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Housing Capital Gains across the Income Distribution*

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Abstract

We show that buyers higher in the income distribution earn higher capital gains on housing. Geographical location accounts for nearly all the difference in capital gains by income rank, whereas market timing, property type, and buyer characteristics matter little. Because high-growth locations are also high-priced, earning higher capital gains is concentrated in markets where lower-income households face binding borrowing constraints. Yet mortgage-market reforms aimed at changing credit access produced no detectable change in the income composition of buyers across locations, consistent with limited re-sorting under inelastic housing supply. Unequal access to high-appreciation markets sustains persistent wealth differences across income groups.

JEL Classifications: D31, G51, R31.
Keywords: Housing, wealth inequality, affordability, spatial sorting, inequality

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1 Introduction

Growing divergence in wealth accumulation across households reflects differences in the returns earned on the assets households hold. A large literature documents substantial heterogeneity in returns to wealth (Fagereng, Guiso, Malacrino and Pistaferri, 2020; Bach, Calvet and Sodini, 2020), providing a plausible explanation for differences in long-run wealth accumulation. Because owner-occupied housing is the dominant asset on the balance sheet for most households (Campbell, 2006; Badarinza, Campbell and Ramadorai, 2016), differences in wealth accumulation through housing are of first-order importance for understanding wealth inequality. However, housing differs from standard financial assets along several dimensions: it is tied to a location, trades infrequently, is subject to borrowing constraints, and provides consumption services (Piazzesi and Schneider, 2016; Ioannides and Ngai, 2025). Together, these features imply that the determinants of capital gains to housing and their distribution across households may fundamentally differ from those of other assets.

In this paper, we document substantial differences in realized housing capital gains across the income distribution and show that these differences are almost entirely statistically explained by where households buy. We focus on unlevered capital gains on owner-occupied housing, which is the margin most directly linked to household wealth accumulation in the existing literature. Using administrative data covering all Danish homeowners and housing transactions since 1996, we find a strong positive income rank gradient: buyers at the 90th income percentile earn roughly 1.36 percentage points higher annualized capital gains on housing than buyers at the 10th percentile, a gap that cumulates to about 14.6 percent over a ten-year holding period. This represents an economically significant difference in outcomes for what is, for a majority of households, their most important asset. We show that nearly all of this gradient is explained statistically by systematic differences in where higher-income households buy.

Our analysis combines comprehensive administrative data on all Danish households with records of property characteristics and housing transactions from 1996 to 2022. We construct income ranks within year and age cohorts to capture relative economic position, and link this ranking to property transactions. The housing data report exact purchase and sale dates, prices, and structural attributes for every dwelling, allowing us to compute repeat-sales capital gains and to link buyers to the specific properties they purchase. This setup provides two key advantages: (i) we observe realized, property-level capital gains directly rather than inferring them from aggregate price indices, and (ii) we link buyer characteristics, renovation activity, and location to subsequent housing outcomes. We focus on unlevered returns to separate house-price movements from variation in leverage and refinancing behavior (Amornsiripanitch, Strahan and Zhang, 2026). Together, the data allow for a detailed decomposition of capital gains heterogeneity and its underlying mechanisms.

We begin by examining whether differences in the types of properties purchased, the markets in which households buy, or timing of purchase and sale can account for the gap between low- and high-income buyers. Higher-income households may opt for property types that appreciate more—apartments, for example, have outperformed single-family homes in Denmark. They

may also purchase in more attractive markets: urban areas have experienced substantial long-run price growth (Gyourko, Mayer and Sinai, 2013). Similarly, higher-income buyers may be better at selecting locations that subsequently appreciate, or may place themselves in areas with tighter supply constraints (Ortalo-Magné and Prat, 2014). Finally, they may time the market more effectively, whereas lower-income buyers may purchase at cyclical peaks and face greater downside risk (Fischer, Khorunzhina and Marx, 2023). To assess these channels, we regress capital gains on income rank and sequentially add buyer and property controls, as well as fixed effects. Buyer characteristics and property attributes have limited explanatory power. By contrast, adding postcode fixed effects reduces the income rank coefficient by about four-fifths. Further allowing the effect of postcode to vary with purchase and sale timing reduces the coefficient to essentially zero. A series of robustness checks covering renovations, leverage, unsold properties, alternative geographical definitions, alternative constructions of income rank, and holding periods supports the conclusion that the gradient is statistically accounted for by location. Where households buy accounts for virtually the entire capital gains differential.

Motivated by these results and by the unique features of housing, we then examine how financial constraints, consumption needs, and local housing supply shape access to locations with high house-price growth. Because housing is indivisible and subject to borrowing limits and minimum consumption requirements, we develop a simple conceptual framework in which households face both loan-to-value (LTV) and payment-to-income (PTI) constraints, and must purchase an entire dwelling that satisfies minimum consumption requirements. Together, these conditions define a feasible choice set: the set of properties a household can finance while meeting its minimum consumption needs. In the data, we measure the feasible set using either the maximum affordable purchase amount based on borrowing constraints and equity, or using the purchase price. The data show that buyers across the income distribution face stark differences in their choice sets: buyers in the bottom third of the income distribution could feasibly buy about 40 percent of transacted properties, compared to more than 60 percent for buyers in the top third. This gap widens substantially when conditioning on consumption needs such as minimum dwelling size or room requirement or when we restrict attention to areas with high house-price growth. Because high-growth areas are also high-priced, lower-income buyers are effectively shut out of the locations with the highest capital gains.

Yet borrowing constraints alone cannot explain access to high-growth areas: after major mortgage-market reforms, we find little change in the income composition of buyers in high-growth areas. Expansions of credit, such as the introduction of interest-only loans in 2003, raised prices but left the buyer mix essentially unchanged, consistent with inelastic housing supply (Greenwald and Guren, 2025). A macroprudential tightening in 2016 had similar effects. We show empirically that higher-income households live in more supply constrained areas, using the housing supply elasticity measure from Guren, McKay, Nakamura and Steinsson (2021). Taken together, the geographical sorting underlying the income gradient in capital gains is consistent with both borrowing constraints and inelastic housing supply, as shocks shift prices more than they shift buyer composition.[1]

[1] An alternative explanation is that lower-income buyers are not considering buying in areas with high house price growth, for example due to local social networks, lack of information, or job opportunities in their current

We also show that the higher capital gains earned by high-income buyers are unlikely to be simply compensation for greater risk. Since the risk-return relationship in housing is empirically weak (Han, 2013), we investigate several measures of risk beyond the standard deviation of house-price growth: idiosyncratic risk (Giacoletti, 2021), liquidity (Amaral, Toth and Zdrzalek, 2025a), the covariance of house-price changes with income and consumption growth, and different measures of downside risk. We find that high-income buyers reside in markets with somewhat higher measured housing risk, but the differences are quantitatively small. Beyond this, taking risk in housing requires buying in the high-price areas where lower-income households face binding borrowing constraints. We also show that the income gradient in capital gains is *negative* within local markets, suggesting that higher income buyers are not more skilled at selecting properties within a given market that subsequently appreciate more. Instead, the income gradient in capital gains is consistent with persistent differences in feasible access to locations with stronger price growth.

Our findings establish a link between income rank, spatial sorting, and house-price dynamics. Because capital gains depend systematically on location, differential access to appreciating markets is associated with persistent differences in wealth accumulation across the income distribution, beyond the role of location in shaping income inequality (Diamond and Gaubert, 2022). A key contribution of this paper is to highlight that the dual role of housing as both a consumption good and an investment shapes capital gains on the largest asset held by most households. Because housing is indivisible and subject to borrowing constraints and local supply frictions, the determinants of housing capital gains differ from those governing financial assets. Unlike equities, where households can acquire even very small positions and face virtually no minimum-investment threshold, housing requires committing to a large, indivisible asset typically financed with leverage. This gives rise to endogenous "housing participation constraints" tied to appreciating locations, similar to those commonly modeled in the stock market (see e.g., Brendler, Kuhn and Steins, 2024).[2]

Finally, we discuss some limitations of our analysis in the conclusion and suggest ways to further investigate the mechanisms involved. First, we document differences in realized capital gains rather than differences in expected returns. An important question is whether the patterns we document are a systematic feature of housing markets or a consequence of idiosyncratic factors over the last three decades. We document that income and population growth are primary drivers of capital gain, trends that tend to be persistent over time (Chodorow-Reich, Guren and McQuade, 2024). Second, we focus on capital gains rather than total returns. Including net rental yields in future research would be a natural extension. In our data, net rental yields are unobserved and may be higher in areas with low house-price growth (Amaral, Dohmen, Kohl and Schularick, 2025b), which could potentially offset some of the capital-gain gap we document. However, we also provide a quantitative exercise that suggests that it is unlikely that rental yield differentials would fully offset the capital-gain gap we document. Third, our

location.

[2]These mechanisms are not specific to Denmark. Using U.S. Zillow data, we show that zip codes with higher price levels in 2000 experienced faster subsequent price growth, consistent with persistent spatial sorting and differential appreciation across locations.

findings are descriptive and not intended to be interpreted as causal. Location fixed effects capture both selection (e.g., information advantages, preferences) and constraints (e.g., credit limits, supply restrictions). Our credit reform evidence shows limited changes in the income composition of buyers across areas with high and low house-price growth around policy shifts. While this pattern is consistent with equilibrium forces, like inelastic supply or competition between buyers, we do not pin down a single mechanism.

Related literature. A prominent literature documents substantial differences in asset returns across the wealth distribution (Fagereng et al., 2020; Bach et al., 2020; Kuhn, Schularick and Steins, 2020). Blanchet and Martínez-Toledano (2023) argue that higher house-price growth in Europe has been important for wealth inequality dynamics. Martínez-Toledano (2020) studies the determinants of wealth inequality during booms and busts and finds large differences in returns between wealth groups. Our contribution is to provide evidence for several mechanisms specific to housing, such as financial constraints, housing indivisibility, and supply constraints. We highlight that capital gains to housing are heterogeneous across buyers and that housing has several features that are of first-order importance for understanding this heterogeneity in capital gains.

Next, we contribute to recent literature leveraging detailed administrative data to examine differences in asset returns across households. Recent papers have examined how housing returns correlate with gender (Goldsmith-Pinkham and Shue, 2023; Girshina, Bach, Sodini and Team, 2021), race (Kermani and Wong, 2024; Gupta, Hansman and Mabille, 2025; Diamond and Diamond, 2024), and wealth (Wolff, 2022). We extend this literature by examining how housing capital gains correlate with income rank using transaction data, by directly characterizing how choice sets differ across buyers, and by studying how financial constraints and housing supply interact to limit the choice set of lower-income buyers.

Our work also contributes to a literature on spatial sorting and inequality. Parkhomenko (2025) documents that rising house prices cause middle-income US households to move out of cities because they cannot afford to purchase a home.[3] Our results on the drivers of differences in capital gains imply that many of the patterns documented in this literature on increased sorting by income will also lead to differences in capital gains to housing and thus to wealth inequality. Spatial differences in productivity shocks or income growth can also raise wealth inequality, as housing capital gains accrue to existing homeowners.

2 The Danish housing market

2.1 Institutional background

Our empirical exercise focuses on capital gains to housing and is therefore conditional on purchasing a property. To contextualize our findings, it is useful to note that homeownership increases sharply with income: Figure 1 shows rates of 50 percent in the bottom half, 67 percent in the 51st–90th percentiles, and 83 percent in the top decile of the income distribution.

[3]This pattern is also apparent in other countries, for example, in China (Fischer, 2023).

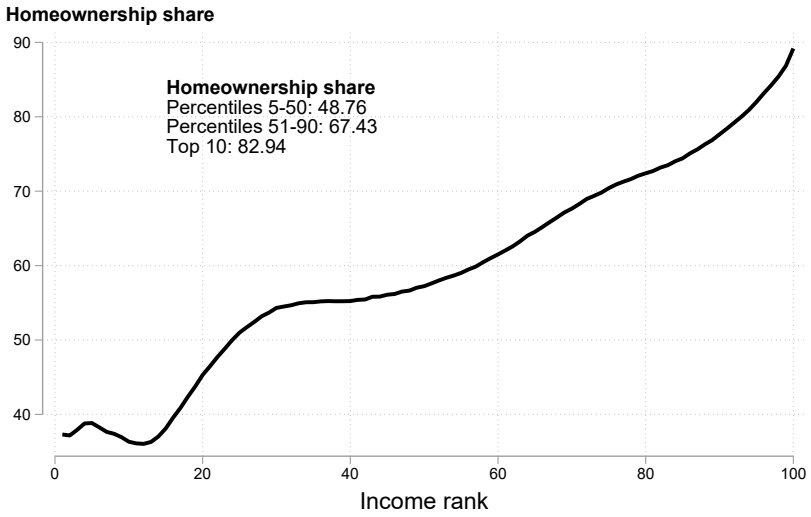


Figure 1: Homeownership rates across the income distribution

Notes: The figure plots the average homeownership rate over the income distribution. Data are collected from Statistics Denmark from 1997 to 2022, where we define a homeowner as a household with positive housing wealth on their balance sheet. Income rank is based on within-age, average household income over a three-year period. Income rank is discussed in Section 3.

As in many other countries, in Denmark housing is the most important asset on the balance sheet for households. In 2014, the first year with comprehensive data on pension wealth, Appendix Figure A1 shows that housing wealth averaged 53.6 percent of total gross wealth, making it the most important asset for all but the lowest-income households.[4] The housing share of gross wealth is lower than in Fagereng et al. (2020) for Norway, where housing represents 66 percent of gross wealth for the 20th-50th percentile and 86 percent for the 50th-90th percentiles of the wealth distribution.[5] In Bach et al. (2020), the share allocated to residential real estate is 45 percent for the 70th-90th percentile of the wealth distribution. Martínez-Toledano (2020) report that housing is the main form of wealth for the middle of the wealth distribution in Spain. Kuhn et al. (2020) similarly report that housing dominates the portfolios of households at the bottom of the income spectrum and in the middle class. Overall, based on these metrics, the importance of housing appears to be similar in Denmark to that in other countries studied in previous work.

Most Danes own housing on their personal balance sheet for consumption purposes. Almost all buyers in Denmark reside in the properties they own. In principle, households could split housing consumption and investment by renting in a location where they want to consume housing and buying in another location where they expect prices to increase. In practice, households in Denmark do not behave this way, so housing consumption and investment are tightly linked to the location of the primary residence.[6] This linkage is reinforced by Denmark's institutional

[4]Note that the data do not include private business wealth. This form of wealth predominantly accrues to the top of the wealth distribution: at the 97th percentile of the wealth distribution, the value of unlisted shares is DKK700,000, or approximately 100,000 Euros.

[5]A potential explanation is the considerably higher homeownership rate in Norway (78.3 percent compared to 59.2 percent). See https://ec.europa.eu/eurostat/cache/digpub/housing/bloc-1a.html.

[6]Households could also get exposure to housing by investing in REITs or real estate companies. A lack of

environment, which makes it difficult to own housing purely as an investment. Denmark has strict tenant-protection laws. To rent out a property for a limited period, the owner typically must provide a valid, legally defensible reason for doing so. Furthermore, properties constructed before 1991 are subject to rent control.

Homeowners are subject to a range of housing-related taxes. Beyond these constraints on separating consumption from investment, the tax system also shapes the net returns to homeownership. These include property taxes, which are levied annually based on the assessed value of a property. These assessed values were effectively frozen in 2002, so property tax liabilities did not track house prices after that year.[7] Capital gains on primary residences are typically exempt, subject to specific conditions (including a lot-size threshold and a residence requirement); capital gains on non-primary residences are taxed upon sale. Homeowners can also deduct 30% of their mortgage interest payments from their taxable income.

2.2 The Danish mortgage market

The Danish mortgage market is dominated by "mortgage credit institutions" known as "realkreditinstitutter." These institutions provide long-term mortgage loans to homeowners, financing these through the issuance of mortgage bonds on capital markets. The mortgage bonds are typically issued with a fixed interest rate and a maturity of up to 30 years. They are highly rated by credit rating agencies due to the strict regulations and collateral requirements imposed on issuers.

