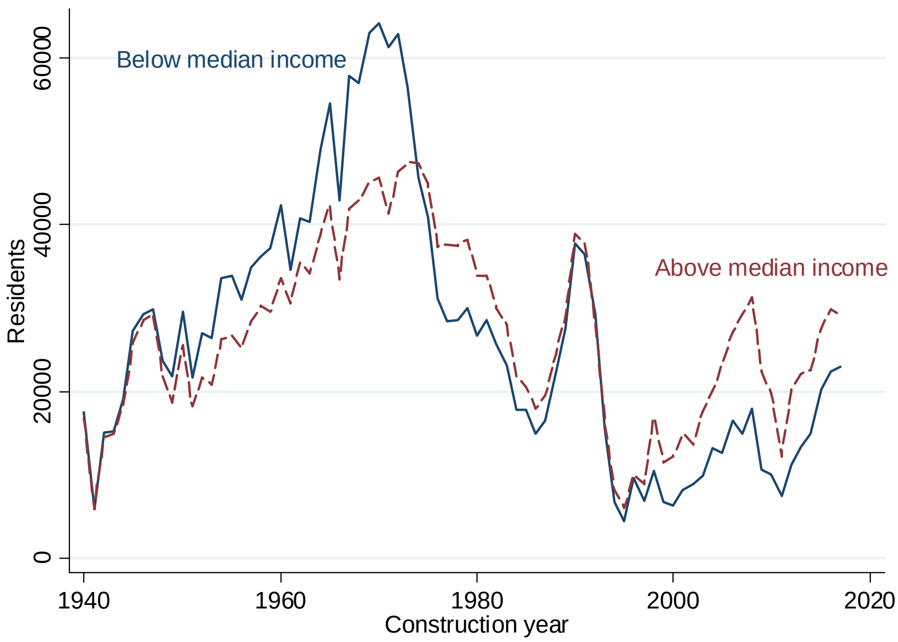

Figure 1. Residential distribution by construction years in 2017

Notes: The graphs are based on data on residents aged 21-65 in 2017 living in homes constructed after 1940.

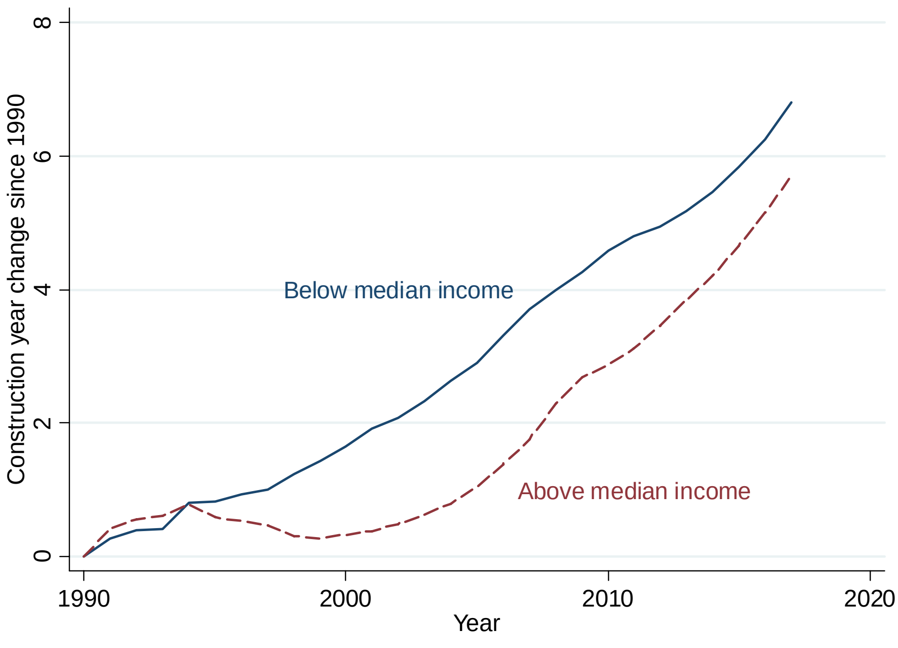

Figure 2. Housing quality improvements since 1990

Notes: The graphs are based on data on residents aged 21-65. Construction year change since 1990 is the mean construction year minus 1990.

Our second major finding is that in the long run, new homes filter down to the poor. Residential buildings that are 30 years old have approximately a proportional mix of residents from different income quartiles. The filtering rate in terms of mean income is approximately 14% in 50 years. This rate is much lower than the 60% in 50 years found by Rosenthal (2014). However, residential incomes in new homes are not very high in Sweden (about 1.25 times the national mean income), and thus poor people already access new homes to a great extent. This is especially true in rental apartments, likely because Swedish rents are regulated and often below the competitive price. Moreover, Sweden has extensive housing allowances for low-income residents with children living in apartments; while this means that policy interventions have been successful in terms of improving access to new housing for the poor, we also find that homes initially occupied by the rich do trickle down over time.

Our final main result is that in municipalities with higher construction rates in terms of new square meter housing space per person, every income quartile gets an improvement in housing quality in terms of newer housing (the mean construction year of their homes) and more housing quantity in terms of housing space (m^2 per person). Whereas the improvement is greater for rich people when it comes to newer housing, it is greater for poor people when it comes to more housing space. The housing space effect does not depend on whether the new homes are owned or rented, and the effect applies to both residential buildings occupied by residents with average income levels above or below the national median income level. Overall, our findings show that building new homes, even expensive ones, leads to important trickle-down effects; thus, stimulating the supply of new homes is a viable approach to improving the housing situation of the poor.

The paper proceeds as follows: In the next section, we provide an institutional background. Section 3 gives a simplistic model connecting moving-chain and filtering functions. Section 4 describes the data. Sections 5–7 present the analysis and results for moving chains emanating from new homes, filtering rates, and the total effect of new housing, respectively. The final section concludes.

2. Institutional background

At the end of the Second World War, some of the previous century's most influential decisions for Swedish housing politics were taken (Swedish National Board of Housing, Building and Planning, 2020). Recognizing the crucial need for a stable housing supply, the temporary system of government loans for new housing constructions was made permanent, and municipal responsibility for the housing supply was established by law. Consequently, most Swedish municipalities created municipal housing companies, and the scope of public housing increased rapidly.

Still today, Swedish municipalities are responsible for assuring the supply of qualitative and adequate homes (Swedish Code of Statutes, 2000). They set an upper limit for new housing constructions through their land use plans and can also affect the housing supply by selling land.

Between 1965 and 1974, about one million new homes were built, commonly referred to as the "Million-Homes Program". This extensive government-driven program was an attempt to combat the housing deficit. The homes constructed as a part of the program have been described as affordable housing with low construction standards.

Economic difficulties along with a new political majority in the early 1990s led to fundamental policy changes (SOU, 2015). The most central reform was the removal of government loans for new housing constructions, which was replaced by a governmental credit guarantee functioning as an insurance against capital loss, which decreased developers' need for capital. The reforms also increased the competition in the housing market by removing previous benefits for the municipal housing companies relative to private actors.

Concurrent with the deregulations after 1990, housing companies privatized a large part of their housing stock by converting rental apartments to tenant-owned co-operative apartments (co-ops). In 2017, 52% of the population lived in privately owned detached or semi-detached houses, 16% lived in co-ops, and 32% lived in rental apartments.

In addition to supply-side policies, several demand-oriented policies aim at improving poor people's ability to consume housing. Perhaps most notably, Sweden has had its particular form of rent regulation since 1968, which, together with the Million-Homes Program, made many homes accessible for low-income households in terms of housing costs (Swedish National Board of Housing, Building and Planning, 2014). Rents are typically set through yearly negotiations between representatives for the landlords and the tenants within the frames of the utilization value. The utilization value depends on factors such as the size, standard, and quality of the apartment. In larger cities, especially in central locations, there has been excess demand with long housing queues, which indicates that rent levels have been below the levels that would have prevailed in a competitive market. Such rents have created low incentives to build rental housing. However, to spur new housing constructions, rents on new homes have been allowed to reflect the construction costs since 2006; this has resulted in higher rents in parts of the housing stock.

At the individual level, housing allowances have been economically important for many families since the 1930s (Swedish National Audit Office, 2017). While the initial focus was on stimulating housing demand, the aim has shifted towards improving the economic situation of poor families in general. However, following the latest reform in 1997, the number of recipients decreased from about 1 million to less than 200,000 today (out of a population of about 10 million), most of them living in rental apartments. The allowance is primarily applicable to low-income families with children and subsidizes half of the housing costs in certain ranges; it costs the government approximately 5 billion SEK (about 0.5 billion USD) per year today.

For homeowners, tax credits amounting to 50% of mortgage interest payments were introduced in 1979 following the parliamentary elections in which the topic was a contentious issue. The credits decreased to 30% in 1991. Part of the argument for the tax credit was to balance the property tax, which was 1% of properties' assessed values with an upper cap before it was abolished in 2008. Most homeowners use the credits which decrease government revenues. However, low levels of interest rates since over a decade ago have reduced the tax revenues foregone by the government, standing at about 15 billion SEK (about 1.5 billion USD) per year today.

Like in most other OECD countries, housing prices have rapidly increased since the 1990s. In Sweden, the low level of municipal land sales and rising production costs are often raised as a reason for the low construction rate (Swedish National Board of Housing, Building and Planning, 2015). However, the Swedish rent regulation and demand-inducing policies are also likely causes. With less affordable owner-occupied housing, economically limited individuals depend more on rental housing. The fact that the rental stock has been shrinking for several decades aggravates the situation.

While politicians are aware of deteriorating housing options for the poor, they profoundly disagree on how to reform the system, which has led to a decade-long political paralysis. In 2021, following a government proposal to move toward market rents, Stefan Löfven became the first Swedish prime minister to lose a parliamentary vote of confidence, and the government resigned. Although part of the political disagreement is ideological, much of it stems from a lack of common understanding about the consequences of different reforms. This elucidates the importance of understanding the effect of housing supply on the distribution of housing across different income groups.

3. Model

3.1 Moving-chain and filtering functions

The purpose of the model is to shed light on how different moving-chain and filtering functions relate to each other. This should also enable us to pinpoint theoretical differences between what we estimate and what has been estimated before. We start with a general setting before discussing a steady-state benchmark with homogenous housing and deviations from this benchmark. Let $i \in \mathrm{I}$ index families, $t \in \mathrm{T}$ index years, and $b \in \mathrm{B}$ index housing units. In year t, family i with income $y_{it} \in \Upsilon$ chooses to reside in housing unit b_{it} constructed in year τ_{it} of age $a_{it} = t - \tau_{it}$. For a housing unit b, we denote its construction year using τ_b.

A family moving into a new housing unit creates a vacancy in their previous home that another family can move into, which in turn creates another vacancy. We could follow this immediate chain of moves emanating from new housing units. Let c index rounds in a moving chain. Then, for a new housing unit:

$$y_b(c = 0)^{chain} = y_{it} : b_{it} = b \text{ and } t = \tau_b. \tag{1}$$

Let i' be the family moving into the home vacated in the previous chain round. As an example, in round 1, i' is the family who moved into the new housing unit b in round 0 (i.e., $b_{i't} = b$ and $t = \tau_b$). For moving chains created by new homes:

$$y_b(c \geq 1)^{chain} = y_{it} : b_{it} = b_{i',t-1}. \tag{2}$$

For new units constructed in year t, we could define the following (normalized) moving-chain function showing the proportional income decay along the chain:

$$Y_t(c)^{chain} = E\left[\frac{y_b(c)^{chain}}{y_b(0)^{chain}}\middle|\tau_b = t\right]. \tag{3}$$

The moving-chain literature (e.g., Mast, 2021; Bratu et al., 2023; Ferchiou, 1982; Magnusson Turner, 2008; Magnusson Turner and Wessel, 2019) studied related versions of such moving-chain functions. Mast (2021) analyzed whether moving chains lead to neighborhoods with lower mean income levels. Magnusson Turner (2008) investigated how moving chains connect different housing types. We focus on the extent to which moving chains free up homes that will be inhabited by families from different income groups.