Danish borrowers can choose between a fixed-rate mortgage and a variable-rate mortgage. The maximum LTV ratio is 80%, but borrowers can add up to 15% in higher-interest bank debt. Denmark tightened these rules in 2013. There is no single statutory PTI cap, but lenders apply affordability tests and supervisory guidance (including tighter requirements in high-growth areas in later years). For variable-rate mortgages, the interest rate is tied to prevailing market interest rates and is adjusted periodically over the life of the loan. Approximately half of outstanding mortgage debt has a maturity of 30 years. From 2003 onwards, Danish borrowers can also choose between annuity repayment plans or a 10-year interest-only period. If a borrower defaults on a mortgage, the mortgage bank can trigger a forced sale of the collateral property. If the proceeds from the sale are insufficient to cover the full loan amount, the residual claim is converted to a personal unsecured loan.

2.3 Housing market dynamics

As in many other countries, Danish house prices have shown considerable volatility over the last twenty years. Figure 2 plots the average house-price growth over time, along with the 10th and 90th percentiles, based on postcode-level data. The average year-over-year growth rate in real house prices at the postcode-level from 1996 to 2022 is 2.7 percent, with substantial increases

portfolio data means that we cannot investigate this hypothesis, but we note that a relatively small share of Danish households invest in stocks, and that most invest in local stocks (Andersen, Hanspal and Nielsen, 2019).

[7] Property valuations were scheduled to be updated in 2020, but were delayed. The new valuations form the basis for property taxes in 2024.

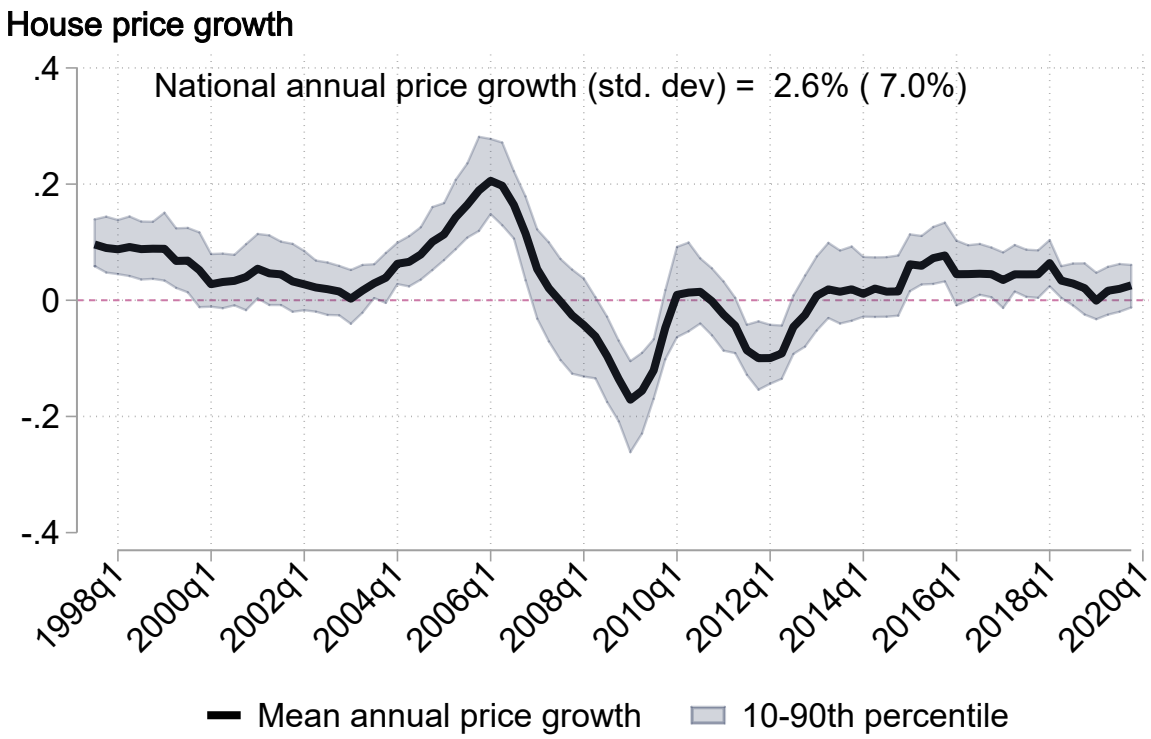


Figure 2: House price growth over time

Notes: The figure plots the average year-over-year growth rate in inflation-adjusted property prices at the postcode level over time in orange, with the 10-90th percentile in gray. The figure uses data on average square meter prices for apartments and houses from Finance Denmark. We use the number of transactions for apartments and houses as weights when calculating property prices. Transactions are available from 2004, and weights pre-2004 are imputed. The results are robust to alternative weighting. The annual national price growth and standard deviation are calculated as the average of the Denmark square meter price growth from 1996 to 2022.

from 2003 to 2007 followed by a rapid decline in 2008 and 2009. The Danish housing boom was more pronounced in high-price areas, like Copenhagen.

Denmark's house-price dynamics are broadly in line with those in other countries. Using data on real house-price growth from the Bank for International Settlements, the average real year-over-year house-price growth in Denmark was 2.9% from 1997 to 2022 (note that this number comes from a different dataset than the 2.7% growth reported in the figure above). These growth rates are comparable to the United States (2.5%) and France (2.9%). Denmark experienced lower real house-price growth than the United Kingdom (3.8%), Norway (4.4%), and Sweden (5.2%), but higher than Germany (0.7%). The standard deviation of house-price growth in Denmark over the same period was 7.5%, which is comparable to the United States and the United Kingdom (7.0% and 6.8%, respectively), but is more volatile than in the other countries mentioned. In addition, Denmark resembles other advanced economies in the dominance of owner-occupied housing in household portfolios, the presence of borrowing constraints, and strong spatial heterogeneity in house-price growth.

3 Data

3.1 Data sources

We use high-quality administrative data from Statistics Denmark covering the period from 1996 to 2022. The data include housing transactions, underlying property characteristics, and linked demographic and financial information for the entire population in Denmark. The data are organized in separate registers that we merge using the unique personal identifier from the Danish Civil Registration System (CPR). This identifier links individuals to a household identifier, allowing us to aggregate outcomes to the household level. Wealth and income measures are obtained from tax records, while demographic variables such as age and place of residence are merged from population registers via the same CPR identifier. We then construct household-level measures using the household identifiers. To keep household resources comparably defined across the samples, we define households to contain at most two adults, so that adult children living at home do not mechanically affect measured income and wealth.

Our main variable of interest is a household's income rank in the national distribution. We measure income as total income that includes labor income, transfers, and capital income, and use average income within the household to account for differences in household composition. For each year, we construct the income distribution using the full population of Danish households and compute within-age-cohort income ranks. To reduce transitory income fluctuations, we base ranks on a three-year average of household income in $t-1$, t and $t+1$. Our results are robust to alternative definitions, including ranks based only on pre-purchase income or using income from a single year rather than a three-year average.

Next, we construct our home buyer sample using the real estate transaction register and property ownership register. We restrict the analysis to transactions where the buyer's identifier is observed and the buyer is an individual (not a company), and we exclude transactions flagged by Statistics Denmark. Our main sample focuses on primary residences, identified using the address where the individual is registered, and we restrict to purchases with at most two individual buyers. We then link the home buyers to the population-based income rank. Specifically, we compute buyers' income from individual-level income data and map this measure to the corresponding percentile of the relevant within-age-cohort household income distribution. In the vast majority of cases, two buyers belong to the same household and therefore share a household identifier; in the remaining cases (e.g., couples who purchase before formally co-residing), we average the two buyers' incomes and match that value to the household income distribution.[8] We exclude individuals under 25 from our sample of homebuyers as Andersen, Johannesen and Sheridan (2020) notes that low-income young households are often students whose observed income is a poor proxy for financial resources. Because homebuyers are a selected (on average higher-income) subset of households, they are unevenly represented across the income distribution, being sparse at low income ranks and increasingly concentrated at

[8]The household identifier is based on residence. In most cases with two buyers, they belong to the same household and therefore have the same household identifier. However, in some cases the identifier is different for two buyers. For example, this could be the case for a couple that buys a property in one year, and moves in together the next year. To include these cases, we average the individual incomes of buyers and match to the household income distribution.

higher ranks, even though ranks themselves are defined relative to the full population.

For our capital gains analysis, we focus on properties with at least two observed transactions (repeat sales). For each repeat sale, we combine the data on the buyer's income rank measured one year prior to purchase, buyer's characteristics at the time of purchase and detailed property characteristics, available in the housing register. The resulting repeat sales sample includes approximately 218,000 transactions. In addition, we retain a dataset of single transactions (only purchase without a subsequent sale) containing about one million observations.

In our main analysis, we use municipalities and postcodes as proxies for local housing markets and neighborhoods. Danish municipalities are relatively small administrative areas nested in larger administrative regions. There are 98 municipalities in Denmark. Municipalities have administrative responsibilities, including the collection of certain taxes. Each municipality belongs to one of five regions. For example, the capital region consists of 29 municipalities, including the central parts of Copenhagen (Copenhagen and Frederiksberg) and the outskirts. In addition, there are 605 postcodes within municipalities. These have no administrative functions. We focus on postcode fixed effects in the decomposition analyses. Municipality-level indices are used when postcode indices are unavailable or are too noisy.

3.2 Measuring the capital gains to housing

We calculate housing capital gains at the repeat sale level. This approach differs from studies that use register data with local house-price indices combined with property types. Our approach allows us to observe realized, property-level capital gains directly instead of relying on aggregate indices.

We use log annualized real capital gains in our main analysis, as log returns are generally more suitable for understanding wealth inequality (Campbell, Ramadorai and Ranish, 2019). For a property bought by household i at time T_{ip} and sold at time T_{is}, with transaction prices P_{ip} and P_{is}, we define the annualized unlevered log capital gain as

$$r_i^u = \frac{\ln(P_{is}) - \ln(P_{ip})}{T_{is} - T_{ip}}, \tag{1}$$

where $T_{is} - T_{ip}$ is the holding period. Because we observe exact transaction dates, we allow T_{ip} and T_{is} to be non-integers. Our results are robust to using a geometric mean of the above formula instead. We deflate transaction prices using the consumer price index and remove outliers in the measured capital gains by winsorizing r_i^u at the 1st and 99th percentile.

To assess whether selection into repeat sales affects our results, we impute unrealized capital gains for properties that are observed only once in our transaction data (i.e., not resold within the sample period). This imputation abstracts from property-specific quality changes and within-municipality price heterogeneity, so we use it as a robustness check rather than the main result. We use municipality-level apartment and house price indices from Finance Denmark and match each purchase to the corresponding municipality and property-type index in the purchase quarter. For each such property, we impute the counterfactual price at the end

of 2022 as the purchase price scaled by cumulative index growth over the holding window; in other words, the imputed annualized capital gain is the annualized growth rate of the matched index from the purchase quarter to 2022Q4.

3.3 Conceptual remarks

A limitation of the capital gains measure is that they overlook dividends in the form of net rents. Properly accounting for the total return to housing would entail measuring net rents on a similar property. Since net rents are unobserved, a common approach to imputing rents is to either assume that imputed rent is equal to a constant fraction of the property value or to impute rents using market-level rent indices. We can implement the first approach using Statistics Denmark's imputed rent measures, calculated as a percentage of the property's value. However, this is an accounting construct and not a true measure of the dividends from homeownership. Consistent with this limitation, we find that the imputed rent rate varies little across income ranks, so adding this imputed dividend has little effect on the estimated income gradient in capital gains. Because this measure is not designed to capture location-specific variation in net yields, this result does not rule out heterogeneity in true net rental yields across locations. Furthermore, we are not aware of a consistent national rent index covering 1996–2022 at the municipality or postcode level. We discuss how to interpret our results in light of the lack of data on net rents in the conclusion. With these caveats in mind, we interpret our results as differences in real capital gains rather than total returns.

Another conceptual limitation is that we study realized (ex-post) returns rather than ex-ante expected returns. Model-based expected returns would require adopting an asset-pricing framework, but expected housing returns are sensitive to how one models infrequent trading, idiosyncratic risk, and borrowing constraints. With noisy asset returns, a long time series is needed to estimate expected returns from realized outcomes (Merton, 1980). We therefore emphasize realized capital gains as a model-free measure directly relevant to wealth accumulation.

3.4 Summary statistics

Table 1 provides summary statistics for the final estimation sample. Statistics for the full sample are presented in column (1), and statistics for three income rank-based groups are presented in columns (2)–(4). We define low, middle, and high-income groups as terciles of the income-rank distribution (0–33, 34–66, and 67–100).

There is little difference in years between transactions (i.e., holding period) and the purchase year between income groups. High-income buyers (column (4)) achieve both higher total capital gains on housing and have higher annualized capital gains compared to low-income buyers (column (2)) and middle-income buyers (column (3)). High-income buyers buy more expensive properties than low- and middle-income buyers, but there are relatively minor differences in property characteristics such as building age and size. High-income buyers are also more likely to renovate and, on average, spend more on renovations. When it comes to buyer characteristics, low-income buyers naturally have less income, but have non-trivial wealth ranks (similar to high-income buyers). These patterns are consistent with the low-income group including

Table 1: Descriptive statistics

		Income groups		
	(1)	(2)	(3)	(4)
Purchase price	1,205,815	953,824	1,036,606	1,360,897
Sales price	1,452,692	1,110,353	1,208,830	1,672,717
Purchase year	2005	2005	2005	2006
Year between transactions	8	8	8	8
Total capital gain	24.7	20.5	21.1	27.8
Annualized real capital gains (%)	3.6	3.2	3.1	4.0
Capital gains by urbanization level (%)				
Capital	5.2	5.6	5.3	5.1
City	3.7	4.0	3.5	3.7
Countryside	3.0	2.4	2.7	3.3
Province	2.8	2.0	2.3	3.3
Rural	2.4	2.0	2.1	3.0
Property characteristics				
Apartment	0.31	0.35	0.24	0.34
Floor number	2	2	2	2
Rooms	4	4	4	4
Size m^2	112	101	112	113
Building age	56	59	55	56
Buyer characteristics				
Total income, pre-purchase	324,452	125,490	220,140	427,337
Mortgage, pre-purchase	467,194	239,948	281,880	628,901
Wealth rank	46	50	39	50
Renovation indicator	0.34	0.26	0.29	0.39
Renovation amount (DKK)	9,452	5,648	7,180	11,605
Age	41	45	38	42
Female	0.5	0.5	0.5	0.4
Number of buyers	1.5	1.5	1.6	1.5
Education	15	13	14	15
Family size	2.4	1.9	2.4	2.4
Share of all transactions		0.09	0.36	0.55
Repeat sale share	0.27	0.31	0.27	0.26
N	217,926	19,826	79,329	118,771

Notes: The table presents the summary statistics for the final estimation sample from 1996 to 2022. The sample includes only repeat sales transactions. We divide the sample into low-, middle-, and high-income based on their income rank (terciles 0–33, 34–66, 67–100). Buyer characteristics are measured one year prior to purchase (labeled "Pre-purchase"). The renovation indicator equals one if one of the buyers used a renovation tax break between purchase and sale, observable from 2011 onward. Urbanization level is based on Statistics Denmark's urbanization classification. Education and age are calculated as the maximum variable among the buyers. All monetary values in Danish Krone (DKK).

older households with accumulated assets (e.g., retirees). Indeed, low-income buyers are older compared to middle- and high-income buyers. Our empirical estimates will account for these differences both by including controls and by constructing rankings based on age-cohorts. Finally, the bottom of the table calculates the share of total transactions and the share of repeat sale transactions by income group. We calculate repeat sale incidence as the share of matched purchases that are observed to resell within 1996–2022 out of the total number of transactions

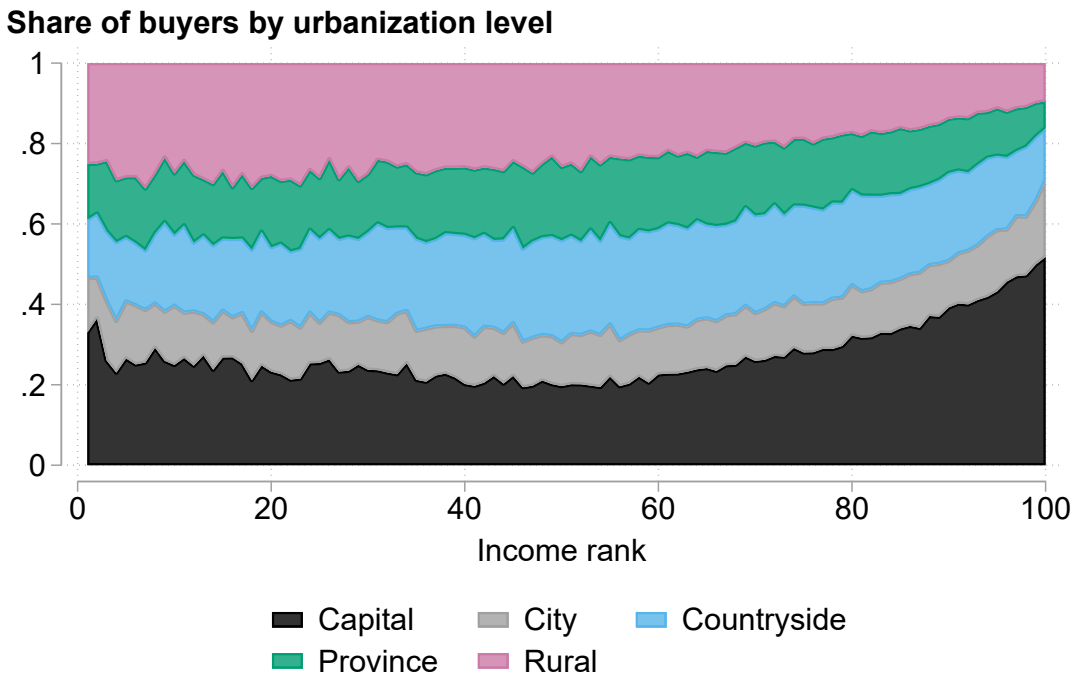


Figure 3: Share of buyers by urbanization level

Notes: This figure plots the share of buyers in different geographical areas by income rank. The geographical areas are designed by Statistics Denmark based on the urbanization level. Income ranks are adjusted for age and are described in Section 3.

within that period. High-income buyers account for 55 percent of total transactions, while low-income buyers account for only 9 percent of the total number of transactions. The share of transactions within each income group that appears more than once (a repeat sale) is somewhat higher for the low-income group (31%), but is similar for middle-income and high-income buyers (27% vs 26%).

Because the repeat sales samples may be selective, Table B1 provides summary statistics on differences between single and repeat sales. We note that the income rank is similar for single and repeat sales. Single transactions have a slightly higher purchase price, which stems from differences in purchase year, small differences in location, and differences in property characteristics, especially whether the property is an apartment. The differences between single and repeat sales are relatively minor and intuitive. Properties sold in a later year and single family houses are less likely to be sold repeatedly. We can account for differences in these variables in our analysis. In addition, we impute unrealized gains for single-transaction properties using municipality indices and obtain similar income-gradient estimates.

Finally, Figure 3 plots the share of repeat sales buyers by urbanization level. There is a gradient in the likelihood of purchasing in the capital region or in big cities (Aarhus, Aalborg, Odense), where the share of buyers purchasing in these areas increases with income rank after the 60th income percentile. These are also the areas with the highest housing capital gains, as documented in Table 1. By contrast, lower- and middle-income buyers are more concentrated in

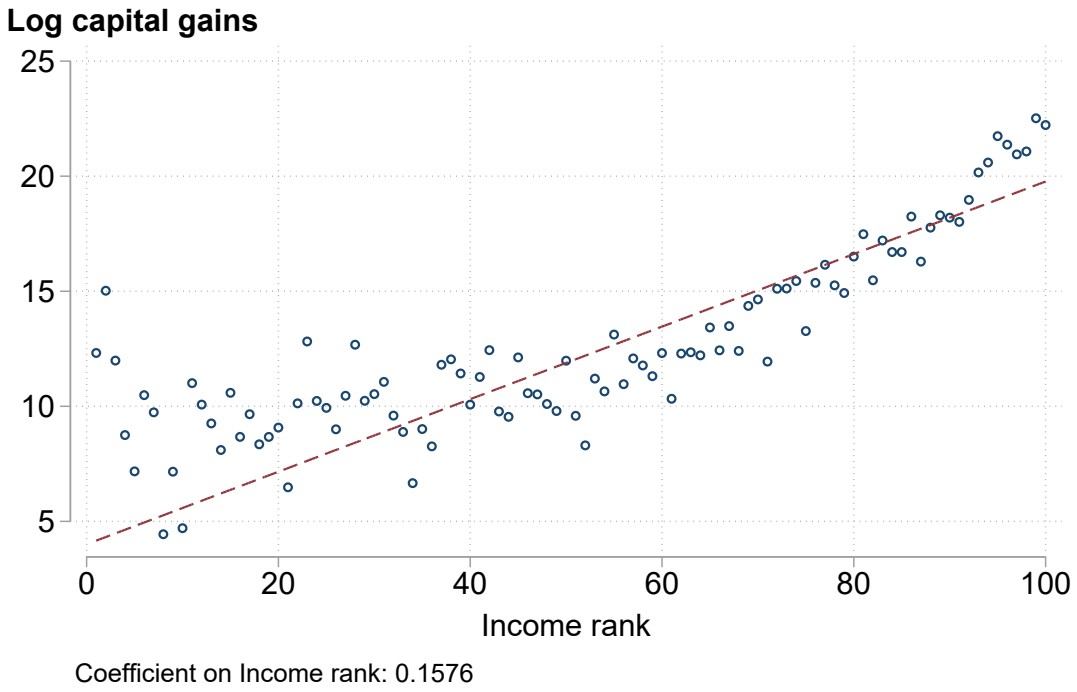


Figure 4: Capital gains to housing by income rank

Notes: This figure plots income rank against the total (non-annualized) capital gain on housing, calculated as $\ln(P_{is}) - \ln(P_{ip})$. Each dot represents the mean within an income rank bin. We do not include any controls or fixed effects. The subsequent regression analysis uses annualized capital gains to account for variation in holding periods. Income ranks are adjusted for age and are described in Section 3.

provinces and rural municipalities, where capital gains are markedly lower. This figure foreshadows our main results, showing that across the income distribution, the composition of buyers varies sharply by urbanization level, and that higher income buyers generally locate in areas with higher capital gains to housing.

4 Income Gaps in Housing Capital Gains

This section documents systematic income differences in realized housing capital gains and investigates which factors account for them. Using repeat sales transactions, Figure 4 plots average capital gains by income rank and shows a strong, approximately linear gradient. In our main empirical exercise, we relate annualized real capital gains to buyers' income rank and decompose the gradient by successively controlling for property characteristics, buyer characteristics, market timing, and local market fixed effects. Our key finding is that higher-income households realize higher capital gains on housing, but this gap is almost entirely statistically accounted for by where households buy (and, to a smaller extent, by the timing of transactions within local markets), rather than by differences in housing characteristics or buyer demographics.

Differences in capital gains to housing may stem from many underlying factors. Higher-income households may purchase properties with characteristics that appreciate more in value. A salient example is the differential effect of property characteristics on prices across space during

COVID-19 (D'Lima, Lopez and Pradhan, 2022; Gupta, Mittal, Peeters and Van Nieuwerburgh, 2022). Similarly, higher-income households may better time the market, purchase in areas that later appreciate more, or invest more in renovations and upgrades due to higher income, wealth, or easier credit availability. Differences in these factors across the income distribution could plausibly explain the gradient in Figure 4.

To analyze the importance of these factors, we employ a linear regression framework to estimate the relationship between income rank and annualized log capital gains, controlling for a wide range of factors for repeat sales i. While Figure 4 plots total log capital gains to illustrate the raw gradient, the regressions use annualized capital gains to account for variation in holding periods across buyers:

$$Y_i = \beta_0 + \beta_1 \text{Income Rank}_i + X_i\Gamma + \epsilon_i \tag{2}$$

The specification regresses the outcome Y_i, defined as the annualized log capital gains r_i^u multiplied by 100 so that a coefficient of 1 corresponds to one percentage point per year, on the main variable of interest, Income Rank$_i$, and a vector of control variables X_i and Γ is a vector of coefficients. Income Rank$_i$ denotes the buyer's income rank based on a three-year average of household income centered on the purchase year, scaled from 0 to 100. The results are robust to different ways of measuring the income rank. We also present specifications that include fixed effects for location and time. We progressively introduce controls and fixed effects to assess the extent to which observed factors account for the estimated relationship between Income Rank$_i$ and the outcome. This approach absorbs both causal effects and selection. The methodology is similar to that of Goldsmith-Pinkham and Shue (2023) and Kermani and Wong (2024), who study differences in housing returns by gender and race, respectively, and similarly use location fixed effects to decompose return differentials. Appendix D1 presents results for levered returns, which account for mortgage financing but require additional assumptions.

Figure 5 graphically plots the coefficient on Income Rank$_i$, whereas the complete regression results are detailed in Appendix Table B2. The baseline specification, shown in the first line, does not include any control variables. The coefficient of 0.017 on income rank is statistically significant at the 1% level, implying that a one-unit increase in rank is associated with a 0.017 percentage point increase in the annualized log capital gains. To assess the economic significance, we compute the differential effects across income ranks. The estimated coefficient implies a 90–10 annualized capital gains gap of $\widehat{\Delta} \equiv 80\hat{\beta}$ percentage points per year. With $\hat{\beta} = 0.017$, this equals $\widehat{\Delta} = 1.36$ percentage points per year. Since Y_i is scaled by 100, the implied cumulative gap over a 10-year holding period is $\exp(10 \times \widehat{\Delta}/100) - 1 = \exp(0.136) - 1 \approx 14.6\%$.

We now proceed to analyze the empirical determinants of differences in capital gains. We begin by controlling for property and buyer characteristics and then turn to market timing and location. Our repeat sales measure already controls for time-invariant property characteristics, but time-varying property characteristics, the pricing of those characteristics, or time-varying local amenities may still matter for returns. Controlling for property, location and buyer characteristics in equation (2) helps to capture differences in capital gains generated by these characteristics. For instance, the price for apartments generally grows faster than the price for single-family homes in Denmark.

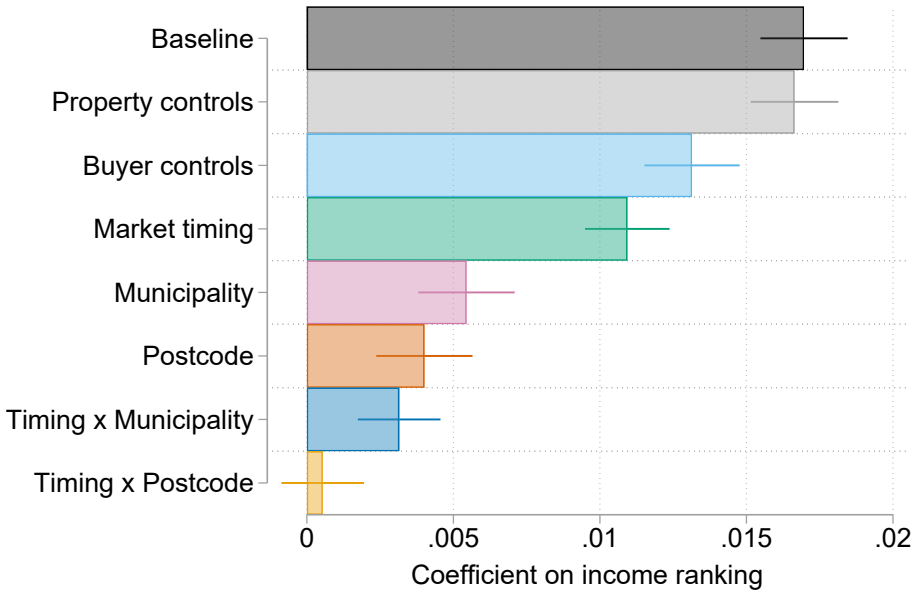


Figure 5: Income-rank gradient in housing capital gains across specifications

Notes: The figure plots the coefficient on Income Rank on the x-axis from estimating Equation (2) for various specifications. The outcome variable is the annualized log capital gains. The *baseline estimate* includes no control variables. *Property controls* includes controls for floor number, number of rooms, square meter size of the property, an apartment indicator, and building age. *Buyer controls* include controls for wealth rank, gender, education, and family size. *Market timing* adds fixed effects for year of purchase and the year of sale. *Municipality* adds fixed effects for municipality, leaving market timing controls out. *Postcode* adds fixed effects for postcodes, leaving out municipality. *Market timing* × *Municipality* includes purchase-year × municipality and sale-year × municipality interaction fixed effects. *Market timing* × *Postcode* includes purchase-year × postcode and sale-year × postcode interaction fixed effects. Standard errors are clustered at the municipality level and 95% confidence intervals are shown as horizontal lines.

Property and homebuyer characteristics. Property characteristics account for only a small share of the difference in capital gains. The second line in Figure 5 shows an estimate of the effect of income rank on capital gains, controlling for property age and type (apartment or single-family home), size and floor number. The coefficient is unchanged and remains statistically significant and economically meaningful. Next, we add controls for homebuyer characteristics (age, gender, within-cohort net wealth rank, education, family size and the number of buyers). The third line depicts the results. The inclusion of these controls slightly decreases the coefficient on income rank to 0.013. We conclude that differences in property or homebuyer characteristics explain only a small share of the variation in capital gains on housing across the income distribution.

Market timing. Next, we introduce controls for market timing and the holding period between transactions. As shown in Figure 2, the Danish housing market experienced considerable volatility during our sample period. Systematic differences in market timing by income rank could plausibly generate large differences in capital gains. To assess this hypothesis, the fourth line in the figure incorporates fixed effects for the year of purchase and the year of sale. This specification accounts for nationwide trends between the purchase and sale years. Table B2 in the Appendix shows that including market timing indicators increases the adjusted R^2 from 0.035 when controlling only for property and buyer characteristics to 0.229 with fixed effects for

market timing. The coefficient on income rank change only slightly, from 0.013 in the specification controlling for property and homeowner characteristics to 0.011 when adding controls for aggregate market timing. There is thus little evidence that higher income households systematically time their housing transactions around *national* booms or busts. Since market timing indicators capture nationwide housing-cycle dynamics but do not explain the capital-gain differential across the income distribution, this suggests that high- and low-income buyers experience similar exposure to aggregate market conditions.

Location. Adding location fixed effects statistically explains a large part of the income gap in housing capital gains. We implement this using municipality and postcode fixed effects. With fixed effects for municipalities (the fifth line of Figure 5), the coefficient on income rank is 0.005, whereas controlling for postcode-level local market conditions reduces the coefficient on income rank further to 0.003. These fixed effects absorb both persistent differences across areas and sorting of buyers into areas.

While Denmark experienced a large housing boom-bust cycle between 2003 and 2009, both the boom and the bust varied across areas and time. If different locations experienced booms and busts at different times (Ferreira and Gyourko, 2023; Çepni and Khorunzhina, 2023), controls for nationwide trends in house-price dynamics as above cannot fully capture local cycle dynamics. Consistent with this, adding market-timing fixed effects jointly with location controls further attenuates the income coefficient, and conditioning on postcode and transaction timing makes the income-rank coefficient statistically insignificant. We are not claiming that location causes higher capital gains, since the fixed effects absorb both causal location effects and selection on unobservables. Rather, conditional on buying in the same postcode at the same time, income rank does not predict differential capital gains, ruling out within-market mechanisms (e.g., superior negotiation or property selection within neighborhoods) as drivers of the aggregate pattern.

We can go one step further and examine the income gradient in capital gains *within* local markets. Appendix Table B3 shows a negative coefficient on income rank within different levels of urbanization. This within-market pattern is consistent with the idea that the aggregate positive gradient is driven by sorting into high-return urban locations. Within these urban markets, however, the coefficient is slightly negative once we include saturated controls. The coefficient of -0.004 for the capital-city area implies a 90-10 gap of -0.32 percentage points per year when controlling for postcode and market timing, compared to a coefficient of essentially zero for the aggregate sample under the same controls. One interpretation is that within expensive urban postcodes, lower-income buyers who successfully purchase may occupy segments with stronger subsequent appreciation (e.g., gentrifying neighborhoods), while high-income buyers already own in established, slower-appreciating areas. However, the effect is modest. Taken together, these results suggest that the aggregate income–returns relationship primarily reflects differential exposure to high-return locations, rather than superior within-market performance.