The moving-chain function $Y_t(c)^{chain}$ only captures short-run effects directly connected to new housing units. However, as units age and deteriorate over a long time, they could become affordable for groups with lower income levels. While a new unit filters in the long run, the moving chain emanating from it also immediately leads to filtering in other units in the existing stock. Moreover, the new unit may affect prices with indirect effects on moving chains between units in the existing stock not directly connected to the new unit. Therefore, filtering functions could capture broader effects of new housing than moving-chain functions.

We let the unit-specific filtering function for housing unit b specify how the income level $y_{it'}$ of the family i occupying b in year $t' \in \mathrm{T}$ varies with the age of the unit a:

$$y_b(a) = y_{it'} : b_{i,t'=a+\tau_b} = b. \tag{4}$$

Let $\mathrm{B}_t \subseteq \mathrm{B}$ be the set of housing units that exist in year t. For housing units in the existing stock in t, we can now define the (normalized) filtering function:

$$Y_t(a) = E\left[\frac{y_b(a)}{y_b(0)}\middle| b \in \mathrm{B}_t\right]. \quad (5)$$

This function measures how mean income proportionally changed as existing units aged.[4] Estimating it properly requires access to long housing panels linked to income data. To our knowledge, we provide the first attempt to estimate it.

When there is only one year of data from year t, one could estimate a cross-sectional function of how mean income levels vary across housing units built in different years:

$$Y_t(\tau)^{cross} = \frac{E[y_{it}|b_{it}\colon \tau_b = \tau]}{E[y_{it}|b_{it}\colon \tau_b = t]}. \quad (6)$$

This function shows how mean income proportionally decays as the construction year is pushed backward in time. However, $Y_t(\tau)^{cross}$ not only reflects the filtering effect due to older units having aged for a longer time but also depends on compositional effects if homes constructed across years have varying quality at the same age.

It is common in the literature to focus on only movers, e.g., in repeat-sales models (e.g., Case and Shiller, 1989; Case and Quigley, 1991; Harding et al, 2007). In year t', a mover is an individual i with $b_{it'} \neq b_{i,t'-1}$ and a mover to building b has the following income:

$$y_b(a)^{movers} = y_{it'} : b_{i,t'=a+\tau_b} = b \text{ if } b_{it'} \neq b_{i,t'-1}. \quad (7)$$

When a family stays in a housing unit ($b_{it'} = b_{i,t'-1}$), $y_b(a)$ is not defined for $a = t' - \tau_b$.[5] We could define the mover-based filtering function:

$$Y_t(a)^{movers} = E\left[\frac{y_b(a)^{movers}}{y_b(0)^{movers}}\middle| b \in \mathrm{B}_t\right]. \quad (8)$$

Rosenthal (2014) and Liu et al. (2020) followed housing units over time; using income data on in-moving residents during turnovers, they provided the only direct estimates of this function so far. Of course, $Y_t(a)^{movers}$ only account for a subsample of residents affecting the income composition in a collection of homes, and it differs from $Y_t(a)$ if income develops differently for staying residents than for in-movers.

While $Y_t(a)$ contains information on how filtering affects the distribution of housing consumption across income groups, it does not capture all effects of changes in the housing stock on this distribution. One possible measure of housing quality for a group of individuals, e.g., those in the poorest income quartile, is the mean construction year of their homes $E(\tau_{it})$. We analyze changes in this variable over time to provide a broader picture of changes in terms of access to units with later construction years. Let $i' \in \mathrm{I}' \subset \mathrm{I}$ index families that in year t' live in new units constructed after year t, and let I' denote their share of all families. Similarly, let $i^* \in \mathrm{I}^* \subset \mathrm{I}$ index families that in year t lived in homes that were demolished before year t', and let I^* denote their share of all families. Let $i^{-\prime}$ and i^{-*} index families that are not elements of

[4] Note that only housing units constructed before year $\tau = t - \bar{a}$ will contribute to $Y_t(a = \bar{a})$.

[5] Also note that $y_b(0) = y_b(0)^{movers}$ since one has to move to live in a new unit.

I' and I^*, respectively. Those families live in homes that existed both in years t and t'. Then, it is easy to show the following:

$$E(\tau_{it'} - \tau_{it}) = E(\tau_{i't'})I' - E(\tau_{i^*t})I^* + E(\tau_{i^{-\prime}t'})(1 - I') - E(\tau_{i^{-*}t})(1 - I^*). \qquad (9)$$

This simple decomposition shows that for a group of residents, the mean change in construction year during a period depends on access to newly constructed units (first term), moves away from demolished units, and a residual difference term (third minus fourth terms). The residual term reflects the degree to which housing units that existed in t have become increasingly accessible in t', i.e., how the units have filtered. Filtering estimates provide no information on the construction year of demolished units, and cannot alone provide an estimate of $E(\tau_{it'} - \tau_{it})$ as time passes.

3.1 Steady-state benchmark with homogenous housing

Suppose that we have a large number of families (I is a continuum) and no population growth. A family has the same positive income every year (no income dynamics and thus $y_{it} = y_i$ for each t), cannot save, and live infinitely. Let the cdf (cumulative distribution function) of the income distribution be $F(y_i)$. Assume that families have lexicographic (but locally non-satiated) preferences meaning that additional spending on housing p_{it} to improve housing quality h_{it} is always preferred to residual consumption of other goods.

All new housing units are identical and provide housing quality $h_{bt} = h_0$ and quality changes as units age according to $h_{bt} = h_0 * h(a = t - \tau_b)$ where $h(a)$ is a depreciation function. Let the cdf of the distribution of housing units with a certain age a in year t be $S_t^a = S_t(a)$ and the corresponding probability mass function $s_t^a = s_t(a)$. Hence, the supply of new housing units in year t is s_t^0.

For simplicity, suppose each housing unit is rented out by one landlord. Individuals bid for units, and landlords rent out to the highest-bidding family. Since families derive positive utility from residual consumption, they will only bid the same rent as the lowest other bidders for units of that age. The market clears when the vector of bids is such that no family can change their bid to improve their housing quality. Without loss of generality, assume that empty units will be demolished (e.g., due to an infinitesimal upkeep cost) to simplify the algebra.

When the market clears, richer families will live in (weakly) newer housing units (a_{it} weakly decreasing in y_{it}). Residents will live in units with an age $a_{it} \leq \bar{a}$. Older units cannot obtain a tenant and will be demolished. With steady-state supply, $s_t^0 = s^0$, which will result in a housing stock with the same age profile each year t. Moreover, there will be the same number of units of each age $< \bar{a}$. Thus, $s_t^a = s^a = s$ for every $a < \bar{a}$. It is simple to solve the model to obtain the income cutoffs between which residents will inhabit units of different ages:

$$a_{it} = \begin{cases} 0 & y_i \geq F^{-1}(1-s), \\ a & F^{-1}[1-(a+1)s] \leq y_i \leq F^{-1}[1-as], \;\; 0 < a < \bar{a}, \\ \bar{a} & y_i \leq F^{-1}[1-\bar{a}s]. \end{cases} \qquad (10)$$

Families at the cutoffs, e.g., with $y_i = F^{-1}(1-s)$, will spend all their income on rent. Families with higher income living in units of the same age will spend the same amount on rent but also have residual consumption.

As time passes, families will continue to live in units of the same age. This means that each family will move every year to a unit that is constructed one year later than their previous home, and more generally:

$$E(\tau_{it'} - \tau_{it}) = t' - t. \quad (11)$$

It follows that there is a simple equivalence between the filtering and moving-chain functions:

$$Y_t(a) = Y_t(a)^{movers} = Y_t^{chain}(c = a) = Y_t(\tau = t - a)^{cross}. \quad (12)$$

Moreover, these functions will not vary with time (thus, e.g., $Y_t(a) = Y(a)$ for every t). Under the assumptions rendering these equalities, the filtering function $Y_t(a)$ can be inferred from estimates of the other functions, which require less data to estimate. For instance, having a representative sample of families from one year and knowing the construction years of their homes would be sufficient for estimating $Y(\tau = t - a)^{cross}$.

In reality, deviations from the simplistic model likely break the equivalence between the filtering function and the other related functions. For instance, allowing for income dynamics or income shocks over time would lead to moves between units constructed many years apart. Thus, moving chains emanating from new units would no longer only lead to units constructed the year before. This connection between units with non-adjacent construction years would lead to a moving-chain function that decays faster than the filtering function. Moreover, a decrease in housing supply in a year will lead to fewer moves. For families living in housing units of a certain age the year before, only those with the highest incomes will move. This systematic difference in income between moving and non-moving residents will break the equivalence between the filtering function and the mover-based functions. It is easy to think of a variety of other real-world factors of importance that break the equivalence in Eq. (12), e.g., variation in housing quality of new units between years and moving frictions. Ultimately, it is an empirical question what the shapes of the different moving-chain and filtering functions are.[6]

4. Data

We use annual data from GeoSweden, a registry-based database compiled (and anonymized) by Statistics Sweden for the Institute for Housing and Urban Research (IBF) at Uppsala University. The database covers the entire Swedish population of around 10 million inhabitants (in 2017) from 1990 to 2017. The same person is linked over time via an anonymized identifier constructed using the social security number. The individual-level data were gathered from RTB and LISA, microdata registries available at Statistics Sweden for researchers in Swedish universities. We have access to various economic and demographic variables, including income sources, taxes, birth year, country of birth, educational attainment, and marital status.

GeoSweden also contains longitudinal real-estate data covering the entire Swedish housing stock from Statistics Sweden's estate registries Fastighetsregistret and Fastighetstaxeringsregistret. The data on residential estates include geographical location, type (e.g., detached house or apartment building), construction year, size, standard, assessed value, judicial owner, and renovation years. Since 2013, we also have access to housing-unit-level data gathered from Lägenhetsregistret. While Swedish social scientists have frequently used good individual-level microdata before,[7] a unique feature of GeoSweden is that individuals are geographically linked to the housing unit and estate in which they reside via their registered

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[6] In estimating these functions, there is no need to assume that the market is in steady state or that housing is a homogenous good.

[7] Edin and Fredriksson (2000) compiled an individual longitudinal data set (around 300,000 individuals) and sparked a wider use of Swedish administrative data in economic research.

addresses. This allows us to follow how individuals move between housing units and estates. Previously, researchers have used GeoSweden to study neighborhood effects.[8]

In our simplistic model, we used homes as housing units, and for our analysis of moving chains, we use the housing-unit data from 2013–2017. For the remaining analysis, it is essential to have data over a long period of time, why we instead use the estate-level data from 1990–2017. A vast majority of real estate have one main residential building and sometimes auxiliary buildings or other structures. Henceforth, we refer to an estate as a residential building. If no housing units were added or removed in buildings over time, the mean filtering rate of housing units in a set of buildings and the filtering rate of the same set of buildings would have been the same. For each building, we know the construction year as well as the value year. The value year is the same as the construction year until there is an extensive renovation or reconstruction, after which the value year is adjusted to reflect the increased quality. The construction year remains constant over time.[9] For single-family buildings, the value year is only updated following an expansion of the living area. In such cases, the value year is a weighted average of the construction year and the expansion year with weights depending on the amount of living area added. We use the construction year to calculate the age of our buildings in the main analysis. Estimates of the filtering function as buildings age are informative about what we can expect over time when constructing a new building and thus relevant for policymakers who, e.g., want to subsidize new housing. However, we also provide results using an age variable based on the value year which better reflects the deterioration of buildings; these results are useful for assessing the impacts of renovations.