Comparison to the literature. Our findings on the differences in capital gains on housing between low- and high-income buyers in Denmark are comparable in magnitude to differences

in housing returns documented in the previous literature. Table 6 of Bach et al. (2020) reports housing returns ranging from 4.19% for the bottom decile to 5.43% for P90-P95, a gap of 1.24 percentage points for Sweden. Figure OA.16 in Fagereng et al. (2020) shows that housing returns for individuals in the 10th and 90th percentile in Norway are approximately 4.3 and 5 percent, respectively, a gap of 0.7 percentage points. These studies measure returns for all homeowners, while we focus on capital gains for homebuyers.

Because we do not observe rental yields, we cannot directly compare our capital gains estimates to the total returns reported in these studies. To assess this concern, we compute how large rental yield differentials would need to be to fully offset our estimated capital gains gap. This calculation requires strong assumptions about yield distributions and should be interpreted as a rough order-of-magnitude exercise. Our baseline estimate implies a 90-10 capital gains gap of 1.36 percentage points per year. Approximately 45% of buyers in the top income decile purchase in the capital region, compared to 27% of buyers in the bottom decile. Because rental yields can only offset capital gains for buyers actually located in relevant areas, the effective yield offset is bounded by this share differential multiplied by the yield gap between locations. With an 18 percentage point difference in location shares, rental yields in low-growth areas would need to exceed those in high-growth areas by approximately $1.36/[0.18] \approx 7.56$ percentage points to fully offset our results. In comparison, Amaral et al. (2025b) document a rental yield gap of 3.14 for Copenhagen versus the rest of the country. Thus, while rental yield differences may partially offset our capital gains results, they are quantitatively unlikely to eliminate the entire income gradient in capital gains.

4.1 Robustness and extensions

4.2 Income rank definition

Our baseline income rank measure uses a three-year average of household income centered on the purchase year ($t-1$, t, $t+1$) to reduce transitory noise. A potential concern with this approach is that including income from the purchase year and subsequent year could conflate pre-determined resources with post-purchase dynamics. If a household relocates to a high-growth municipality because of a contemporaneous income shock, such as a new job that both raises income and determines location, the observed correlation between income rank and housing capital gains could partly reflect reverse causality rather than ex-ante sorting based on permanent financial resources.

To address this concern, Figure 6 presents the income-rank coefficient under alternative definitions of the income-rank measure. The first bar shows our baseline specification. The second bar, labeled "Range, pre-purchase," uses income only from years prior to purchase, ensuring the measure is strictly pre-determined relative to the housing transaction. The third bar uses total family income rather than individual buyer income, with age adjustment. The fourth bar ranks buyers relative to other buyers in the same year rather than relative to the full population.

The coefficient using strictly pre-purchase income (0.016) is nearly identical to the baseline (0.017). The specifications using family-level income and ranking among buyers yield somewhat

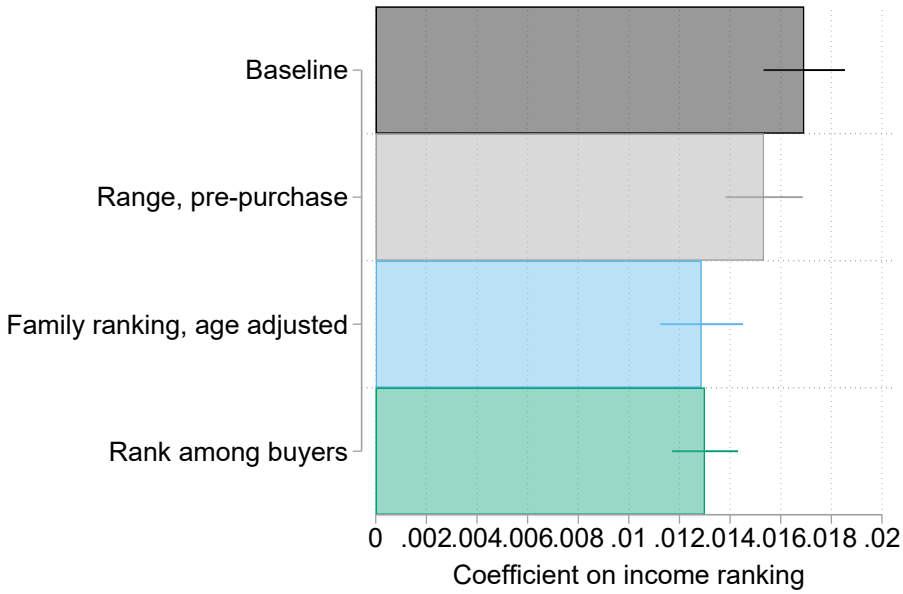


Figure 6: Income-rank gradient under alternative ranking definitions

Notes: The figure plots the coefficient on income rank from estimating Equation (2) using alternative definitions of income rank. "Baseline" uses average household income over $t-1$, t, and $t+1$. "Range, pre-purchase" uses only pre-purchase income ($t-3$ to $t-1$). "Family ranking, age adjusted" uses total family income ranked within age cohorts. "Rank among buyers" ranks households relative to other buyers in the same purchase year. Bars show point estimates; horizontal lines show 95% confidence intervals. Standard errors are clustered at the municipality level. 95% confidence intervals are shown.

smaller coefficients (approximately 0.013), but remain economically and statistically significant. These differences likely reflect measurement: ranking among buyers mechanically compresses the income distribution since homebuyers are positively selected on income, while family-level measures may introduce noise from non-purchasing household members. Overall, the results are stable across different specifications.

Imputing returns for single-transactions. Since we focus on repeat sales, many ownership spells are right-censored: properties purchased during the sample period but not sold by 2022 have no observed selling price and are excluded from the repeat-sales sample. To investigate how incomplete spells affect our findings, we impute capital gains for single-transaction properties using municipality-level house-price indices as a robustness check.

Figure 7 shows a relationship between total imputed capital gains and income rank similar to the one in Figure 4 for the repeat-sales capital gains. The regression of total imputed capital gains on income rank yields a coefficient of 0.097. Note that this coefficient is not annualized and should be compared to the coefficient on income rank of 0.1576 in **??** and not to the baseline coefficient for annualized returns. Selection into repeat sales also appears similar across the income distribution: the share of repeat transactions is similar by income rank (Table 1), and summary statistics at the bottom of Table 1 show that differences in censoring by income rank are not substantial.

A limitation of this imputation is that it assigns each buyer the municipality-level price change by construction, so it cannot distinguish market-wide movements from buyer or property-

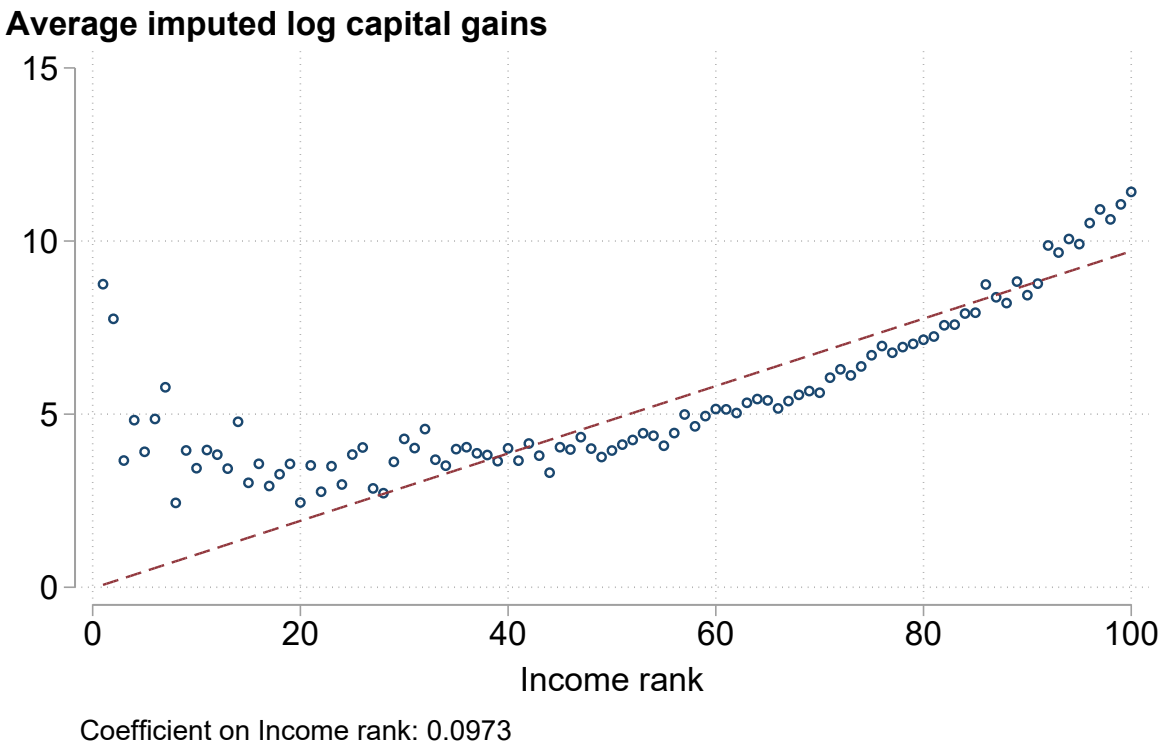


Figure 7: Imputed housing capital gains and income rank for single transactions

Notes: The figure plots the average imputed capital gains against income rank. Income ranks are adjusted for age and are described in Section 3. Imputed capital gains are calculated for all single transactions using the purchase price and the average municipality house price growth from the purchase year-quarter until 2022Q4. The sample does not include repeat sales transactions.

specific factors. This is why our baseline analysis relies on repeat sales, which allow us to study individual-level variation in housing investment performance.

Level of geographical aggregation. We have shown that municipality and postcode fixed effects along with market timing statistically explain the differences in capital gains to housing across the income distribution. Our analysis of geographical location has focused on municipalities and postcodes, as this level of aggregation provides enough observations for reliable estimation while capturing the local aspect of housing markets. We now also examine how other geographical levels affect the estimated coefficient on income rank.

Figure 8 shows that region fixed effects explain a sizable share of the difference in capital gains across the income distribution. Danish regions are larger administrative areas that enclose both cities and the surrounding area, including suburbs and the countryside. For example, the Capital region consists of Copenhagen Municipality and 28 other municipalities. Using Google Maps, we estimate that traveling from central Copenhagen to one of the municipalities located the farthest away, Halsnæs, would take around one hour by car. A Danish region is therefore akin to a Metropolitan Statistical area in the United States. Municipality fixed effects explain a somewhat larger share, and both postcode and parish fixed effects explain most of the coefficient on their own. In larger cities, postcodes capture smaller neighborhoods better than

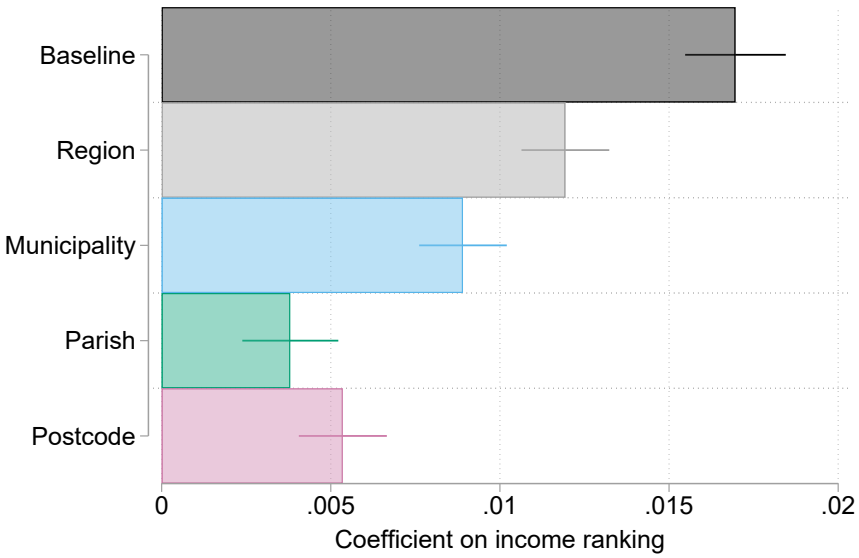


Figure 8: Level of geographical aggregation

Notes: The figure plots the coefficient on income rank on the x-axis from estimating Equation (2) for various levels of geographic aggregation. To isolate how much geography explains on its own, each specification includes only income rank and the indicated geographic fixed effects, with no additional controls for property characteristics, buyer characteristics, or market timing. The outcome variable is annualized log capital gains. Income ranks are adjusted for age and are described in Section 3. The results show the coefficient on income rank using region, municipality, parish, and postcode fixed effects. Standard errors are clustered at the municipality level. 95% confidence intervals are shown.

municipalities. There is substantial variation in house-price growth across postcodes that is not captured by broader geographic units. Regressing postcode-level capital gains on municipality-by-quarter fixed effects yields an R^2 of 0.34, implying that most postcode-level variation occurs within municipalities over time.[9]

Renovations. The observed relationship between income rank and capital gains may stem from higher-income households renovating more. This in turn could reflect differences in financial constraints or different consumption preferences. Renovations represent a fundamentally different channel for differences in returns than what is usually emphasized in the wealth inequality literature, which predominantly focuses on individual characteristics such as differences in risk aversion, financial sophistication, and investment skill. Crucially, renovations are also subject to borrowing constraints: households must finance renovations either from savings or by borrowing against home equity. Location may itself shape the ability to renovate. Homeowners in areas with strong price appreciation accumulate home equity that can serve as collateral for additional borrowing. When homeowners can borrow against home equity, rising local house prices increase borrowing capacity for renovations (Bäckman and Khorunzhina, 2024). This creates a feedback mechanism, where households in high-growth locations not only benefit from passive price appreciation but also gain greater capacity to finance improvements. The renovation channel is therefore not independent of location. Lower-income households, who face

[9]Note that these estimates are larger than those reported in Table B2 because the specifications here include *only* income rank and geographic fixed effects, whereas Table B2 progressively adds property, buyer, and market timing controls.

Table 2: Income-rank gradient in housing capital gains with controls for renovations

	(1)	(2)	(3)	(4)
Income rank	0.0280***	0.0252***	0.0255***	0.0246***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Ren. indicator		0.9786***		
		(0.0433)		
Ren. count			0.1691***	
			(0.0066)	
Ren. amount (DKK)				0.0000***
				(0.0000)
Adjusted R-squared	0.007	0.011	0.010	0.011
Observations	139,617	139,617	139,617	139,617

Notes: This table presents the regression results that relate housing capital gains and income ranks when we control for renovations. The outcome variable is the annualized log housing capital gains. The sample is limited to include only sales occurring after 2011, when the tax break was in place. *Ren. indicator* is a dummy variable equal to one if one buyer applied for the renovation tax break in any year between purchase and sale, *Ren. count* is the count of the number of tax breaks applied for between purchase and sale, and *Ren. amount (DKK)* is the total sum of the tax break in DKK. No controls or fixed effects are included. Standard errors in parentheses, clustered at the municipality level. *** p¡0.01, ** p¡0.05, * p¡0.10.

tighter credit limits and lower liquid wealth, may be unable to finance improvements even when they own a home and can in principle borrow against home equity. This creates a distinct mechanism through which financial constraints generate return heterogeneity.

We examine the impact of renovations on housing capital gains using data from a renovation tax break. We use the number of tax breaks reported by each buyer between purchase and sale dates. Because the tax break is available only since 2011, this analysis is relevant for properties sold after 2011. As our transaction data begin in 1996, restricting to sales from 2011 onward affects the sample as follows. Properties purchased before 1997 and held until 2011 or later have holding periods of at least 14 years, so these long-holding transactions remain in the sample. Some shorter-term transactions are lost (properties purchased 1998–2010 and sold before 2011), but many short- and medium-term holdings remain from purchases made closer to or after 2011. The baseline coefficient in this restricted sample (column 1) is larger than in the full sample (Table B2, column 1).

Appendix Figure A3 shows higher-income buyers are more likely to report the tax break and, on average, apply for a larger amount. However, Table 2 shows that the coefficient on income rank is mostly unaffected by controls for renovations. The first column replicates the baseline result with no control variables, showing that there is a strong income gradient in annualized log capital gains. However, including different proxies for renovations only leads to a small reduction in the coefficient.

5 Housing risk

In frictionless asset markets with full arbitrage and rational expectations, risk-adjusted returns should equalize across locations, leaving investors indifferent between cities (Amaral et

Table 3: Regressions of housing risk measures on income rank

	(1) Std.dev	(2) Beta Denmark	(3) Sum negative	(4) Return if negative
Income rank	0.00009*** (0.00000)	0.00245*** (0.00003)	-0.01391*** (0.00019)	-0.00011*** (0.00000)
Adjusted R-squared	0.0144	0.0298	0.0245	0.0102
Observations	217,926	217,926	217,926	217,926
	(1) Sales time	(2) Cov. Cons (x100)	(3) Cov. Inc(x100)	(4) Id. Risk
Income rank	-0.30381*** (0.00372)	0.00044*** (0.00001)	0.00022*** (0.00000)	0.00001*** (0.00000)
Adjusted R-squared	0.0321	0.0112	0.0161	0.0016
Observations	217,926	217,926	217,926	216,255

Notes: The table reports univariate regressions of each municipal risk measure on buyers' income rank. Risk measures are computed at the municipality level and merged to each buyer based on their purchased property's location. *Std. dev.* is the standard deviation of annual house price growth across municipalities, computed from average transaction prices over 1997–2022. *Beta Denmark* are estimated municipality-level sensitivities of local house price growth to national house price growth. *Sum negative* counts the number of years with negative municipal house price growth. *Return if negative* is the average return conditional on a negative return. *Sales time* is the mean number of days from the date a property is first listed to the date a purchase agreement is signed; data from Finance Denmark at the municipality level from 2004 onward. *Covariance, consumption growth* and *Covariance, income growth* are the covariances between municipality-level house price growth and (i) imputed consumption growth and (ii) income growth, respectively, where consumption is imputed from the budget constraint. *Id. risk* is idiosyncratic risk. See Appendix 8 for details on the construction of all risk measures. Standard errors clustered by municipality in parentheses. *** p¡0.01, ** p¡0.05, * p¡0.10

al., 2025b). Housing differs from this benchmark because returns combine asset payoffs with local consumption and hedging benefits, and because trading, search frictions, and borrowing constraints limit arbitrage across space (Badarinza, Balasubramaniam and Ramadorai, 2024; Greenwald and Guren, 2025). In principle, these wedges can sustain persistent cross-city differences in expected returns, even after adjusting for risk. We ask to what extent the capital gains earned by high-income buyers can be explained by their exposure to differential housing risk. We consider several dimensions of housing risk and how they vary across the income distribution. Overall, we find that risk is positively related to income rank, but the magnitudes are small.

To construct the risk measures, we use municipality-level house-price growth. The underlying data consist of the same transactions used in our main analysis. We study several sources of risk plausibly priced in housing markets: standard deviation of house-price growth, covariance of consumption and income with house-price growth, idiosyncratic risk, and housing market liquidity. The details on how we construct these measures are reported in Appendix 8. We merge municipal-level risk measures to each buyer based on the location of their purchased property. For this analysis, we consider both single and repeat buyers. All results are consistent if we focus on repeat transactions. In unreported results, we have also examined results across all households (not just buyers).

Table 3 reports regressions of each municipal risk measure on buyers' income rank. All risk measures are expressed in annual return units (e.g., standard deviation in decimals). The coefficients point to a positive relationship, but the magnitudes are small. For example, moving from the 10th to the 90th percentile in the income distribution raises the standard deviation of log house price growth by only $(90 - 10) \times 0.00009 = 0.0072$. To illustrate how this volatility difference maps into an order-of-magnitude risk premium, one can apply a benchmark Sharpe ratio of 0.36 for the global market portfolio documented in Doeswijk, Lam and Swinkels (2020).

Under a mean–variance benchmark where expected excess returns scale with volatility, the difference in the standard deviation of house-price growth corresponds to $0.0072 \times 0.36 = 0.0026$, or 0.26 percentage points per year in expected capital gains. Our baseline estimate implies that the same percentile move is associated with a $80 \times 0.017 = 0.0136$ increase in annualized log capital gains. This means that risk explains about $0.0026/0.0136 \approx 0.19$, or 19% of the baseline 90-10 gap. However, the cross-sectional relationship between risk and house-price growth in Denmark is weak (Appendix Figure A2). A plausible explanation is that, in markets with inelastic supply, part of the variation in risk reflects hedging demand: households may be willing to accept lower average capital gains in exchange for owning a property that better hedges future housing consumption (Han, 2013). As a result, differences in the standard deviation of house-price growth can account for at most a modest share of the observed capital gain gap.

We also examine other indicators of risk. The estimation results in Table 3 suggest higher-income-ranked buyers are less likely to experience a period of negative house price growth, but conditional on doing so, they experience larger declines. Higher-income buyers are also buying properties in more liquid markets, as measured by time-on-market. This speaks against a risk-based explanation, as higher income buyers buy in more liquid markets and liquidity is likely positively priced in housing (Amaral et al., 2025a). Further, higher-income buyers tend to live in areas where house-price growth covaries more strongly with income and consumption growth, although the magnitudes are small. Finally, Eichholtz, Korevaar, Lindenthal and Tallec (2021) find that housing risk is dominated by idiosyncratic variation, particularly over shorter horizons. Similarly, we find that higher-income buyers take on more idiosyncratic risk, though the difference remains small.

Finally, we find that higher-income buyers have higher housing market beta. We calculate beta by regressing house price growth on national market returns. We can use a back-of-the-envelope calculation to map this beta difference into an order-of-magnitude risk premium. The difference in beta between the 10th and 90th percentile in the income distribution is $(90-10) \times 0.00245 = 0.196$. For this difference to explain the difference in capital gains, the gap between the market return on housing and the risk-free rate would have to be $r_{market} - r_{riskfree} = 0.0136/0.196 = 6.9\%$. This far exceeds the mean annual real house price appreciation in our sample of 2.7%. With a risk free rate of 1-2%, the required threshold is even harder to reach. Systematic risk is therefore not likely to account for the income gradient in capital gains.

The housing market beta also connects to the supply-elasticity of housing. Guren et al. (2021) argue that the responsiveness of house prices to regional (or national, in our case) house price growth is a proxy for the supply elasticity of housing: in markets where zoning restrictions, geographical barriers or high density limit new supply, demand shocks pass through into prices rather than being absorbed by quantities. Under this interpretation, beta reflects both a systematic risk component and supply constraints. Crucially, however, it is less clear that the mechanism that equalizes risk-adjusted returns for stocks applies cleanly to housing. A key difference between housing and financial assets is that housing is an indivisible, location-specific asset, so households cannot easily scale their exposure to high-growth markets. Instead, down-payment requirements, LTV limits, and affordability constraints restrict which locations are

feasible to buy in. In the next section, we show that low-income households do not have access to the same assets as high-income households, which limits their ability to buy in high-beta, supply-constrained areas. We also later show that higher-income households buy in more supply inelastic areas.

6 Determinants of location

Higher-income buyers earn systematically higher capital gains on their housing investments. This pattern is largely statistically accounted for by differences in the locations they buy in, which raises a central question for understanding capital gains inequality: why do households of different incomes locate in different areas?

Our focus is on forces specific to housing markets: financial constraints and supply limitations. Unlike standard financial assets, housing bundles investment and consumption, and the choice set is restricted by mortgage-market rules and the indivisibility of dwellings. To illustrate why these constraints matter for capital gains, we contrast housing with other financial assets. For equities, households face essentially no minimum-investment constraint. With the introduction of fractional trading, a lower-income household can purchase nearly any individual stock, albeit in a very small amount. Differences in financial portfolio returns therefore primarily reflect differences in skill, risk tolerance, or information, rather than differences in access. Owner-occupied housing is different: households cannot buy a "fraction" of a high-return neighborhood (Parkhomenko, 2025). Consistent with this, most Danish households own only one property, and investment-only housing is concentrated among the wealthiest 10%.[10] This makes financial constraints and housing supply first-order for understanding inequality in capital gains.

6.1 Conceptual Framework

Lower-income households tend to purchase properties in areas with lower capital gains. Importantly, they also tend to buy less expensive properties in less expensive areas. To understand the role of financial constraints and consumption needs in shaping this pattern, we first consider a simple theoretical framework that links housing consumption to financial constraints. The relevant object is the household's feasible choice set: the properties it can finance while meeting its minimum housing needs.

Housing provides both a flow of consumption services and a capital gain. When a household buys a home in location j, it obtains a flow of consumption services (based on size, amenities, schools, or commuting distances) and an expected capital gain.

As in most countries, buyers in Denmark must satisfy two sets of borrowing conditions. First, the LTV constraint limits the maximum mortgage loan M to a fraction θ_H of the property price

$$M \leq \theta_H P.$$

If a household uses its entire net wealth W as down payment, the LTV rule implies a maximum

[10] See Causa, Woloszko and Leite (2020).

affordable price of $P = W/(1-\theta_H)$ and hence a maximum mortgage loan $\bar{M}^{LTV} = \theta_H W/(1-\theta_H)$. Second, payment-to-income constraints restrict monthly mortgage payments relative to income

$$p(M, r, n) \leq \kappa \cdot y,$$

where $p(M, r, n)$ is the mortgage payment, which directly implies a maximum mortgage loan $\bar{M}^{PTI}$ as a function of income and contract length n. $\kappa \in (0, 1)$ is the maximum payment-to-income ratio, set to 0.35 in the empirical application. Both constraints must be satisfied simultaneously. The binding constraint is the tighter of the two, so maximum borrowing equals $M^{\max} = \min(\bar{M}^{LTV}, \bar{M}^{PTI})$, as in Bäckman and Khorunzhina (2024). The maximum purchase price is then $P^{\max} = M^{\max} + W$, which ensures both the LTV constraint ($M^{\max} \leq \theta_H P^{\max}$) and PTI constraint are satisfied.

A second feature of housing is the consumption flow, which makes indivisibility central. Households must purchase an entire dwelling that satisfies their minimum consumption requirement q. Because housing demand is empirically income-inelastic (Gaubert and Robert-Nicoud, 2025), this minimum size constraint likely binds more tightly for lower-income households. Let $P_j(q)$ denote the minimum price of a dwelling in location j that satisfies q. To reside in location j, the household must be able to afford at least $P_j(q)$, so location j is feasible only if $P_j(q) \leq P^{\max}$. The feasible set is therefore

$$\mathcal{J}(M^{\max}) = \{\, j : P_j(q) \leq P^{\max} \,\}.$$

Some areas drop out of the choice set altogether when even the least expensive dwelling that meets a household's housing needs is unaffordable.

This structure yields two predictions. First, conditioning on income, the choice set shrinks once we take consumption needs into account. This constraint acts by putting a minimum affordable price threshold on the set of feasible properties. To test this prediction, we document how property size affects the choice set below. Second, if borrowing constraints are the primary force keeping lower-income households out of areas with high house-price growth, loosening these constraints (higher LTV, lower PTI limits, interest-only mortgages) should raise $P^{\max}$, widen $\mathcal{J}(M^{\max})$, and allow households on the margin to enter these areas. This idea is consistent with the model in Kaplan, Mitman and Violante (2020), where changes in credit conditions affect the ability of households to afford housing. Under elastic supply, this predicts that relaxing borrowing constraints increases the share of lower-income buyers in high-growth areas by allowing marginal households to meet required purchase prices. This mechanism of borrowing constraints and location choice is documented in recent work by Gupta et al. (2025), who show that down-payment constraints distort location choices in the U.S.

When housing supply is inelastic, it is unclear whether lower-income buyers can outbid higher-income buyers for the limited number of homes available in areas with high house-price growth. Greenwald and Guren (2025) show that when the number of homes available to owner-occupiers is limited, easier credit tends to show up more in prices than in higher homeownership. In such markets, additional demand from lower-income households is likely to be capitalized into prices.

This alternative mechanism delivers the opposite prediction from above: credit expansions raise prices in areas with high house price growth but leave the income composition essentially unchanged. We test this implication by examining whether credit expansions shift prices, the income composition of buyers, or both.

6.2 The feasible set and financial constraints

We construct a simple proxy for each household's feasible choice set.[11] We use a 25% random sample of transactions, and for each buyer we define the set of potential options as all homes sold in the same year as the buyer's purchase within this transaction sample. A property is considered to be within the feasible set if its transaction price is at or below the buyer's maximum purchase price, $P^{\max} = M^{\max} + W$, where $M^{\max}$ is maximum borrowing and W is available wealth measured in the year prior to purchase. We determine the maximum borrowing capacity according to either LTV or PTI constraint. For maximum borrowing according to the LTV constraint, we calculate total assets available for the downpayment in the year prior to purchase as total liquid assets (stocks, bonds, bank deposits, and a small residual asset category) plus any housing equity.[12] We assume a 20% down payment, implying an 80% LTV mortgage, even though borrowers can in principle supplement financing with bank debt up to an effective 95% LTV. Allowing such higher leverage would expand choice sets and make the LTV constraint bind less often relative to the PTI constraint, particularly for lower-income buyers with limited liquid wealth.

For the PTI limit, we assume that households can spend at most 35% of their monthly income on mortgage payments. There is no legal guidance on maximum PTI limits in Danish law, so we test robustness to alternative thresholds and find similar results. We use income measured one year prior to purchase to compute the maximum monthly payment buyers can afford, and then use a 30-year annuity schedule (at the relevant mortgage interest rate) to translate this payment limit into an implied maximum loan size. As a robustness check, we also construct a measure based on the actual purchase price paid by the household (Appendix Table B5). This measure represents a conservative lower bound for what buyers can afford, and captures revealed feasibility based on observed purchases. For example, a buyer may have low wealth on their balance sheet, but their parents may be able to contribute toward the down payment. Although the two measures are similar, the model-implied borrowing capacity maps more directly into the conceptual framework and the later credit reforms.

Figure 9 shows the share of affordable transactions (based on maximum borrowing) by income rank.[13] Several patterns stand out. First, the slope of the choice set with respect to income is

[11] See also Soerlie Kvaerner, Pavanini and Peng (2023) for a similar approach.

[12] Both housing value and mortgage debt value in the income data are noisy measures that may deviate from market values. Housing wealth in the income tax data are based on a tax assessment, which we adjust by a scaling factor to account for differences between tax values and market values for housing. A similar procedure is used in e.g. Andersen, Johannesen, Jørgensen and Peydró (2023) and Bäckman and Khorunzhina (2024). In case the calculated home equity value is negative, we set it to zero. The gradients by income rank are similar if we use only total assets instead, or only liquid assets, although the level differs.

[13] Appendix Table B4 reports regression estimates for different samples. The constant gives the share of properties affordable to the lowest income rank, while the coefficient on income rank captures how quickly the choice set expands with income. Results are robust to alternative affordability definitions.