In our analyses of the distribution of housing by income, we focus on working-age individuals between 21 and 65 years old and calculate their disposable income, which is pre-tax income minus taxes plus transfers. Pre-tax income includes income from all recorded sources, with labor and capital incomes being the dominant components. Disposable income captures individuals' purchasing power. To account for productivity changes over time, we normalize and use relative disposable income (the population mean equals one in each year). When calculating building-level income variables, e.g., the mean income in a building, we work with individuals. As noted by Hu and Liang (2022), this avoids three complications surrounding working with family or household income due to: i) There are many unmarried cohabiting couples with or without children in Sweden. ii) The number of members across families or households varies. iii) Family units are not comparable over time due to the high and changing divorce rate. When constructing income quartile shares, we use the national income quartile cutoffs year by year; thus, the four quantiles are equal-sized population-wise.

[8] Examples of studies include those by Edin et al. (2003), Galster et al. (2008), and Hedman et al. (2015).

[9] In some cases where a building was fully or partly demolished and a new structure was erected in the same plot (potentially on a larger building area), the estate identifier was not updated; instead, the construction year was updated. This update could also occur when auxiliary residential buildings were added to the same estate. When there is an update in construction year, we treat the estate as a new estate.

Table 1. Mean characteristics of residential buildings

	(1) All	(2) Detached	(3) Co-ops	(4) Rentals
	A. Year 2017			
Buildings	1,459,777	1,376,102	23,201	60,474
Residents (/building)	5.9	3.3	62.5	44.7
Residents age 21-65 (/building)	3.7	2.0	38.1	27.5
Construction year	1964.4	1961.0	1969.1	1967.4
Building age	52.6	56.0	47.9	49.6
Value year	1971.7	1968.1	1976.2	1975.3
Housing space (m^2/person)	40.5	40.2	47.3	37.5
Disposable income (2017 SEK)	190,500	213,400	213,300	139,900
Share in income quartile 1 (%)	24.6	17.3	21.7	38.5
Share in income quartile 2 (%)	24.8	22.6	22.2	29.9
Share in income quartile 3 (%)	25.0	27.6	25.0	20.7
Share in income quartile 4 (%)	25.5	32.5	31.2	10.9
Share age < 21 (%)	26.4	32.1	15.7	22.8
Share age > 65 (%)	11.7	5.5	23.3	15.7
	B. Year 1990			
Buildings	1,372,655	1,297,713	11,285	63,657
Residents (/building)	5.3	3.3	63.6	35.6
Residents age 21-65 (/building)	3.2	2.1	36.4	21.3
Construction year	1957.7	1956.1	1960.3	1959.9
Building age	32.3	33.9	29.7	30.1
Value year	1964.1	1962.4	1965.2	1967.0
Housing space (m^2/person)	41.3	38.1	52.6	44.0
Disposable income (2017 SEK)	106,400	111,500	105,600	96,700
Share in income quartile 1 (%)	24.8	23.4	22.9	27.9
Share in income quartile 2 (%)	24.8	21.5	27.0	30.6
Share in income quartile 3 (%)	24.9	23.9	27.6	26.1
Share in income quartile 4 (%)	25.5	31.2	22.5	15.3
Share age < 21 (%)	27.8	33.9	14.3	20.6
Share age > 65 (%)	11.6	4.5	28.5	19.6

Notes: The table is based on data on inhabited residential buildings for which we observe building year, value year, and housing space. Income variables are based on residents aged 21-65.

Table 2. Mean characteristics of housing units in 2017

	(1) All homes	(2) Detached	(3) Co-ops	(4) Rentals
Housing units	3,590,303	1,481,491	771,829	1,336,983
Residents	2.30	2.93	1.79	1.90
Residents age 20+	1.44	1.85	1.10	1.19
Homes per building	2.49	1.09	34.04	22.96

Notes: The table is based on housing units in the residential buildings in Table 1.

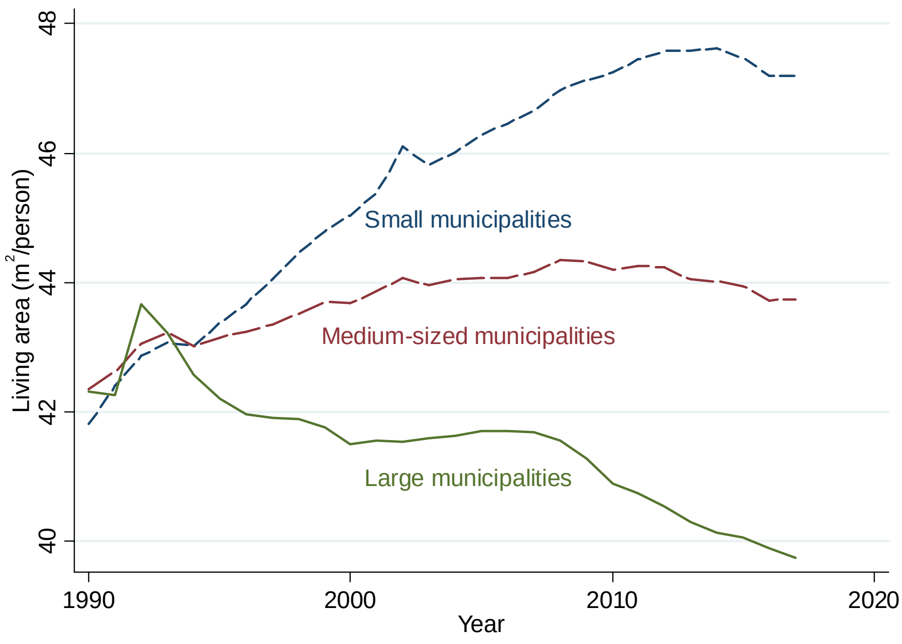

Figure 3. Housing space per person over time

Notes: The graphs are based on all residential space including space in uninhabited buildings and all registered individuals including those without a registered address.

Table 1 provides descriptive statistics for inhabited residential buildings in 1990 and 2017, i.e., the first and last years that GeoSweden covers. We provide means for several variables for the full population as well as for subsamples of the population living in detached or semi-detached houses (henceforth, detached houses), owned apartments (co-ops), and rental apartments, respectively. In the table and throughout the regression analysis using building-level data, we restrict the data sample to inhabited residential buildings for which we observe building year, value year, and housing space (living area). About 85% of the Swedish population live in these buildings.

There are approximately 1.5 million buildings in 2017 with a vast majority of them being detached homes. However, while an average detached house has 3.3 residents, the multi-family apartment buildings have many more residents per building, with about 63 residents in buildings with owned apartments and 45 residents in buildings with rental apartments. The age of buildings is around 50 years old in co-ops and rentals, and a bit more in detached homes. The average housing space is about 40 m^2 per person. The income level in rentals is approximately two-thirds of the income level is owned homes. Young people aged 20 or less are overrepresented in detached homes and old people aged 66 or more are overrepresented in co-ops. Comparing panels A and B, the most notable development from 1990 to 2017 is that the number of co-ops has more than doubled. Moreover, the difference in mean income between tenure types was much smaller in 1990.

Table 2 reports variable means at the housing-unit level. We see that, on average, 2.9 persons lived in a detached home and 1.8-1.9 persons lived in an apartment. On average, there are 34 apartments in buildings with co-ops and 23 apartments in buildings with rentals.[10]

We already mentioned that the construction rate has decreased since the 1980s. However, total housing space can also be expanded through extensions of existing homes. Moreover, it also depends on the demolition rate of existing homes. Figure 3 shows how per capita m^2

[10] The mean number of housing units in detached houses is above 1 because this category includes semi-detached houses and also because, in a few cases, multiple housing units in one or more detached houses belong to the same real estate.

housing space changed during our sample period for large, medium-sized, and small municipalities (population-wise), where each type of municipality hosted around one-third of the Swedish population in 2017. While the construction rate has decreased, it is clear that housing space per person primarily dropped in large municipalities, in particular after 2008, potentially leading to issues with increased overcrowding.

5. Moving chains

5.1 Moving-chain estimation

In this section, we use our individual and apartment data from 2013–2017 to investigate how income levels change across moving-chain rounds for moving chains emanating from housing units in new residential buildings. The moving-chain function $Y_t(c)^{chain}$ was formally defined in Eq. (3) and captures short-run effects directly connected to new housing units.

We start by identifying the sample of individuals above the age of 20 moving into new homes built in year t for the years between 2014 and 2017 and call their average income round 0 income. We then track in which housing units these residents lived in year $t-1$ to find the "vacancy" that has been created in year t. After that, we identify the sample of individuals moving into those homes in year t for calculating the average round 1 income, i.e., the income of the in-moving resident filling up the vacancy in year t.[11] In round 2, we repeat the process to find the vacancies created by each of the in-moving residents in round 1 and calculate the average round 2 income. Incomes in subsequent moving-chain rounds are calculated analogously. Some buildings from which residents move have no in-moving residents, e.g., this is typically the case when children move away from their parents. Our way of calculating the average income in each round is an average income conditional on non-termination.

It is debatable which time horizon is of greatest interest. Conceptually, a moving chain could materialize almost immediately; as a family moves out of a home, another family could move into that home the next month. Given that we use annual data, our estimates do not represent immediate moving chains since some housing units have multiple within-year turnovers. However, even if the purpose is to identify effects materialized in the short run, policymakers should be interested in effects lasting at least one year.[12]

5.2 Moving-chain estimates

Figure 4 reports how relative income and number of in-movers change across moving-chain rounds. Because the income distribution of in-movers is particularly right-skewed, much more skewed than for the rest of the population, we use two measures of relative income in each moving chain round in Panel A: the mean of individual income divided by the national mean (in the same year) and the median of individual income divided by the national median (in the same year). In Panel B, we display the number of individuals in each moving chain round divided by the round-0 number of individuals moving into new homes. Figure 4A shows that residents moving into new homes in round 0 have, on average, 37% higher income than the population mean income. Although income falls with each round, it is still 4% higher than the population mean income in round 5. In contrast, the median income of in-movers is lower

[11] Note that a vacancy thus defined only means a home from which a person moved; that home could still have other residents and is not necessary empty before new residents move in.

[12] Of course, policymakers should be more interested in longer-run effects. But we think filtering estimates better capture such effects than moving-chain estimates based on longer time horizons. Yet, we still provide moving chain estimates as they are intuitive, and versions have been estimated before.

relative to the population median income with a level of 12% higher than the population median income in round 0. In rounds 2 and on forth, the median income is lower than the population median income and about 90% of the population median income in rounds 4 and 5. Overall, income decreases substantially and quickly each round initially.

Figure 4B shows that the number of enabled in-moves also decays quickly each round; each in-move in round 0 only enables 0.07 in-moves in round 5. Cumulatively, one in-mover to a new home generates vacancies that enable another 1.26 in-moves. While the vacancies generated are more important than the in-move into the new home, their influence is still quite limited when assessed against the potential effects of moving chains; with no decay, five additional in-moves would have been enabled in five rounds.[13]

To explore distributional effects in detail, Figure 5 presents the shares of residents from different income quartiles across moving-chain rounds. We see that 37% of residents in new homes belong to the richest income quartile. In contrast, individuals from the poorest income quartile are under-represented in new homes: they make up 18% of the residents in those homes. However, they are already more than proportionally represented and make up more than 25% of residents moving into the second round of vacancies. Given that rich individuals move less on average, it is not surprising that poor individuals take part in the moving chains we study. We conclude that new homes do benefit every income group, even in the short run, via the moving chains they create.