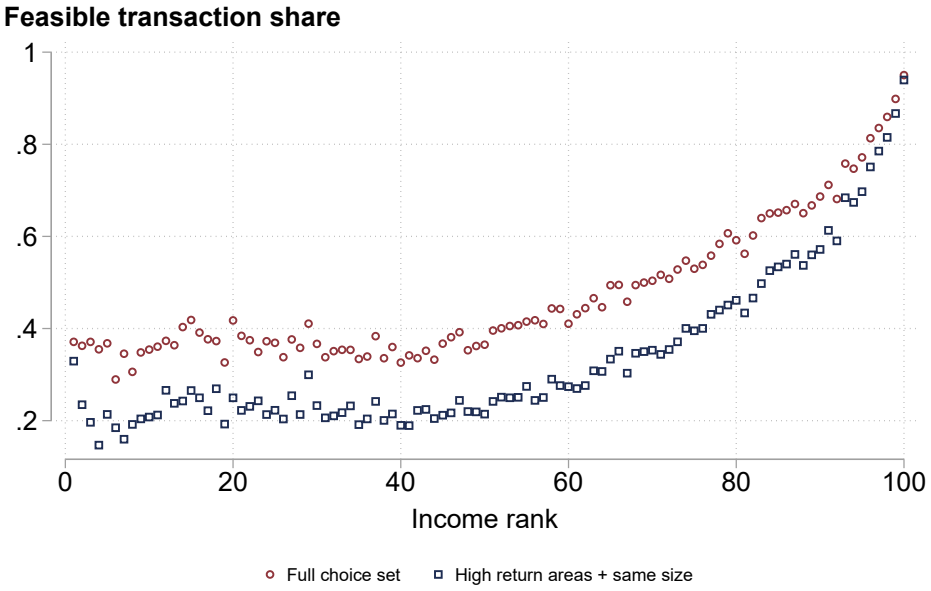
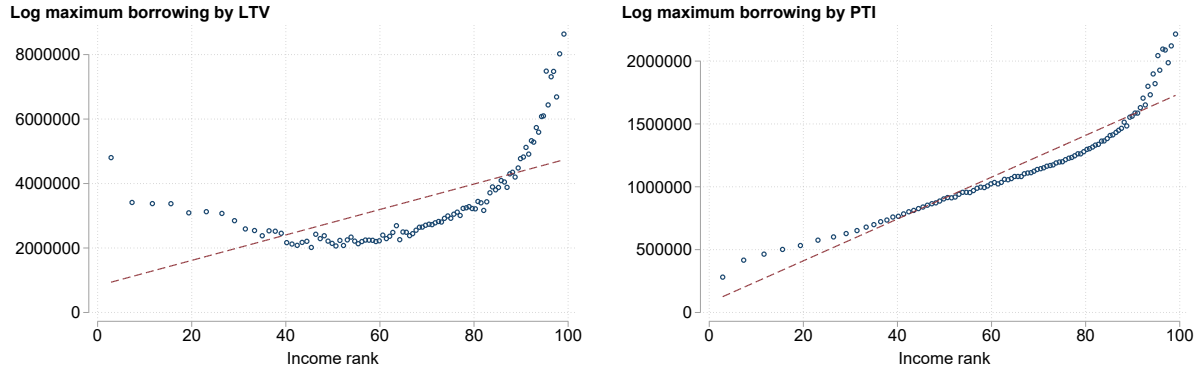


Figure 9: Choice set over income rank

Notes: The figure plots income rank and choice set for each buyer. We first compute each buyer's maximum borrowing $M^{\max}$ as the minimum of the LTV- and PTI-implied loan ceilings, then add available wealth to obtain maximum purchase price $P^{\max}$. The choice set denotes the share of transactions with prices at or below $P^{\max}$. The orange dots use all transactions within the choice set, and the blue dots restrict the choice set to high house price growth areas where the property size is within 10% of the chosen size. High house price growth areas are defined as municipalities in the top quintile of the average returns. The results are based on a 25% sample of all transactions for computational feasibility.

similar for both the full choice set and for high-growth areas with a fixed house size: higher-income households face a systematically larger set of potential purchases. In this graph we use all other transactions in Denmark during the same year, but the results are almost identical if we only use transactions within the same region. Appendix Table B4 also shows that the slope is similar across other subsets of the choice set. Second, conditioning on high-growth areas holding dwelling size fixed, the choice set is considerably smaller for all income groups. This pattern reflects the higher purchase price in high-growth areas. Together, these findings suggest that consumption needs limit access to the locations where buyers can benefit from high house price growth.

To assess the empirical relevance of the constraints in the conceptual framework, we examine which financial constraint binds in determining maximum borrowing. When households face two financial constraints, the tighter constraint determines their borrowing capacity. Appendix Figure A4 plots the binding constraints by income rank. Across the income distribution, the share of households for whom the LTV constraint binds is U-shaped, with relatively few buyers constrained at both the bottom and the top of the distribution; this pattern is stable over time and appears in both high- and low-return municipalities. On average, slightly above 50% of borrowers are bound by the PTI limit. Figure 10(a) shows that the maximum borrowing according to the LTV constraint is relatively similar between high- and lower-income buyers. Instead, the main difference in maximum borrowing comes from the PTI constraint, shown in panel (b), where higher-income buyers have a considerable advantage. Relatedly, Rhode Nissen,



(a) LTV

(b) PTI

Figure 10: Maximum borrowing for different financial constraints

Notes: The figure plots maximum borrowing according to the LTV (panel a) and PTI constraint (panel b). The sample consists of buyers with repeat sales transactions. All numbers in Danish kroner (DKK). For maximum borrowing according to the LTV constraint, we measure total assets in the year prior to purchase and assume that the borrower uses a down-payment of 20%. For the PTI limit, we assume that households can spend maximum 35% of their monthly income on mortgage payments. We use the annual mortgage rate and calculate the monthly mortgage payment using an annuity schedule.

Tang-Andersen Martinello, Hviid and Sinding Bentzen (2022) find that LTV restrictions disproportionately affect younger and less wealthy households, while limits based on debt-to-income and debt-service-to-income ratios primarily affect buyers in the largest cities and lower-income buyers.

The choice-set calculations are by construction partial-equilibrium: they evaluate affordability at current prices. Figure 9 shows that buyers in the 40th percentile have a feasible set covering around 20% of properties in high-growth areas in the same size category. In equilibrium, prices in these supply-constrained, high-growth areas would not remain fixed if marginal buyers suddenly received more borrowing capacity. Because high-income buyers have higher ability-to-pay, they would bid up scarce homes as prices rose. In that case, the allocation of properties across income groups would remain unchanged, but transaction prices would increase. Our empirical test below exploits variation in credit conditions to examine this mechanism: whether relaxing borrowing capacity alters who buys in high-growth areas or mainly raises prices paid by the winning bidders.

6.3 Loosening financial constraints and location choice

We now ask whether mortgage reforms that change borrowing constraints alter the income composition of buyers in high-growth areas. In Denmark, several major mortgage-market reforms directly altered PTI and LTV constraints. Specifically, we study the introduction of interest-only mortgages in 2003 and the credit-assessment guidance in 2016 that tightened mortgage credit rules in the high-growth municipalities of Copenhagen and Aarhus. The empirical analysis below tests whether these policy changes shifted the share of lower-income buyers in these municipalities. We show that the share of lower-income buyers remains remarkably stable across all reforms.

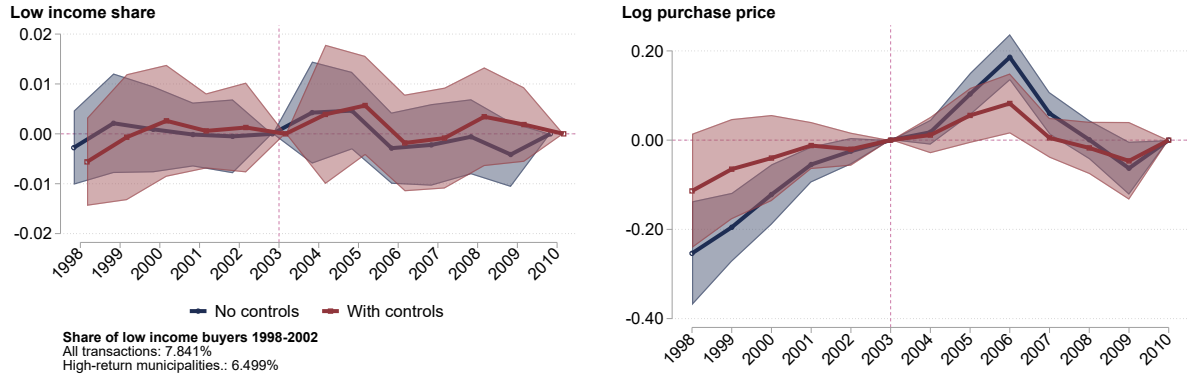
Introduction of interest-only mortgages in 2003. This reform loosened PTI constraints (Bäckman and Lutz, 2020), but, consistent with the inelastic-supply mechanism, had little impact on the ability of lower-income households to buy in areas with high house-price growth. We show this formally by estimating the following regression for buyer i in municipality m in year t:

$$Y_{imt} = \alpha_m + \gamma_t + \sum_{k=1998,\, k\neq 2003}^{2010} \beta_k (HighGrowth_m \times \mathbf{1}_{t=k}) + X_{it}\Gamma + \epsilon_{imt}, \tag{3}$$

where the dependent variable Y_{imt} is either the log purchase price or a binary variable equal to one if the buyer income rank is in the lower third of the income distribution, and $HighGrowth_m$ is a dummy equal to one if the municipality was in the upper quintile of average house price growth between 1997 and 2002. The results are unchanged if we define high-growth municipalities over the entire sample period. We also include control variables X_{it}, along with municipality and year fixed effects α_m and γ_t, respectively. We include controls for floor number, number of rooms, square meter size of the property, an apartment indicator, and building age, as well as controls for age, wealth rank, gender, education, and family size. We cluster standard errors at the municipality level. The sample includes all transactions to increase statistical power.

Figure 11(a) shows that there is no detectable change in the share of lower-income buyers around the 2003 reform. A similar finding is reported in Bäckman and Lutz (2020) for homeownership rates. These results are even more striking once we consider that the reform affects the payment-to-income constraint, which is often the binding constraint for lower-income buyers. In addition, uptake was broad: interest-only mortgages were used in more than 60% of purchases across the income distribution (Bäckman and Lutz, 2020). The share of interest-only mortgages is also considerably higher in areas with high price levels (Bäckman and Lutz, 2025). Instead, Figure 11(b) shows that house prices rise with the 2003 reform. This result aligns with the findings in Bäckman and Lutz (2025) and is consistent with the mechanism in Greenwald and Guren (2025) in which credit expansions are primarily reflected in prices when supply is tight. We discuss how to interpret these estimates in the next section, where we also provide evidence on the supply-side mechanism.

Credit-assessment guidance in growth areas. In February 2016 the Danish Financial Supervisory Authority (FSA) issued credit-assessment guidance (*Vejledning om forsigtighed i kreditvurderingen ved belåning af boliger i vækstområder*) that applied to Copenhagen and its surrounding municipalities, as well as Aarhus, Denmark's second-largest city. The guidance was motivated by rapidly rising house prices in these municipalities, combined with historically low interest rates, which raised concerns about excessive credit risk among financially vulnerable borrowers. The FSA instructed banks and mortgage institutions to apply stricter credit assessments when financing owner-occupied housing in these "growth areas," including the use of stressed interest rates, more conservative evaluations of borrowers' disposable income, and explicit consideration of the risk of price declines. Although the guidance formally applied to all borrowers in growth areas, the FSA emphasized that it would bind primarily for "economically sensitive" households—those with low or negative net wealth, high debt ratios, or thin liquidity



(a) Share of lower-income buyers

(b) Log house prices

Figure 11: Introduction of Interest-only mortgages and housing market outcomes for municipalities with high house price growth

Notes: The figure plots the coefficients on β_k estimating Equation (3). The outcome variable in panel a) is a dummy equal to one if the buyer is in the lower third of the income distribution. The outcome variable in panel b) is log transaction prices. The omitted year is 2003. The data are at the transaction level. High-return municipalities are defined as municipalities in the top quintile of average house price growth between 1997 and 2002. Both specifications include municipality and year fixed effects. "No controls" includes only the fixed effects. "With controls" adds property controls (floor number, rooms, square meters, apartment indicator, building age) and buyer controls (wealth rank, gender, education, family size). We cluster standard errors at the municipality level. 95% confidence intervals are shown.

buffers.[14]

The 2016 guidance represents a geographically targeted tightening of effective payment constraints. In the language of our conceptual framework, borrowers purchasing in treated municipalities faced a stricter PTI requirement through mandatory interest-rate stress tests and more conservative assessments of disposable income. Because our maximum-borrowing decomposition in Section 6 shows that lower-income households are predominantly PTI-limited, the guidance should reduce their ability to purchase in treated municipalities. These municipalities also experienced high house-price growth. In our partial-equilibrium choice-set framework, holding prices fixed, the guidance implies a decline in the share of lower-income buyers in these locations following its introduction.

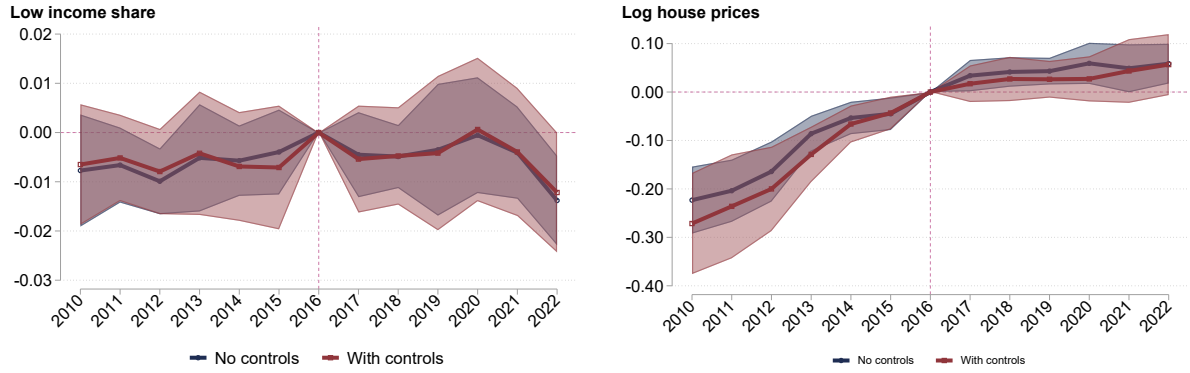
We test this prediction using the following event-study specification for buyer i in municipality m in year t:

$$Y_{imt} = \alpha_m + \gamma_t + \sum_{k=2010,\, k\neq 2016}^{2022} \beta_k (Treated_m \times \mathbf{1}_{t=k}) + X_{it}\Gamma + \epsilon_{imt}, \tag{4}$$

where the dependent variable is a dummy equal to one if the buyer is in the lower third of the income distribution or the log transaction price, and $Treated_m$ is a dummy equal to one if the buyer purchases in municipalities covered by the 2016 guidance. The rest of the specification and the control variables are the same as in Equation (3). We cluster standard errors at the municipality level.

Figure 12 shows that the income composition of buyers remains stable before and after 2016.

[14] See FSA, Vejledning om kreditvurdering ved belåning af boliger i vækstområder, 1 February 2016.



(a) Share of lower-income buyers

(b) Log house prices

Figure 12: Growth guidance and housing market outcomes

Notes: The figure plots the coefficients on β_k estimating Equation (4). The outcome variable in panel a) is a dummy equal to one if the buyer is in the lower third of the income distribution. The outcome variable in panel b) is the log transaction price. The omitted year is 2016. The data are at the transaction level. Both specifications include municipality and year fixed effects. "No controls" includes only the fixed effects. "With controls" adds property controls (floor number, rooms, square meters, apartment indicator, building age) and buyer controls (wealth rank, gender, education, family size). Standard errors are clustered at the municipality level. 95% confidence intervals are shown.

The event-study coefficients for the share of lower-income buyers are small and statistically indistinguishable from zero, with no detectable break at the time of the policy. These findings reinforce the conclusion from the previous subsection: mortgage-market reforms that expand credit nationwide, and targeted guidance that tightens credit in specific locations, have limited effects on who buys in higher-growth locations. Instead, the 2003 interest-only reform is associated mainly with higher prices without a shift in the buyer mix toward lower-income buyers, and the 2016 guidance likewise appears to have operated primarily through prices, not buyer composition.

6.4 Why Credit Reforms Do Not Shift Buyer Composition

Taken together, the Danish mortgage-market reforms provide empirical tests of whether credit constraints limit access to higher-growth areas. If borrowing constraints were a primary barrier to lower-income households accessing these areas, then the introduction of interest-only mortgages in 2003 should have expanded the feasible set for constrained buyers and increased their presence in higher-growth municipalities. The reverse goes for the 2016 guidance: if it tightened credit constraints, it should have reduced the presence of lower-income buyers in higher-growth municipalities. Instead, we find no measurable change in the income composition of buyers in these municipalities around these large reforms.