To investigate whether certain types of new homes lead to moving chains more beneficial for the poor, we conduct a heterogeneous effects analysis. Figure 6 shows how income varies across moving-chain rounds by subgroups of new homes depending on tenure type. We find a high median-income decay across rounds for owned homes (detached homes and co-ops). Rented homes start with lower income than the national median income in round 0 and the income remains constant across rounds. The share of residents from the poorest income quartile is around 10–12% in owned homes but converges quickly towards that of rented homes in later rounds.

We also perform a heterogeneity analysis by the initial income level in new residential buildings. In defining new buildings with high and low initial income levels, we use as income cutoff the median income of individuals residing in newly built homes of age zero between 1990 and 2017. Although this is not the sample period used for the moving-chain analysis, we use it here for the purpose of defining high- and low-income buildings to stay consistent with the other analysis that is conducted below. Figure 7 plots how moving chains differ between residential buildings with above- and below-median initial income levels defined as described. We see that people with considerably less than the national median income benefit from moving chains in later rounds, no matter whether they access new homes directly.

[13] For Stockholm, Magnusson Turner (2008) found an average chain length of 3.7. While it is hard to translate this number into enabled in-moves, both her and our results indicate that moving chains die out quite fast in Sweden.

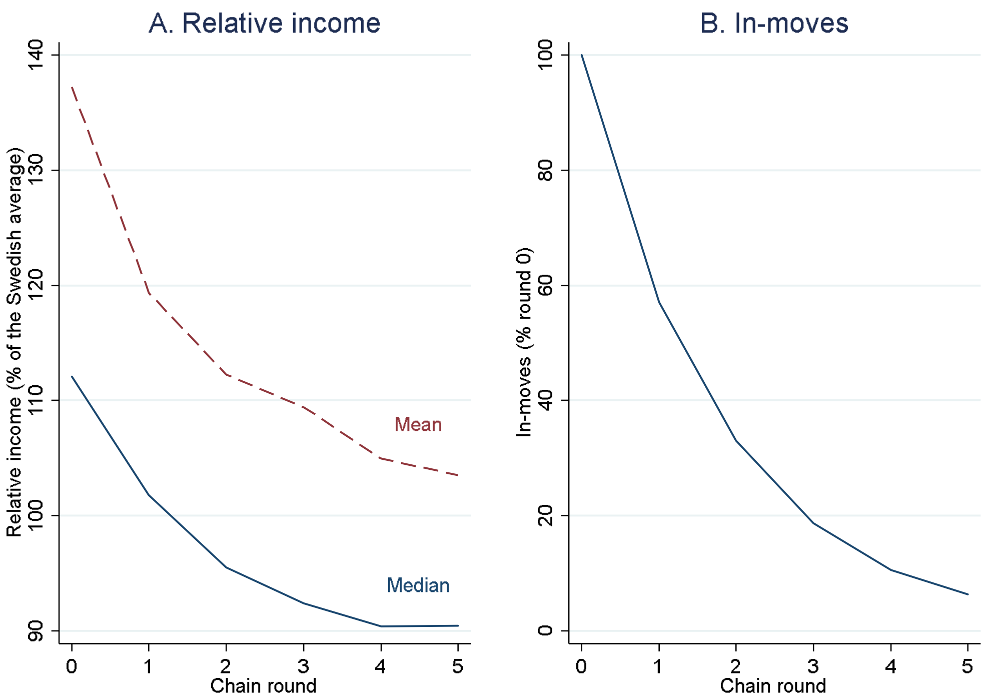

Figure 4. Relative income and in-moves across moving-chain rounds

Notes: In Panel A, the dashed graph displays the mean of relative income in each chain round where relative income is individual income divided by the national mean (in the same year), whereas the solid graph displays the median of relative income where relative income is individual income divided by the national median (in the same year). The graphs are based on moving chains emanating from all housing units built in 2014–2017.

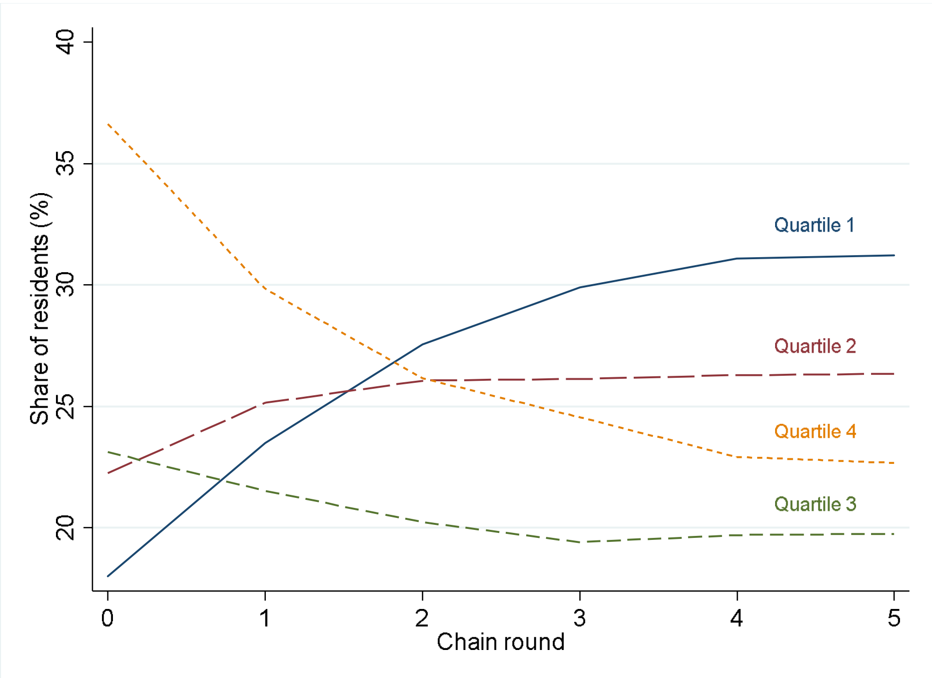

Figure 5. Income quartile shares across moving-chain rounds

Notes: The income quartile cutoffs in a year are the national cutoffs in the same year. The graphs are based on moving chains from all housing units built in 2014–2017.

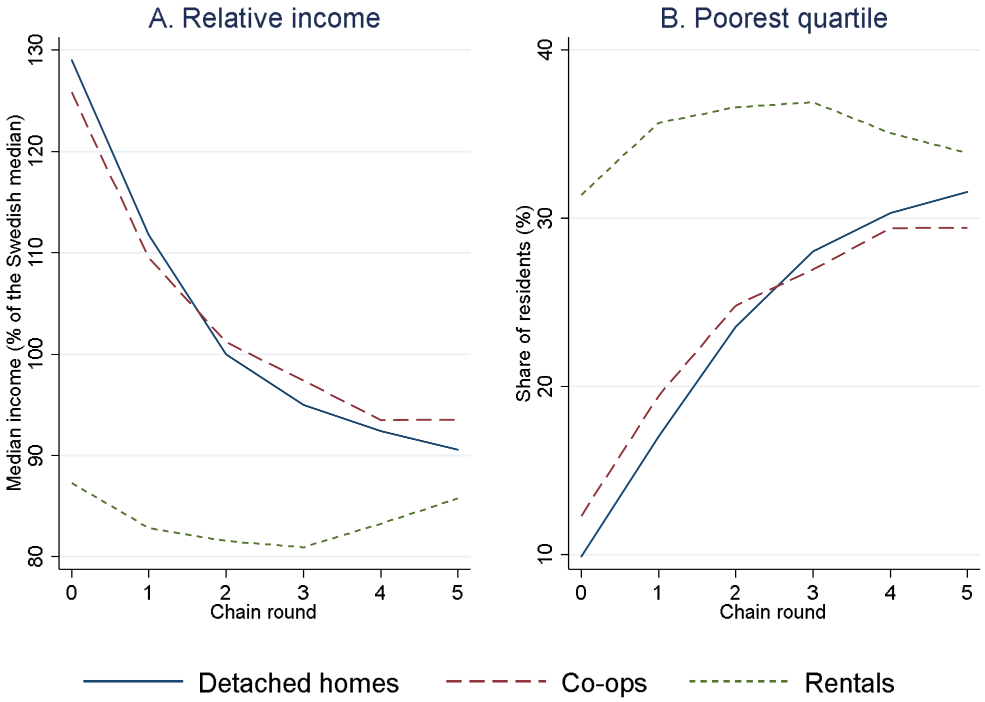

Figure 6. Moving chains by building type
Notes: See the notes in Figures 4 and 5 for technical details.

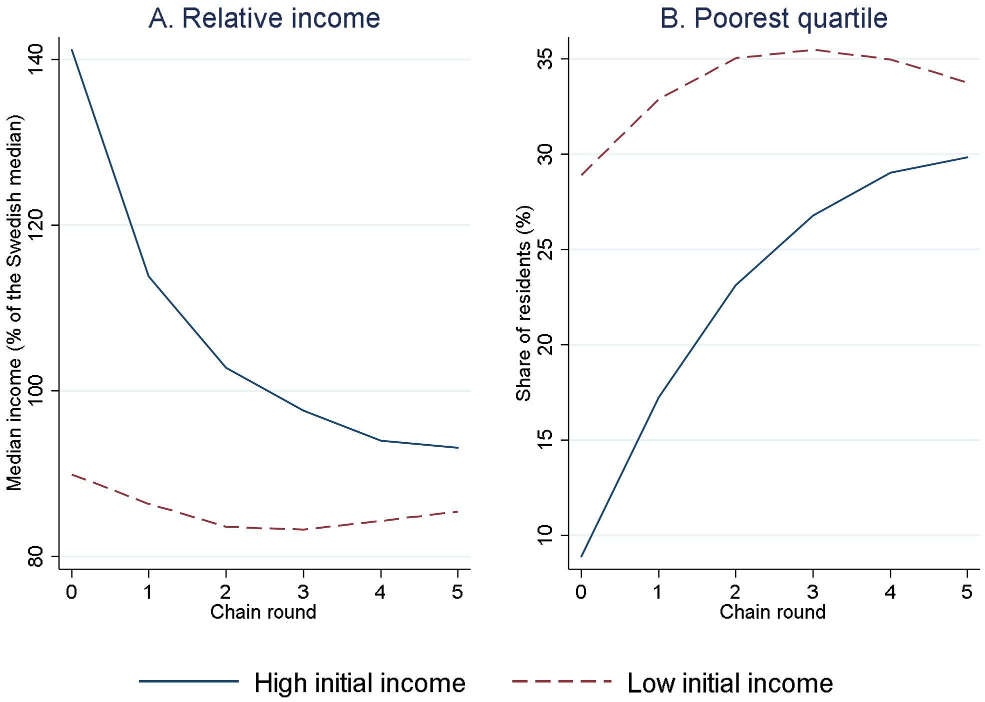

Figure 7. Moving chains by initial income in building
Notes: See the notes in Figures 4 and 5 for technical details.