How can we explain these results? If higher-income buyers systematically sort into municipalities with tighter supply constraints, demand shocks in those areas will be absorbed by price increases rather than new construction, generating persistent price appreciation but no change in access. Figure 13 is consistent with this mechanism: buyers in the top income quintile purchase in municipalities with significantly higher inverse housing supply elasticity than buyers in the bottom quintile. We estimate housing supply elasticities using the procedure in Guren

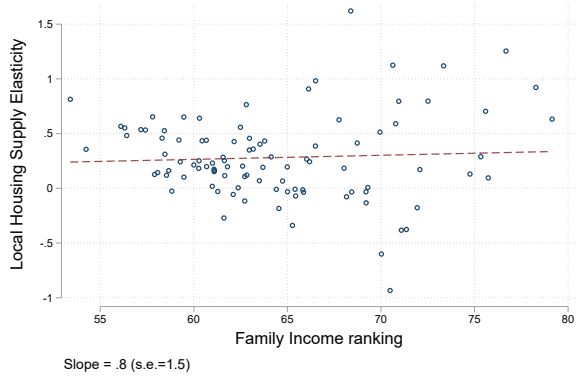


Figure 13: Inverse housing supply elasticity by income rank

Notes: The figure plots the inverse housing supply elasticity against income rank. Housing supply elasticities are estimated using the procedure in Guren et al. (2021), where we regress local house price growth on national or regional house price growth. We calculate elasticities for all municipalities and merge the elasticities based on each buyer's property location. We then average the elasticities by income rank.

et al. (2021), where we regress local house price growth on national or regional house price growth.

The results suggest that credit expansions in supply-constrained markets are largely absorbed by prices rather than by increased entry of lower-income households. Prices adjust and the buyer mix changes little. The persistent income gap in housing capital gains is therefore consistent with an equilibrium in which affordability constraints and inelastic supply sustain spatial sorting: credit constraints matter for baseline access, but loosening them primarily raises prices in higher-growth municipalities.

The spatial-sorting literature has suggested several additional frictions shaping where households choose to live. A long-standing observation in this literature is that mobility among lower-income workers is generally lower than expected (for recent evidence, see Sprung-Keyser, Hendren, Porter et al., 2022). For instance, lower-income households may have a preference for living near their birthplace (Diamond, 2016), may face high search or moving costs (Bergman, Chan and Kapor, 2020), or may have local social networks that raise the cost of moving (Koenen and Johnston, 2025). Unlike financial assets, which are easy to evaluate and trade at a distance, housing search typically requires physical visits, local knowledge, and familiarity with neighborhoods. Badarinza et al. (2024) show that buyers' consideration sets are highly local: most online search activity falls within a 10-mile (16 km) radius. Commuting costs provide another friction that ties households to particular labor markets. Workers must balance housing costs against commuting time and expense, and the optimal location depends on job location and wage. High-return areas in Denmark are concentrated around Copenhagen and Aarhus, so workers employed outside these labor markets face a trade-off: relocating requires either changing jobs or accepting a costly commute. These frictions are relevant in our setting and may help explain why some households do not sort into higher-growth areas.

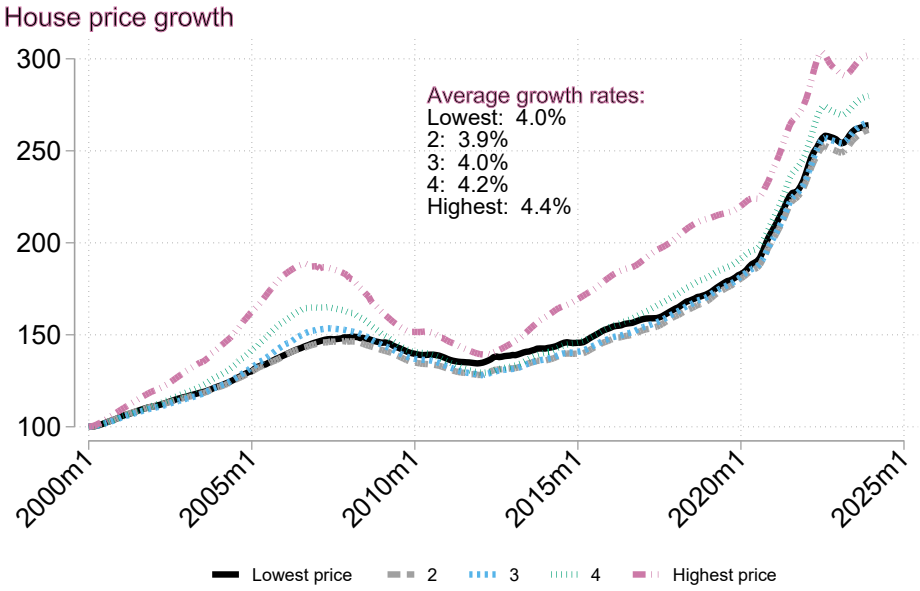


Figure 14: House price growth by price level in the United States

Notes: The figure plots indexed house prices over time on the y-axis for five groups using data from Zillow from 2000m1 to 2025m2. The x-axis shows the month and year. We divide all US zip-codes into groups based on the price levels in 2000. Average growth rates are calculated as the year-over-year log difference in monthly house prices for each group.

7 External validity

The mechanisms that we highlight are not unique to Denmark. Our findings speak to general equilibrium forces that arise whenever housing markets combine (i) persistent spatial heterogeneity in economic growth, (ii) borrowing constraints, and (iii) limited supply adjustment. We now discuss how the key parts of the results generalize to other settings.

A central feature of housing markets is that housing differs fundamentally from standard financial assets: it is indivisible, location-specific, and simultaneously provides consumption and investment value. As a result, households cannot easily arbitrage capital gains across space. Even among households with similar risk preferences and information, feasible choice sets can differ with income, wealth, and borrowing capacity. These factors are common to owner-occupied housing markets in most advanced economies, including the United States, the United Kingdom, and much of continental Europe. Higher-income households earn higher realized capital gains largely by sorting into locations with persistently higher house-price growth, and such persistent differences in local house-price growth are not unique to Denmark. A large literature documents long-run heterogeneity in house-price growth across cities and neighborhoods, often linked to differences in population growth, income growth, and local productivity (Gyourko et al., 2013; Lyons, Shertzer, Gray and Agorastos, 2026; Amaral et al., 2025b). In particular, higher house-price growth in high-price areas is also present in other countries such as the United States. To illustrate this, Figure 14 plots house-price indices over time for different price groups in the United States using data from Zillow. We rank zip codes by house prices in 2000 and form groups based on this ranking. Zip codes with the highest price *levels* in 2000

also experienced the highest house price growth over the subsequent 25 years. This pattern is consistent with persistent spatial sorting in appreciation.

Denmark provides a useful setting for studying the role of credit constraints because it underwent large mortgage-market reforms during our sample period. We show that substantial expansions and contractions in effective borrowing capacity had little effect on the income composition of buyers across high- and low-growth locations, while prices responded strongly. This pattern is consistent with equilibrium models in which housing supply is inelastic and credit shocks are capitalized into prices rather than expanding access to higher-growth locations for lower-income buyers. Similar products to Danish interest-only mortgages are or have been present in the United States, Sweden, the Netherlands, and elsewhere (Scanlon, Lunde and Whitehead, 2008). In markets where supply is constrained by geography, regulation, or political economy, changes in credit conditions are unlikely to overturn existing sorting patterns. Instead, households with greater purchasing power continue to outbid lower-income buyers. The same logic applies in high-demand urban housing markets.

At the same time, our results are not intended to apply universally. These mechanisms are likely weaker in environments where housing supply is highly elastic, where owner-occupation is lower (such as Germany), or where access to housing is heavily mediated through non-market allocation (e.g., large-scale social housing systems). Countries with high recurring property taxes or substantial capital gains taxation on owner-occupied housing may exhibit different incentives and return patterns.

8 Conclusion

We document substantial differences in housing capital gains across the income distribution. We show that the income–capital-gains relationship is largely accounted for by location. Differences in risk-exposure have little explanatory power, whereas municipality-level gains are closely related to income and population growth. We investigate how financial constraints and preferences shape location choice and, through this sorting, generate differences in realized capital gains. Our results emphasize that where households buy is central for understanding inequality in housing capital gains. In addition, we highlight that the dual role of housing as both a consumption good and an investment shapes capital gains on the largest asset held by most households. Because housing is indivisible and subject to borrowing constraints and local supply frictions, the determinants of housing capital gains differ from those governing financial assets.

Our findings are descriptive and not intended to be interpreted as causal. Location fixed effects capture both selection (e.g., information advantages, preferences) and constraints (e.g., credit limits, supply restrictions). Our credit reform evidence shows limited changes in the income composition of buyers across areas with high and low house-price growth around policy shifts. This pattern is consistent with equilibrium forces, like inelastic supply and competition, but we do not pin down a single mechanism. Our contribution is to document robust patterns in how housing shapes wealth inequality and to test specific hypotheses about the channels

involved. Moreover, we do not attempt to disentangle the two-way relationship between location choice and capital gains. We document in Appendix E1 that municipalities with higher income and population growth experience higher house-price growth. If spatial sorting is driven by other factors, such as homophily, social networks, or preferences for local amenities, then the observed relationship between income and housing capital gains may reflect both the direct effect of location on capital gains and selection into locations with different income-growth trajectories. In particular, if higher-income households sort into areas that also experience faster income growth (as documented for college-educated workers in the United States since the 1980s and in Appendix E1), then spatial sorting contributes to both income inequality and wealth inequality through multiple channels. A complementary channel operates through human capital: households in higher house-price growth locations may also earn higher returns to education and labor-market investments, a channel we do not measure. Better schools and educational opportunities are capitalized into house prices (Black, 1999). If households in higher-growth locations also benefit from superior human capital investments, through better schools, peer effects, or access to high-skill employment networks, then spatial sorting generates wealth inequality not only through differential housing capital gains but also through differential human-capital returns (Ioannides and Ngai, 2025). Importantly, however, this mechanism would have to involve growing *divergence* in school quality over time in order to generate differential capital gains.

Our analysis has a number of limitations that suggest a way forward for future research. We document differences in realized capital gains rather than differences in expected returns. We also focus on capital gains rather than total returns. Including net rental yields in future research would be a natural extension. In our data, net rental yields are unobserved and may be higher in areas with low house-price growth (Amaral et al., 2025b), which could potentially offset some of the capital-gain gap we document.

An important question is whether the patterns we document are a systematic feature of housing markets or a consequence of idiosyncratic factors over the last three decades. With noisy asset returns, a long time series is needed to estimate expected returns from realized outcomes (Merton, 1980), so we interpret our estimates as realized capital gains over this sample period rather than long-run expected returns. We document that income and population growth are primary drivers of capital gains. These trends tend to be persistent over time (Chodorow-Reich et al., 2024). As long as these trends continue, our results suggest that spatial sorting and shifts in economic activity between locations will continue to contribute to both income and wealth inequality.

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INTERNET APPENDIX
FOR ONLINE PUBLICATION

Appendix: Figures

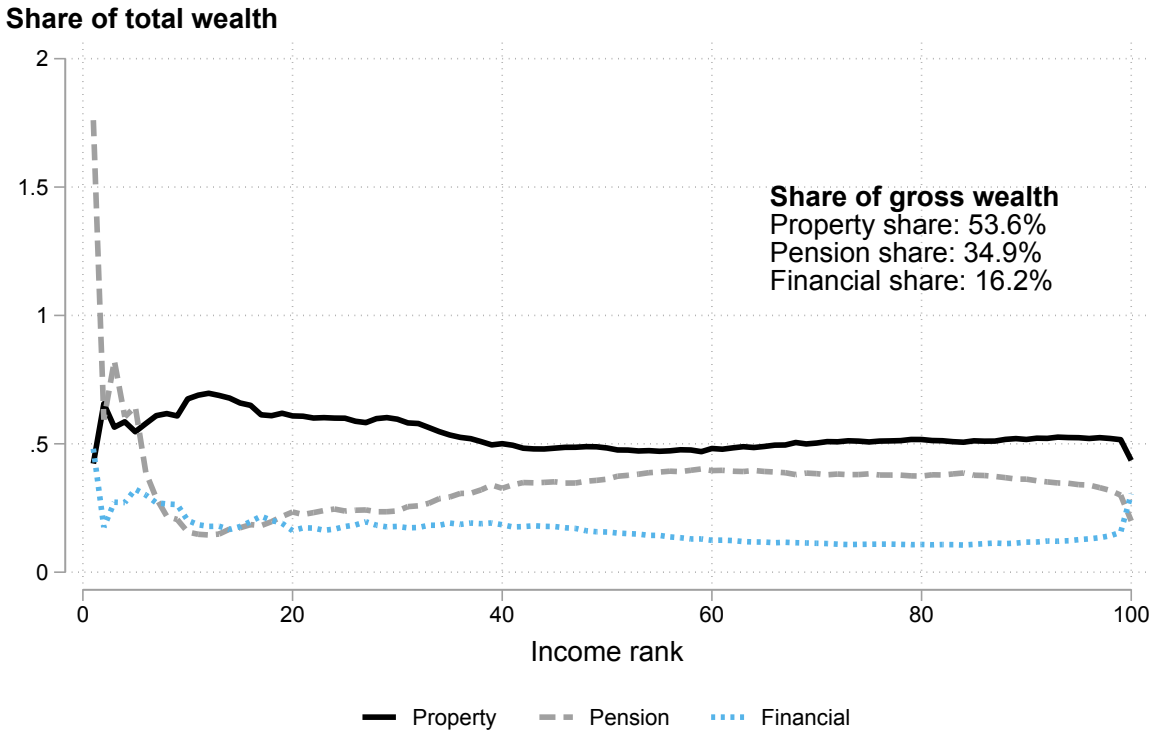


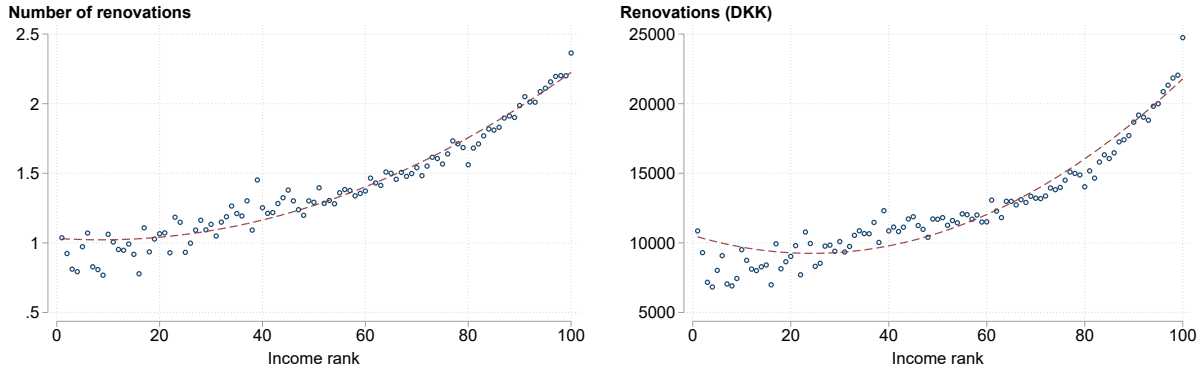
Figure A1: Asset allocation by income rank

Notes: The figure plots the share of wealth invested in different assets by income rank in 2014. The black solid line plots the share of wealth in housing, the dashed gray line plots the share of wealth in pension wealth, and the dotted line plots the share of wealth in financial wealth. Total assets is the sum of property, pension, and financial wealth. Financial wealth is the sum of stocks, bonds, bank deposits, and a small residual asset category.



Figure A2: Average and standard deviation house price growth for Danish municipalities

Notes: The figure plots average house price growth against the standard deviation of house price growth on the municipality level for 98 municipalities. Municipality-level housing returns are calculated as the average year-over-year log difference in square meter prices on the quarterly level. Data are collected from Finance Denmark.



(a) Renovation Usage and Income Rank

(b) Renovation Amount and Income Rank

Figure A3: Renovations and Income Rank

Notes: These figures plot renovation usage in panel a) and renovation amount in panel b), both plotted against income rank. Income rankings are adjusted for age and are described in Section 3. Renovations are calculated using data on a tax break for home improvements, available from 2011. We use the sum and count of tax breaks utilized by each buyer between purchase and sale dates. Since the tax break is available only since 2011, the sample is limited to properties where the sale occurred after 2011.