Table 3. Average relative income and quantile shares aggregated over moving chain rounds

	(1) Mean inc	(2) Median inc	(3) Quartile 1	(4) Quartile 2	(5) Quartile 3	(6) Quartile 4
			A. All homes			
All	124.3	103.8	22.8	24.2	21.7	31.4
			B. By building type			
Detached	133.9	114.0	17.2	22.1	23.2	37.5
Co-ops	143.6	112.9	18.7	21.6	22.0	37.7
Rental	90.3	84.8	33.7	29.5	19.8	17.0
			C. By initial income in the building			
High	150.6	120.2	16.6	20.0	21.3	42.1
Low	87.0	87.4	31.5	30.1	22.4	16.0

Notes: This table provides in-mover-weighted means of average relative income and quartile shares across the chain rounds 0 to 5. In column (1) average relative income is the mean of income divided by the national mean. In column (2) average relative income in a round is the median of income divided by the national median. We use the income moving-chain functions shown in Figures 4–7 and similarly estimated in-mover moving-chain functions as weighting functions.

One way to summarize the aggregated benefit of the moving chains created by new homes is to quantify the cumulative gains across moving chain rounds; we do this by calculating the in-mover-weighted mean of average relative income across the chain rounds up to round 5. Table 3 reports such aggregated averages for our mean and median income measures, as well as aggregated averages for shares in different income quartiles. We see in columns (1) and (2) that a representative individual benefiting from moving chains from new homes has an income level below the average income in rentals and homes in initially low-income buildings. Columns (3) and (4) show that the two lower quartiles are also overrepresented in moving chains from those homes. While the opposite is true for detached homes, co-ops, and homes in initially high-income buildings, a substantial share of low-income residents in the poorest quartile also benefits from those homes once the moving chains have been accounted for. They make up 17-19% (column 3) of in-movers across chain rounds compared to around 10% in round 0 (see Figures 6 and 7).

6. Filtering

6.1 Filtering estimation

Having shown that new housing units lead to short-run moving chains beneficial even to low-income individuals, although in total not as much as to high-income individuals, we move on to the empirical estimation of the long-run filtering effects created by moving chains or by poor people potentially staying in aging homes to a greater extent than rich people. To explore the relationship between income and building age, Figure 8 plots the mean relative income against building age for the pooled cross-section of buildings aged 80 or less between 1990–2017. In this section, we use relative income, defined as income relative to the national mean income. The raw means and the fitted cubic polynomial show a steep decrease in income from around 120% of the national mean in new buildings to slightly over 90% of the national mean around age 50; income levels increase after age 50.[14]

[14] Mean income in new homes (age 0) is lower in Figure 8 than in Figure 4 (round 0); the discrepancy is due to the use of different sample periods (1990–2017 in Figure 8 vs. 2013–2017 in Figure 4).

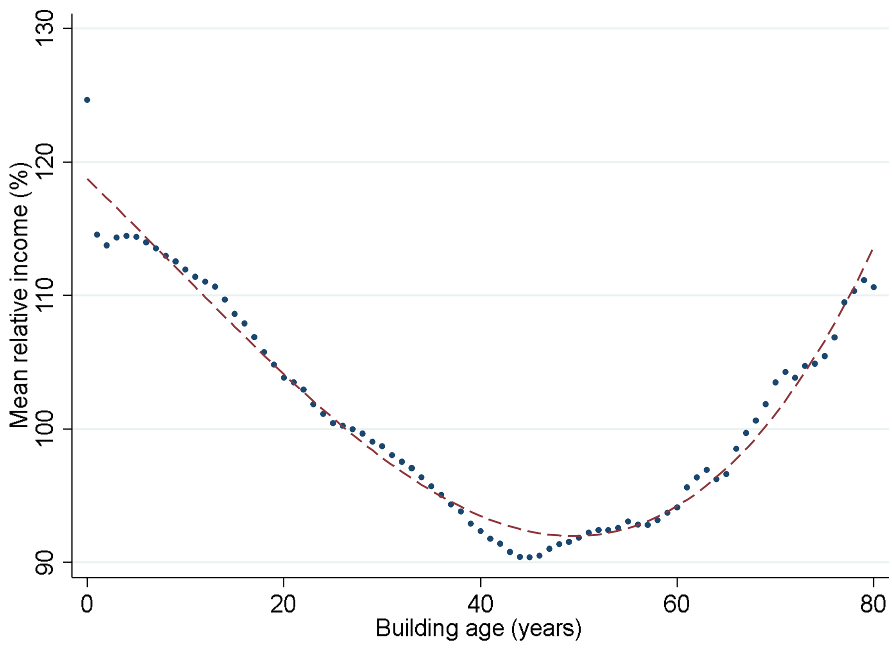

Figure 8. Relative income across building ages

Notes: The dots are raw means based on residents aged 21-65 living in residential buildings in the years 1990–2017 fulfilling the sample restriction described in the notes in Table 1. The curve is a cubic polynomial fit to the raw means.

The fitted curve in Figure 8 provides an estimate of the cross-sectional function $Y_t(a)^{cross}$ in Eq. (6). Part of an association between income and age could reflect compositional effects if buildings constructed in different years have varying quality at the same age. For instance, most buildings of age 40 in the sample period are low-standard rentals constructed in the 1960s, whereas many younger buildings are high-standard co-ops constructed after the 1990s. The filtering function $Y_t(a)$ defined in Eq. (5) applies to the same buildings as they age over time. Let y_{jt} be mean disposable income in building j in year t expressed in terms of income relative to the national mean in year t, and let τ_{jt} be the age of building j in year t (i.e., t minus the construction year). To obtain the filtering function, we estimate the following two-way fixed effects regression equation:

$$y_{jt} = f(\tau_{jt}) + \gamma_j + \delta_t + \varepsilon_{it}. \tag{13}$$

We approximate the nonlinear function $f(\tau_{jt})$ by either a linear function or a third-order polynomial function. Thus, we allow up to cubic terms in τ_{jt} as regressors. The factors γ_j and δ_t are the building- and year-fixed effects, respectively, and ε_{it} is an idiosyncratic error term. We weight the regression by the number of residents (varying across buildings and years). To better investigate distributional effects, we also estimate four versions of Eq. (13) with y_{jt} replaced by $ShareQ1_{jt}$, $ShareQ2_{jt}$, $ShareQ3_{jt}$, $ShareQ4_{jt}$, which are the building-j year-t shares of residents from income quartiles 1, 2, 3, and 4, respectively.

When including building-fixed effects in panel data estimation, cross-sectional variation is removed and identification is based on changes in residential income within each building (and housing units) over time. Thus, we could isolate the filtering effect as buildings deteriorate. However, our results only represent the filtering taking place between 1990 and 2017. For buildings constructed during the sample period, we capture the filtering effect from age 0 to $2017 - \tau$. Thus, we capture longer periods of filtering for older units. For buildings constructed before 1990, we capture 27 years of filtering from age $1990 - \tau$ to $2017 - \tau$.[15] Overall, at higher ages, filtering rates (slopes of the filtering function) are primarily identified by filtering among buildings with earlier construction years.

6.2 Filtering estimates

Table 4 reports linear filtering estimates (Eq. 13 with $f(\tau_{jt}) = \beta\tau_{jt}$). The linear functional form might be a better approximation for younger buildings; to limit the influence of potential vintage effects with upward filtering such that income levels increase as old buildings get even older, we restrict the sample to buildings aged 40 or less. Column (1) displays the raw correlation. We then add the fixed effects in column (2) and control variables in column (3). They account for building-year variation in housing space (m^2 living area) and basic residential demographics (number of residents and shares of young and old, respectively). Column (1) shows a negative correlation between building age and income levels. However, when accounting for compositional effects in column (2), the estimated filtering rate decreases; as buildings age one year, they will be inhabited by residents with 0.27% lower income levels. This corresponds to 14% in 50 years. Adding covariates lowers the estimated filtering rate to 0.12% per year. Thus, a substantial part of the 0.27% income decay per year is due to changes in housing space and age distribution over time. We use the specification without building-level controls hereafter as the full effect that policymakers can expect over time includes the effects due to such changes.

Table 4. Linear filtering estimates

	(1)	(2)	(3)
Age (τ_{jt})	-0.639**	-0.273*	-0.120**
	(0.0111)	(0.00842)	(0.00867)
Building-fixed effects	No	Yes	Yes
Year-fixed effects	No	Yes	Yes
Building-level controls	No	No	Yes

Notes: Regressions are based on 19,260,122 observations (about 0.69 million buildings per year for 28 years 1990-2017). Building-level controls include the following: share of young residents/children (aged 20 or below), share of old residents (aged 66 or above), number of residents, and square meter housing space. We weight regressions by the average yearly number of residents in a building and year, and we report standard errors clustered at the building level in parentheses. * p<0.05, ** p<0.01.

[15] For buildings demolished during the sample period, we will only capture filtering effects until the year of demolition.

Figure 9 shows estimated filtering functions allowing for a more functional form than in Table 4. We allow up to cubic age terms and plot the predicted filtering function $E(y_{it})$ using estimated parameters from Eq. (13). In addition to this main filtering function, we reproduce the cross-sectional function from Figure 8 in Figure 9A. The two graphs diverge, which illustrates the importance of accounting for compositional effects using fixed effects. The solid graph shows that it takes less than 30 years for the income level in buildings to achieve the national mean income (decrease from 1.12 to 1.00). The income decay is approximately 14% (from 1.12 to 0.96) in 50 years. Soon after 50 years, buildings start to filter upwards with increasing income levels as time passes; thus, there is a vintage effect. Comparing our estimates with those obtained by Rosenthal (2014), his estimated decay rate of 60% in 50 years is much higher. One important reason for the difference is that even for newly constructed homes, the mean income is not very high in Sweden (the raw mean is about 125% of the national mean income); thus, poor people already access new homes to a great extent.

As buildings age, renovations can counteract deterioration and even significantly improve the condition of homes. Thus, the calendar age might not fully capture deterioration. An age variable based on the value year described in the data section accounts for major renovations. Figure 9B displays the estimated filtering function (dashed graph) using this “value age”-variable. This renovation-adjusted filtering function reflects the change in income composition as buildings get older had the buildings not been renovated. As expected, the renovation-adjusted function is much steeper than the unadjusted function. In the remainder of this paper, we focus on the building-age specification as those capture the full effects policymakers can expect over time from building new homes.

To explore distributional effects in detail, Figure 10 shows how estimated shares of residents from different income quartiles change as buildings age. It shows apparent filtering effects where the poorest income quartile increases in representation as new buildings age. It takes approximately 30 years for the buildings to reach a representative income distribution with the same number of residents from the different income quartiles.

Figure 11 provides a subgroup analysis of heterogeneous effects with buildings grouped by types of residential buildings. We find that the initial mean income and share of residents from the poorest income quartile are similar across tenure types. At ages below 40, there are also filtering effects for each housing type. However, rental apartments filter at a much higher pace than owned apartments (co-ops), which filter a bit faster than owned detached homes. During the first 40 years in rental apartments, income drops by almost 30% (from 1.14 to 0.80), and the number of residents from the poorest income quartile more than doubles (from 0.16 to 0.36).

Figure 12 plots how the filtering process differs between residential buildings with above-median income levels and those with below-median income levels. Since we only observe initial income for buildings constructed after 1990, we only show the filtering function for these newer buildings at ages less than 30 years old. In terms of relative income, the mean relative income changes little when buildings are less than 20 years old. However, for buildings with high initial income levels, the share of residents from the poorest income quartile increases steadily as the buildings age. Given the relatively shorter time span in the near past during which we can study the filtering for newly built homes, we should avoid extending the interpretation of these results to new homes constructed further back in time as well as extrapolating filtering rates to higher building ages here.

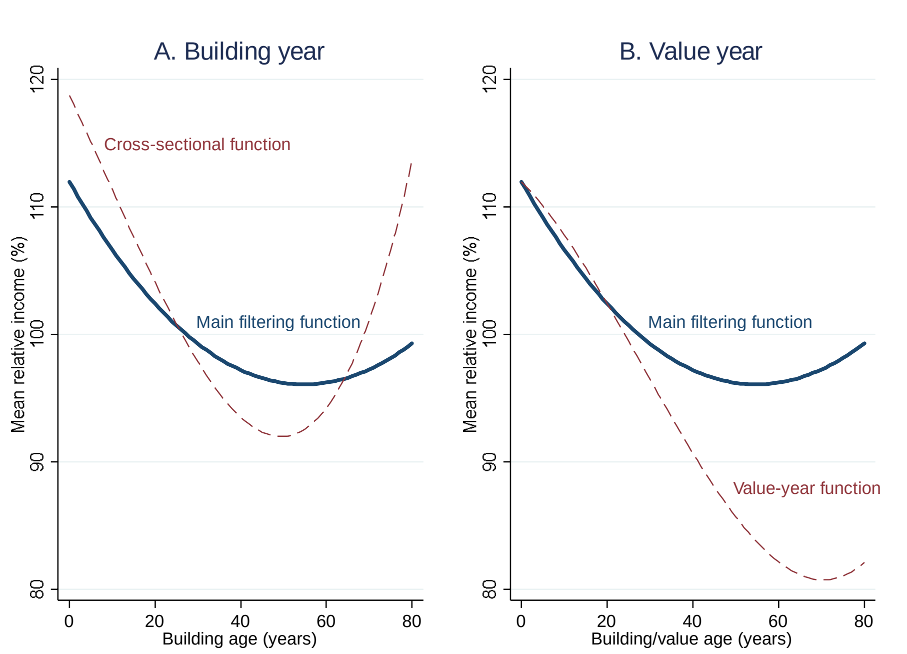

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Figure 9. Estimated relative-income filtering functions

Notes: The graphs represent the predicted filtering function $E(y_{it})$ using estimated parameters from Eq. (13). In Panel A, the main cross-sectional function is a reproduction of the cubic fit to the raw means in Figure 8, i.e., based on estimates from a version of Eq. (13) that omits the fixed effects. The main filtering function is based on a regression that includes fixed effects. In Panel B, the value-year function is based on the value age defined as year minus the value year. The graphs are based on data on inhabited residential buildings 1990–2017.

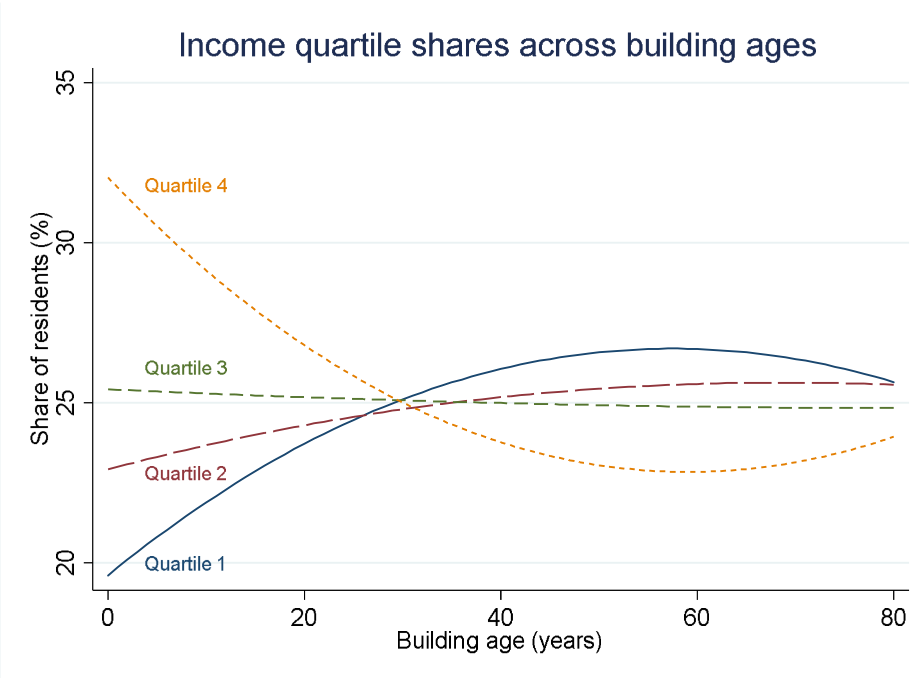

Figure 10. Income quartile shares across building ages

Notes: The income quartile cutoffs in a year are the national cutoffs in the same year. The graphs are based on inhabited residential buildings 1990–2017.

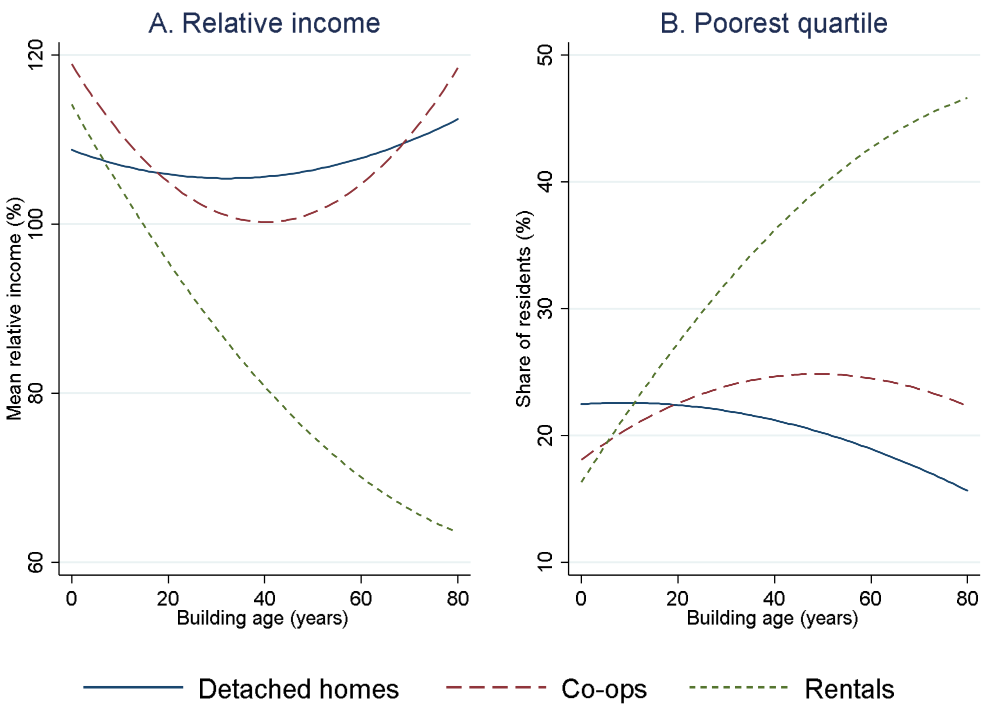

Figure 11. Filtering by building type

Notes: See the notes in Figures 9 and 10 for technical details.

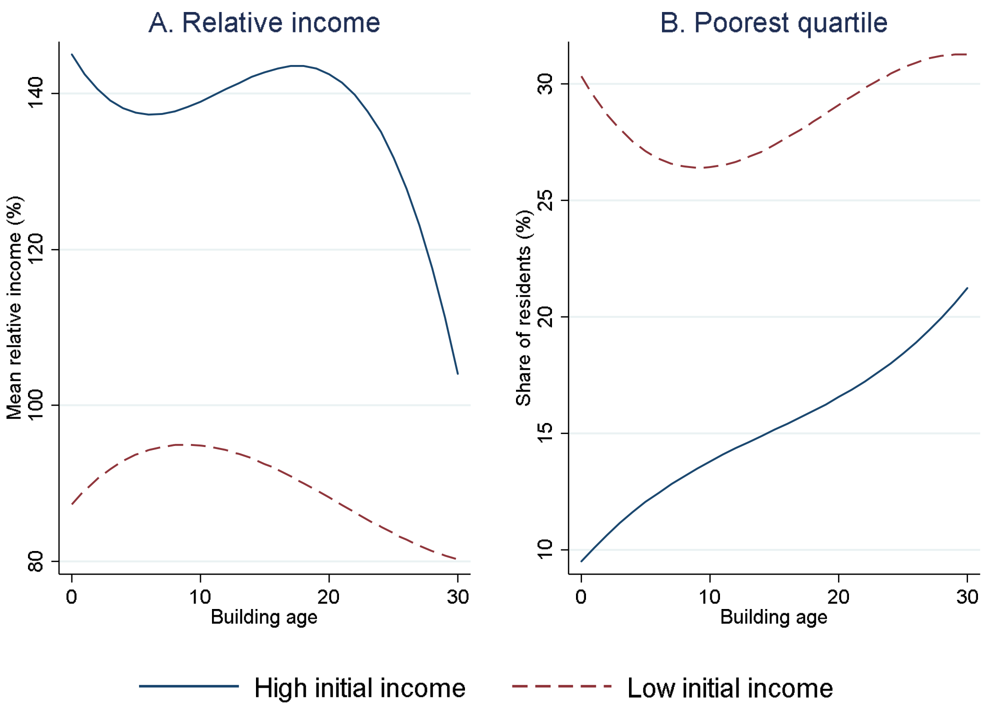

Figure 12. Filtering by buildings with different initial income levels

Notes: See the notes in Figures 9 and 10 for technical details.

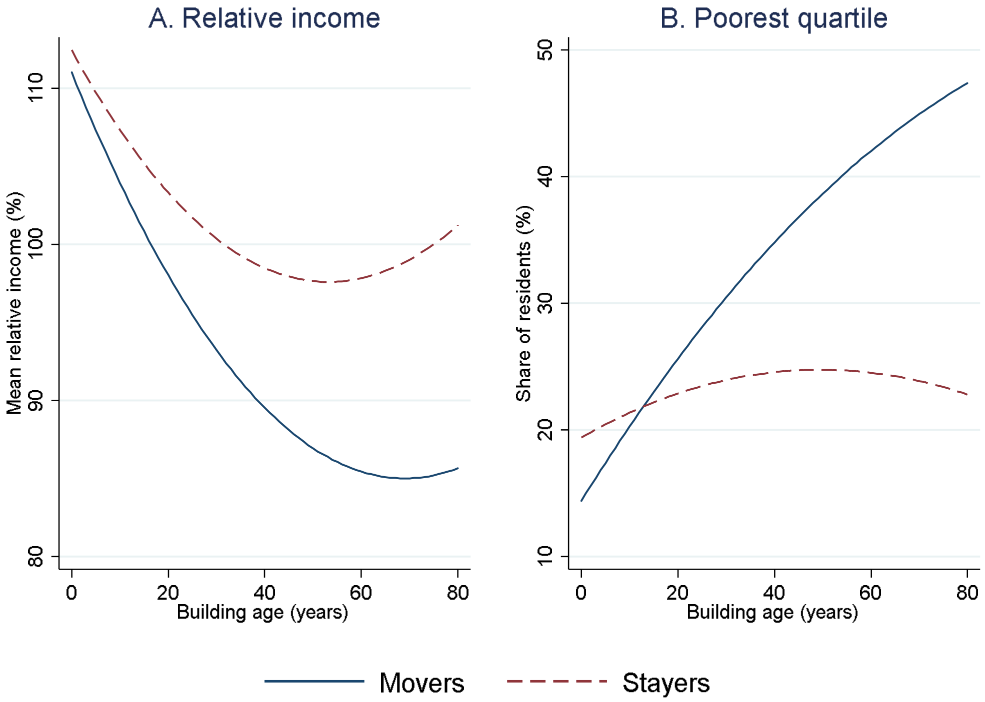

Figure 13. Mover- and stayer-based filtering estimates

Notes: The mover-based functions are based on data including on in-moving residents. The stayer-based functions are based on the remaining staying residents.

Table 5. Average income and quantile shares aggregated over building ages

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean relative income			Poorest quartile		
	Age <= 10	Age <= 30	Age <= 50	Age <= 10	Age <= 30	Age <= 50
			A. All homes			
All	109.2	104.8	101.8	20.8	22.7	24.0
			B. By building type			
Detached	107.9	106.7	106.3	22.6	22.4	21.9
Co-ops	114.7	108.8	105.7	19.4	21.3	22.6
Rental	108.9	98.6	89.7	19.4	25.5	30.9
			C. By initial income in the building			
High	139.2	135.7		11.9	15.4	
Low	92.8	89.1		27.6	28.7	

Notes: This table provides resident-weighted means of relative income and share of residents from quartile 1 across building ages. We use the income filtering functions shown in Figures 9–13 and similarly estimated resident filtering functions as weighting functions.

In Figure 13, we provide filtering estimates based on only movers (i.e., estimates of $Y_t(a)^{movers}$ in Eq. 8). Like in Rosenthal (2014) and Liu et al. (2020), this analysis would only use income data on in-moving residents during turnover. As a comparison, we provide estimates based on only stayers.[16] Around 12% of residents move each year, and they have a different income distribution than the stayers. The substantial differences between mover-based, stayer-based, and previous full-sample estimates are therefore not surprising. They also highlight the pitfall of only using turnovers as done in the previous literature. We find stronger filtering when using only movers; thus, mover-based estimates overestimate the extent of filtering in the housing stock, which also depends on the substantially lower income decay among stayers as homes age. Whereas mean income decays by 14% in 50 years according to our main estimates (from 1.12 to 0.96 in Figure 9A), the decay is 21% according to our mover-based estimates (from 1.11 to 0.87 in Figure 13A); thus, there is an overestimation of 50%.

One way to summarize the cumulative benefit as new homes age is to calculate the resident-weighted mean of relative income across building ages. In addition to the income filtering functions showing how relative income changes as buildings age, such calculations require knowing how the number of residents changes as buildings get older, and we estimate "resident filtering functions" by replacing the outcome with number of residents in Eq. (13) for this purpose. Using the income and resident filtering functions, we calculate and report average income and quantile shares aggregated over building ages in Table 5; we include averages for different age spans, 0–10 years, 0–30 years, and 0–50 years. In Panel A, column (1) shows that a representative resident in a building during the first 10 years has 9% higher income than the national mean income. Column (3) shows that over the course of 50 years, the average resident has a mean income close to the national mean income (2% higher). Column (6) shows that rentals will within 30 years have more than proportionally hosted poor people from the lowest income quartile. Furthermore, even buildings with high initial income will within 30 years have hosted over 15% of residents from the poorest quartile, which is much higher than the below 10% that they host initially (see Figure 12B). Overall, filtering leads to substantial benefits for poor people in the long-run.

7. Effects of the construction rate on housing quality and quantity

7.1 Estimating effects of the construction rate on housing quality and quantity

While moving chain and filtering analyses provide concrete evidence of trickling-down effects, such analyses do not fully capture all indirect ripple effects. The fundamental problem is that they do not address how moving patterns would have looked in counterfactual situations with other different construction rates in the city. A person moving into a new home might otherwise have moved into another vacancy in the existing stock – a home that now could benefit another person. Moreover, moving chain and filtering effects per new building could depend on the total supply of new homes, which is a variable under policy control.

We now move on to estimating the effects of varying the municipal construction rate on the distribution of housing units of different quality across different income groups, which is an analysis overcoming the limitations of moving-chain and filtering methods. The mean change in the construction year of homes for a group of families ($E(\tau_{it'} - \tau_{it})$ in Eq. 9) represents one dimension of housing quality change. For municipality m in year t, let τ_{mt} be the mean construction year of homes for a group of residents g in an income quartile. Between year t and t', mean construction year improved by $\Delta\tau_{mt} = \tau_{mt'} - \tau_{mt}$. We measure new

[16] There are no stayers in new homes (the stayer graph is extrapolated at age 0).

housing supply by Δh_{mt}^{new} denoting m^2 housing space per person in new housing units constructed between t and t'. Demolitions and extensions of existing residential buildings are captured by Δh_{mt}^{old} which denotes the change in m^2 housing space per person among those buildings. We estimate the following first-difference type of regression equation:

$$\Delta \tau_{mt}^{g} = \beta^{new} \Delta h_{mt}^{new} + \beta^{old} \Delta h_{mt}^{old} + \alpha Z_{mt} + \delta_t + \varepsilon_{mt}. \quad (14)$$

The parameter β^{new} captures the effects of one m^2 of new housing space per person in the municipality on access to years of newer housing space per person for group g. The factor δ_t represent year-fixed effects and account for, e.g., national construction trends over time, and ε_{mt} is an idiosyncratic error term. The vector Z_{mt} includes several demographic control variables related to population, age, education, and country of birth. We use the following control variables: log population, change in log population, share of young residents/children (aged 20 or below), share of old residents (aged 66 or above), shares in eight age groups (five-year intervals), share that did not graduate high school, share with a university degree, share born in Europe but outside Sweden, and share born outside Europe. We weight the regression by the number of residents (varying across municipalities and years). All level variables are from the base years in the differences.

For each income quartile, we also estimate the effects of new housing space per person on another measure of housing change, namely, the mean change in housing space per person in that income quartile:

$$\Delta h_{mt}^{g} = \beta^{new} \Delta h_{mt}^{new} + \beta^{old} \Delta h_{mt}^{old} + \alpha Z_{mt} + \delta_t + \varepsilon_{mt}. \quad (15)$$

In constructing housing space per person, we assume that every individual in a residential building occupies an equal share of the total living area in the building; thus, the per-person housing space in a building is the total living area divided by the number of residents.

When estimating β^{new} in Eqs. (14) and (15), identification is based on municipal variation in new housing supply. It corresponds to using municipal-year variation in the housing stock accounting for both municipality- and year-specific non-interacted fixed effects. Controlling for demolitions and extensions in the existing stock is important as those affect available housing of different ages and likely also new supply. The demographic covariates account for the initial demographic condition that could affect both new supply and changes in housing distribution.

There is a tradeoff in choosing the difference length. Using shorter differences exploits finer variation in new housing supply and also yields more observations. However, it may take some time for the effects of new housing supply to materialize, which favors using longer differences. We strike a balance by using five-year differences and we stack all available differences (1990–1995, 1991–1996, …, 2012–2017). Our main results are, however, insensitive to using most other difference lengths.

7.2 Estimated effects of the construction rate on housing quality and quantity

To first provide some visual evidence, Figure 14 shows scatter plots of improvement in mean construction year ($\Delta \tau_{mt}$) against per-person m^2 of housing in new buildings (Δh_{mt}^{new}) during the entire sample period (27-year differences). We display four panels, one for each income quartile. Each municipality is represented by a dot, and the size of the dots is proportional to the municipal population in 2017. We see that all estimated slope coefficients are positive; thus, new housing supply appears to lead to newer housing for every income group.

Figure 15 shows scatter plots of per-person changes in m^2 of housing in each income quartile against overall municipal per-person change in m^2 of housing. All estimated slope coefficients are positive and new housing space seems to lead to more housing space for every income quartile.

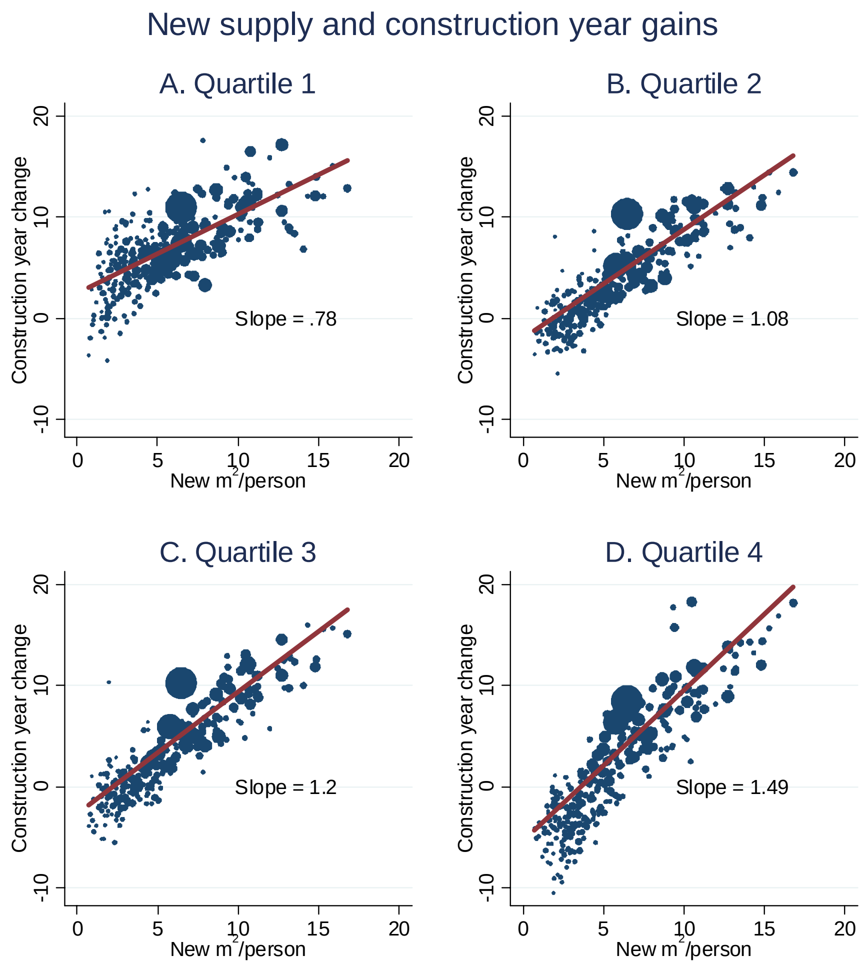

Figure 14. New supply and the distribution of construction year gains 1990-2017
Notes: Each dot represents one of the 290 municipalities in Sweden. We use the municipal population in 1990 as weights when fitting the line.

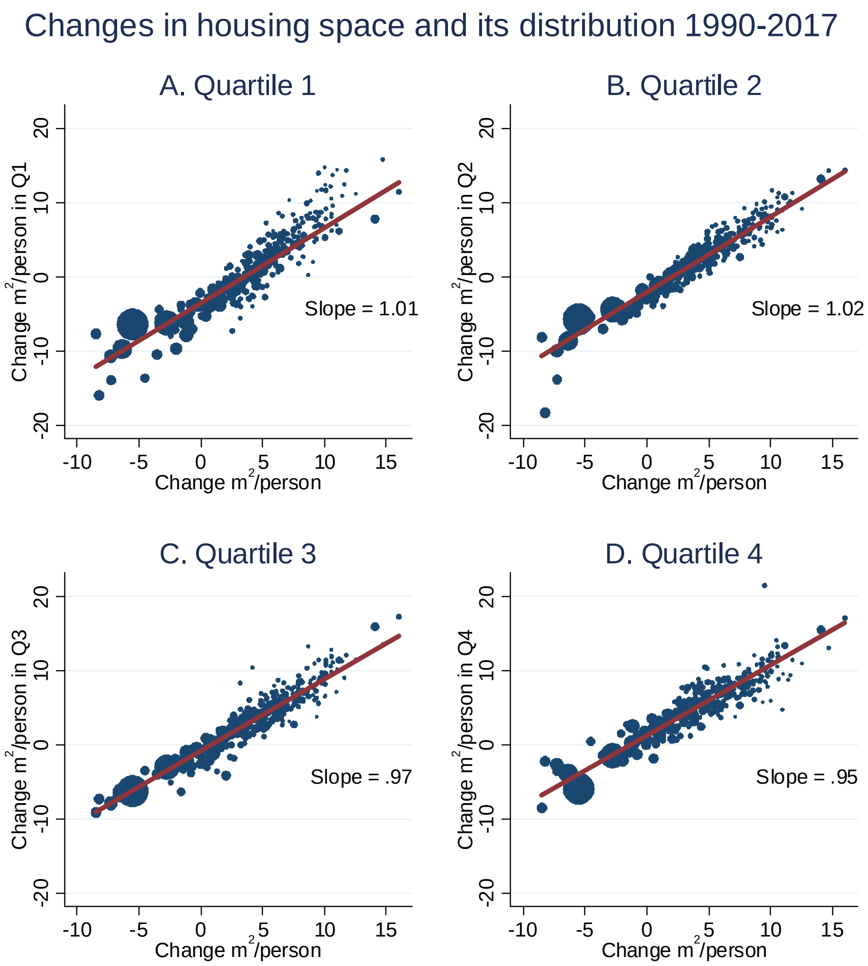

Figure 15. Changes in housing space and its distribution 1990-2017

Notes: Each dot represents one of the 290 municipalities in Sweden. We use the municipal population in 1990 as weights when fitting the line.

While Figures 14 and 15 suggest strong trickle-down effects, we can provide a more rigorous analysis by accounting for that new housing supply correlates with several potential confounders that also affect the housing distribution across income groups. Table 6 reports our estimated effects of new housing measured as new m^2 per person (Eqs. 14 and 15). Panel A shows that the estimated effects on housing quality, as measured by improvement in the construction year, vary between 0.72 to 1.19, with higher estimates for richer income quartiles. Thus, richer people disproportionately benefit from more housing space in terms of access to newer housing. The estimated effects of changes in m^2 per person in the existing stock are small and not statistically significant, indicating that extensions and demolitions of existing housing do not affect access to newer housing.

Table 6. Estimated effects of new housing supply

	(1) Quartile 1	(2) Quartile 2	(3) Quartile 3	(4) Quartile 4
	A. Improvement in construction year ($\Delta\tau_{mt}^{g}$)			
New m^2/person (Δh_{mt}^{new})	0.723**	0.812**	0.862**	1.190**
	(0.0683)	(0.0490)	(0.0466)	(0.0651)
ΔOld m^2/person (Δh_{mt}^{old})	-0.139**	-0.111**	-0.0741**	0.0259
	(0.0482)	(0.0342)	(0.0247)	(0.0247)
	B. Change in m^2/person (Δh_{mt}^{g})			
New m^2/person (Δh_{mt}^{new})	1.590**	1.018**	0.810**	0.723**
	(0.0596)	(0.0592)	(0.0457)	(0.0548)
ΔOld m^2/person (Δh_{mt}^{old})	1.461**	1.211**	0.919**	0.703**
	(0.104)	(0.0437)	(0.0283)	(0.114)
Year-fixed effects	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes

Notes: Regressions are based on 6,670 observations of five-year changes (290 municipalities and 23 base years 1990–2012). Municipal demographic controls include the following: log population (base-year), change in log population, share of young residents/children (aged 20 or below), share of old residents (aged 66 or above), shares in eight age groups (five-year intervals), share that did not graduate high school, share with a university degree, share born in Europe but outside Sweden, and share born outside Europe. All level variables are from the base years in the differences. We weight regressions by the base-year population (varying across municipalities and years), and we report standard errors clustered at the municipality level in parentheses. * p<0.05, ** p<0.01.

Panel B of Table 6 shows that the estimated effects of new m^2 per person on housing quantity, in terms of m^2 living area per person, in different income quartiles vary between 0.72 and 1.59. Higher estimates for higher-income groups mean that poor people gain more housing space when the construction rate increases. The flip side is that a limited new supply leads to worse overcrowding among poor people. The estimated effects of changes in m^2 per person in the existing stock are also around one. These results indicate that adding housing space has similar effects whether that is done via extensions, limiting demolitions, or building new homes.

Table 7 reports our estimated effects allowing for effect heterogeneity by housing type. Instead of one new housing regressor, we include three new housing regressors in each regression: new m^2 per person for detached homes, co-ops, and rentals, respectively. Panel A reveals that each of the different types of new homes benefits every income group in terms of improvement in the construction year of their homes, as the estimated effects are all positive and statistically significant. However, the effects are heterogeneous as the point estimates vary substantially across housing types for each quartile. Whereas new rentals disproportionately benefit poor people, especially those in income quartile one, new detached homes are more beneficial for rich people in higher income quartiles. When it comes to housing quantity, Panel B shows that every type of new home and space extension of old homes benefit every income group in terms of living area per person. While estimated effects are larger for poor people, especially in the lowest income quartile, they are fairly homogeneous across housing types for each quartile.

Table 7. Estimated effects of new housing supply by housing type

	(1) Quartile 1	(2) Quartile 2	(3) Quartile 3	(4) Quartile 4
Added m^2/person	A. Improvement in construction year ($\Delta\tau_{mt}^{g}$)			
Detached homes	0.292**	0.605**	0.799**	1.539**
	(0.0886)	(0.0604)	(0.0696)	(0.0771)
Co-ops	0.761**	0.960**	1.059**	1.395**
	(0.118)	(0.106)	(0.111)	(0.124)
Rentals	1.415**	1.030**	0.796**	0.424**
	(0.147)	(0.101)	(0.106)	(0.0908)
ΔOld m^2/person	-0.109*	-0.0984**	-0.0729**	-0.00256
	(0.0529)	(0.0361)	(0.0247)	(0.0202)
Added m^2/person	B. Change in m^2/person (Δh_{mt}^{g})			
Detached	1.430**	0.843**	0.745**	0.760**
	(0.0806)	(0.0685)	(0.0555)	(0.0570)
Co-ops	1.713**	1.045**	0.822**	0.696**
	(0.0913)	(0.0916)	(0.0637)	(0.109)
Rentals	1.752**	1.290**	0.909**	0.683**
	(0.160)	(0.0994)	(0.0906)	(0.103)
ΔOld m^2/person	1.470**	1.223**	0.924**	0.701**
	(0.104)	(0.0423)	(0.0292)	(0.116)
Year-fixed effects	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes

Notes: Regressions are based on 6,670 observations of five-year changes (290 municipalities and 23 base years 1990–2012). Municipal demographic controls include the following: log population (base-year), change in log population, share of young residents/children (aged 20 or below), share of old residents (aged 66 or above), shares in eight age groups (five-year intervals), share that did not graduate high school, share with a university degree, share born in Europe but outside Sweden, and share born outside Europe. All level variables are from the base years in the differences. We weight regressions by the base-year population (varying across municipalities and years), and we report standard errors clustered at the municipality level in parentheses. * p<0.05, ** p<0.01.

Table 8 shows how effects differ depending on the initial income level of constructed residential buildings. The new housing regressors are now the supply of i) above-median income level buildings, ii) below-median income level buildings, and iii) other buildings with only residents from the non-working age population. Panel A shows that above-median buildings disproportionately benefit people with higher income levels in terms of access to newer homes, whereas the opposite is true for below-median buildings. This pattern is consistent with the fact that above-median income buildings are more often owned homes rather than rentals and that owned homes benefit richer people more, as we found in Panel A of Table 7. As in Panel B of Table 7, Panel B of Table 8 shows that new homes of all types (now grouped by initial income levels instead of tenure type) lead to more housing space for poor people than rich people. Thus, it is not essential to build homes directly affordable for low-income residents; they will reap the benefits of more housing space anyway through ripple effects.

Table 8. Estimated effects of new housing supply by initial income levels

	(1) Quartile 1	(2) Quartile 2	(3) Quartile 3	(4) Quartile 4
Added m^2/person	A. Improvement in construction year ($\Delta\tau_{mt}^{g}$)			
Above-median buildings	0.331**	0.657**	0.982**	1.722**
	(0.0838)	(0.0772)	(0.0755)	(0.0907)
Below-median buildings	1.339**	1.141**	0.878**	0.720**
	(0.133)	(0.0902)	(0.0756)	(0.105)
Other homes	0.184	0.321*	0.359*	0.728**
	(0.152)	(0.138)	(0.140)	(0.150)
ΔOld m^2/person	-0.122*	-0.101**	-0.0733**	0.0137
	(0.0501)	(0.0353)	(0.0249)	(0.0220)
Added m^2/person	B. Change in m^2/person (Δh_{mt}^{g})			
Over-median homes	1.518**	0.973**	0.778**	0.739**
	(0.112)	(0.0818)	(0.0639)	(0.0746)
Under-median homes	1.652**	1.096**	0.881**	0.693**
	(0.118)	(0.103)	(0.0867)	(0.0771)
Other homes	1.660**	0.933**	0.695**	0.759**
	(0.278)	(0.156)	(0.148)	(0.138)
ΔOld m^2/person	1.463**	1.213**	0.921**	0.702**
	(0.104)	(0.0433)	(0.0289)	(0.115)
Year-fixed effects	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes

Notes: Regressions are based on 6,670 observations of five-year changes (290 municipalities and 23 base years 1990–2012). Municipal demographic controls include the following: log population (base-year), change in log population, share of young residents/children (aged 20 or below), share of old residents (aged 66 or above), shares in eight age groups (five-year intervals), share that did not graduate high school, share with a university degree, share born in Europe but outside Sweden, and share born outside Europe. All level variables are from the base years in the differences. We weight regressions by population (varying across municipalities and years), and we report standard errors clustered at the municipality level in parentheses. * p<0.05, ** p<0.01.

Unlike the moving-chain and filtering results with weaker trickle-down effects for some types of new housing, the estimates in this section vary little by tenure type and initial income in the new building; the strong trickle-down effects are similar in magnitude across different types of new housing constructions. Since the analysis here more completely captures the full effects of trickle-down effects, we conclude that moving-chain and filtering analyses miss important trickle-down effects.

8. Conclusion

We used microdata on the Swedish population and housing stock (1990–2017) to investigate how building new homes affects the housing distribution across income groups. We found that while primarily rich people move into new homes, poor people are almost proportionally represented among in-movers to vacated homes. The study of moving chains emanating from new homes provides insights into short-run effects. However, they miss that new homes can filter down to the poor in the long run as well as affect filtering in the existing stock. Estimating filtering functions, we showed that it takes approximately 30 years for new homes to reach an even income distribution. Moreover, accounting for staying residents is important as substantially stronger filtering was detected when only movers involved in turnovers were used in the estimation.

The analyses of moving chains and filtering effects ignore that trickle-down effects could vary with new housing supply and housing demolitions. We proposed a more comprehensive analysis of trickle-down effects based on responses to changes in the municipal housing stock. We found that in municipalities with more new housing space per person, every income quartile gets an improvement in the mean construction year of their homes and housing space per person. Whereas the improvement is greater for rich people when it comes to newer housing, it is greater for poor people when it comes to more housing space. The housing space effect does not depend on whether the new homes are owned or rented, and the effect applies to both new residential buildings occupied by residents with average income levels above or below the national median income level. Overall, our findings show that building new homes, even expensive ones, leads to important trickle-down effects; thus, stimulating the supply of new homes is a viable approach to improving the housing situation of the poor.

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