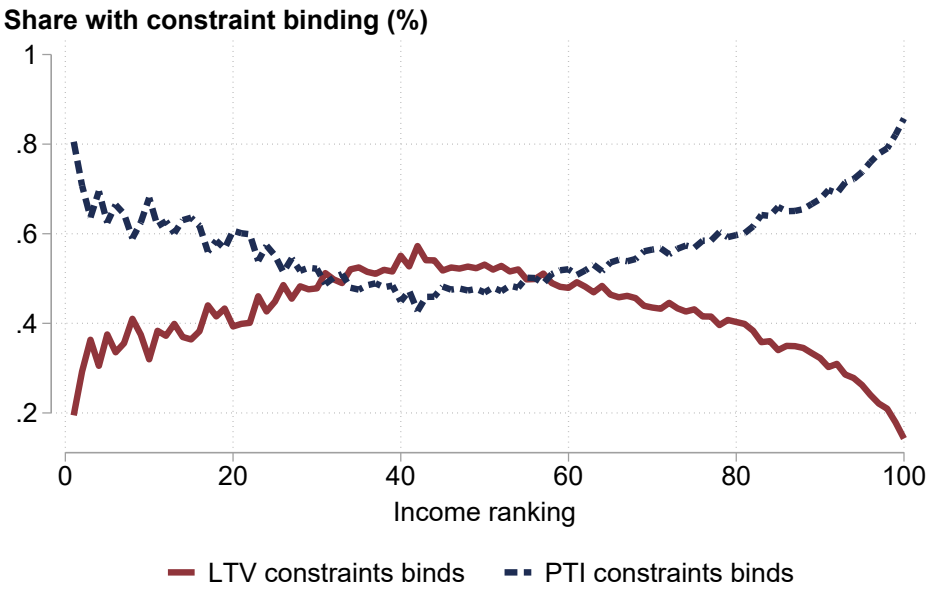


Figure A4: Binding constraints by income rank

Notes: The figure plots the binding constraint, either LTV or PTI, by income rank. We take the minimum of the borrowing amount according to each constraint as the binding constraint. The sample consists of buyers with repeat-sales transactions. For maximum borrowing according to the LTV constraint, we measure total assets in the year prior to purchase and assume that the borrower uses a down-payment of 20%. For the PTI limit, we assume that households can spend maximum 35% of their monthly income on mortgage payments. We use the annual mortgage rate and calculate the monthly mortgage payment using an annuity schedule.

Appendix: Tables

Table B1: Descriptive statistics for single and repeat sales

	(1) All transactions	(2) Repeat transactions	(3) Single transactions
Income rank	69	68	70
Repeat sale	0.27	1.00	0.00
Purchase price	1,352,102	1,375,237	1,343,553
Purchase year	2010	2006	2012
Apartment	0.19	0.26	0.16
Floor number	2	2	1
Rooms	4	4	4
Building m^2	217	247	205
Size m^2	113	104	116
Building age	54	52	55
Capital	0.22	0.25	0.21
City	0.11	0.11	0.11
Countryside	0.21	0.20	0.21
Province	0.19	0.18	0.19
Rural	0.28	0.26	0.29
Share of all transactions		0.270	0.730
N	1,008,813	272,205	736,608

Notes: The table compares descriptive statistics for repeat and single sales. *Repeat sale* is an indicator for whether a property appears at twice in the transaction data during the sample period (1996–2022). *Income rank* is the buyer's percentile rank, measured in the year prior to purchase. We measure income as total income that includes labor income, transfers, and capital income, and use average income within the household to account for differences in household composition. For each year, we construct the income distribution using the full population of Danish households and compute within–age-cohort income ranks. To reduce transitory income fluctuations, we base ranks on a three-year average of household income in $t-1$, t and $t+1$. *Purchase year* is the year of purchase. *Purchase price* is reported in Danish kroner (DKK). *Apartment* is an indicator equal to one for apartment properties and zero for single-family houses. *Rooms* is the number of rooms in the property. *Floor number* is the floor number of the property. *Building* m^2 is the total footprint of the building, and *Size* m^2 is the dwelling's living area. *Building age* is measured in years at the time of purchase. *Capital*, *City*, *Province*, *Countryside*, and *Rural* are mutually exclusive municipality-type classifications defined by Statistics Denmark. *Share of all transactions* reports the fraction of the full sample accounted for by each column.

Table B2: Income-rank gradient in housing capital gains across specifications

	(1) Baseline	(2) Property	(3) Buyers	(4) Timing	(5) Mun.	(6) Post.	(7) Timing x Mun.	(8) Timing x Post.
Income rank	0.017***	0.017***	0.013***	0.011***	0.005***	0.003***	0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Apartment		0.232***	-0.038	-0.281***	-0.776***	-1.032***	-1.166***	-1.431***
		(0.062)	(0.062)	(0.054)	(0.063)	(0.065)	(0.054)	(0.058)
Floor number		0.252***	0.265***	0.294***	0.019	0.002	0.022*	-0.002
		(0.015)	(0.015)	(0.013)	(0.017)	(0.018)	(0.013)	(0.015)
Rooms		0.117***	0.147***	0.135***	0.099***	0.084***	0.076***	0.079***
		(0.024)	(0.024)	(0.022)	(0.024)	(0.024)	(0.022)	(0.022)
Size m^2		-0.017***	-0.012***	-0.010***	-0.006***	-0.005***	-0.005***	-0.004***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Building age		0.013***	0.011***	0.010***	0.010***	0.010***	0.009***	0.009***
		(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Age			-0.045***	-0.029***	-0.031***	-0.030***	-0.019***	-0.018***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of buyers			-1.916***	-1.745***	-2.284***	-2.346***	-2.048***	-2.040***
			(0.045)	(0.041)	(0.046)	(0.046)	(0.041)	(0.042)
Wealth rank			-0.009***	-0.000	-0.014***	-0.015***	-0.002***	-0.003***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female			-0.502***	-0.442***	-0.675***	-0.705***	-0.598***	-0.611***
			(0.053)	(0.047)	(0.053)	(0.053)	(0.045)	(0.045)
Education			0.025***	0.079***	-0.033***	-0.053***	0.022***	-0.009
			(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)
Family size			-0.043**	-0.009	-0.038**	-0.036*	-0.011	-0.014
			(0.019)	(0.017)	(0.019)	(0.019)	(0.017)	(0.017)
Adjusted R-squared	0.002	0.020	0.035	0.229	0.050	0.056	0.308	0.391
Observations	217,926	217,926	217,926	217,926	217,926	217,926	217,851	214,745

Notes: This table presents the regression results that relate housing capital gains and income rank. The outcome variable is the annualized log housing capital gains. *Property* includes controls for floor number, number of rooms, square meter size of the property, an apartment indicator, and building age. *Buyers* include controls for age, wealth rank, gender, education, and family size. For buyer pairs, we calculate the maximum age and education level. *Timing* adds fixed effects for year of purchase and year of sale. *Mun.* adds fixed effects for municipality. *Post.* adds fixed effects for postcodes, leaving out municipality. *Timing* × *Mun.* includes purchase-year × municipality and sale-year × municipality fixed effects. *Timing* × *Post.* includes purchase-year × postcode and sale-year × postcode fixed effects. Standard errors in parentheses, clustered at the municipality level. *** p¡0.01, ** p¡0.05, * p¡0.10.

Table B3: Housing capital gains and income rank within urbanization levels

	(1) Capital area	(2) Capital & 3 major cities	(3) 10 big cities	(4) 9 big cities w/out Copenhagen
Income rank	-0.004***	-0.003***	-0.003***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Apartment	-1.356***	-1.201***	-1.331***	-1.344***
	(0.079)	(0.089)	(0.074)	(0.105)
Floor number	0.021	0.001	0.024	0.044*
	(0.016)	(0.020)	(0.016)	(0.025)
Rooms	0.048	0.037	0.069**	0.136***
	(0.033)	(0.036)	(0.030)	(0.043)
Size m^2	-0.001	-0.002*	-0.002**	-0.004***
	(0.001)	(0.001)	(0.001)	(0.002)
Building age	0.011***	0.009***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.021***	-0.017***	-0.021***	-0.023***
	(0.002)	(0.002)	(0.002)	(0.003)
Number of buyers	-1.493***	-1.415***	-1.560***	-1.858***
	(0.055)	(0.062)	(0.053)	(0.080)
Wealth rank	-0.005***	-0.005***	-0.005***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Female	-0.443***	-0.525***	-0.478***	-0.501***
	(0.055)	(0.063)	(0.054)	(0.086)
Education	-0.061***	-0.048***	-0.045***	-0.026**
	(0.009)	(0.010)	(0.008)	(0.013)
Family size	0.023	0.045*	0.010	-0.025
	(0.023)	(0.025)	(0.022)	(0.032)
Adjusted R-squared	0.439	0.472	0.423	0.347
Observations	86,544	68,849	98,490	47,761

Notes: This table presents the regression results that relate annualized log housing capital gains and income rank for various urban classifications. All regressions control for property characteristics, buyer characteristics, year-of-purchase, year-of-sale and postcode fixed effects. Major cities are Copenhagen, Aarhus, Odense, Aalborg, and big cities add Esbjerg, Randers, Horsens, Kolding, Vejle and Roskilde to the major cities. Standard errors in parentheses, clustered at the municipality level. *** p¡0.01, ** p¡0.05, * p¡0.10.

Table B4: Choice set and income rank using maximum borrowing

	All areas				High return areas			
	(1) All	(2) Same size	(3) Same rooms	(4) Same type	(5) All	(6) Same size	(7) Same rooms	(8) Same type
Income rank	0.0055***	0.0052***	0.0052***	0.0053***	0.0061***	0.0065***	0.0064***	0.0069***
	(0.000001)	(0.000003)	(0.000003)	(0.000002)	(0.000002)	(0.000006)	(0.000005)	(0.000003)
Constant	0.1946***	0.2039***	0.2067***	0.1993***	0.1002***	0.0265***	0.0590***	0.0128***
	(0.000092)	(0.000245)	(0.000204)	(0.000125)	(0.000154)	(0.000405)	(0.000334)	(0.000218)
Adjusted R-squared	0.081	0.068	0.072	0.073	0.099	0.116	0.114	0.131
Observations	202,988,178	29,627,938	41,390,052	114,477,330	69,077,446	8,810,759	13,261,837	30,609,688

Notes: The table provides results when we regress the choice set on income rank for each buyer. Choice set is defined using maximum borrowing plus any equity for each buyer pair and denotes the share of transactions for each buyer that is below their maximum purchase price. We set the PTI constraint to 35% and the LTV constraint to 20%. The results are based on a 25% sample of all transactions for computational feasibility. Columns 1-4 use all transactions within the choice set, and columns 5-8 restrict the choice set to high house price growth areas. High house price growth areas are defined as municipalities in the top quintile of average house price growth. Same size is defined as the size of the purchased property, plus or minus 10%, same rooms is defined as having the same number of rooms as the chosen property, and same type is defined as the same type (apartment or house). Standard errors in parentheses, clustered at the municipality level. *** p¡0.01, ** p¡0.05, * p¡0.10.

Table B5: Choice set and income rank using transaction prices

	All areas				High return areas			
	(1) All	(2) Same size	(3) Same rooms	(4) Same type	(5) All	(6) Same size	(7) Same rooms	(8) Same type
Income rank	0.0027***	0.0030***	0.0028***	0.0032***	0.0028***	0.0025***	0.0026***	0.0026***
	(0.000001)	(0.000004)	(0.000003)	(0.000002)	(0.000002)	(0.000006)	(0.000005)	(0.000003)
Constant	0.3233***	0.3059***	0.3183***	0.2936***	0.1878***	0.0808***	0.1073***	0.1260***
	(0.000095)	(0.000251)	(0.000210)	(0.000128)	(0.000152)	(0.000378)	(0.000319)	(0.000220)
Adjusted R-squared	0.019	0.023	0.021	0.026	0.022	0.023	0.024	0.023
Observations	202,988,178	29,627,938	41,390,052	114,477,330	69,077,446	8,810,759	13,261,837	30,609,688

Notes: The table provides results when we regress the choice set on income rank for each buyer. Choice set is defined using the actual purchase price for each buyer pair and denotes the share of transactions for each buyer that is below their actual purchase price. The results are based on a 25% sample of all transactions for computational feasibility. Columns 1-4 use all transactions within the choice set, and columns 5-8 restrict the choice set to high house price growth areas. High house price growth areas are defined as municipalities in the top quintile of average house price growth. Standard errors in parentheses, clustered at the municipality level. *** p¡0.01, ** p¡0.05, * p¡0.10.

Online Appendix: Data and variables

C1 Housing risk

This section describes how we calculate measures of housing risk.

C1.1 Covariance risk

In standard asset pricing models, the covariance between returns and marginal utility gives rise to risk premia. Cochrane (2009) shows that for a utility-maximizing household allocating resources between consumption and investments, the following equation holds:

$$E[\ln R_{t+1}] - \ln R_f = \gamma \operatorname{Cov}\left[\ln\left(\frac{C_{t+1}}{C_t}\right), \ln R_{t+1} - \ln R_f\right], \tag{5}$$

where R_{t+1} is the total return on the asset in the next period, R_f is the risk-free rate, γ is the risk-aversion parameter, and $\frac{C_{t+1}}{C_t}$ is consumption growth. An asset that has higher covariance with consumption growth is riskier because it cannot hedge consumption shocks, and thus commands a greater excess return.

The covariance of house price growth with marginal utility may differ across areas inhabited by rich and poor households. For example, higher-income households may face greater income risk (Braxton, Herkenhoff, Rothbaum and Schmidt, 2021), leading to a higher covariance between house prices and income growth in their residential areas. To test this hypothesis, we impute consumption using income and balance sheet data (Bäckman and Khorunzhina, 2024) and calculate the covariance between consumption growth and house price growth.[15]

C1.2 Idiosyncratic housing risk

A second source of risk in housing markets is idiosyncratic risk. In contrast to other financial assets, idiosyncratic risk is likely priced in returns. Housing is a large, indivisible, and illiquid asset; most homebuyers invest in a single property rather than a diversified housing portfolio (Piazzesi, Schneider and Tuzel, 2007). Higher house price growth for high-income buyers may stem from higher idiosyncratic risk, possibly because they live in more expensive or illiquid properties.

To test this hypothesis, we follow Giacoletti (2021) and calculate the idiosyncratic risk for each repeat-sale. Specifically, we calculate house price indices using all transactions, then use these to construct the Local Market Equivalent (LME). The LME measures the distance between each transaction and the index, thereby accounting for local developments in house prices.

Let $P_{i,p}$ and $P_{i,s}$ denote the purchase and resale prices of house i.The LME is defined as:

$$\text{LME}_i = \frac{P_{i,s}/R^{\text{Mun}}_{t,s} - P_{i,p}}{P_{i,p}}, \tag{6}$$

[15] Imputed consumption includes both durable and non-durable goods, complicating result interpretation. To address this and enable comparison with existing literature, we also provide results using income growth.

where $R^{\text{Mun}}_{t,s}$ is the cumulative return of the municipality-level price index between t and T. Next, we regress the log-transformed LME returns, normalized by the square root of the holding period, on a set of controls:

$$\frac{\log(1+\text{LME}_i)}{\sqrt{\tau_i}} = X_i'\pi + \alpha_m + \eta_t + u_i, \tag{7}$$

where $\tau_i = T_{is} - T_{ip}$ is the holding period for house i, X_i includes the same house characteristics as in the return regressions (size, age, floors, and type), and α_m and η_t are municipality and purchase-month fixed effects, respectively. The residual u_i captures *idiosyncratic capital gain*, which by construction is orthogonal to local trends and observable features. To calculate idiosyncratic risk, we compute the standard deviation of idiosyncratic capital gain for each municipality, scaling it by τ_i to normalize for holding period differences in Equation (7), as in Amaral et al. (2025b).

C1.3 Liquidity and other measures of risk

We also compile data on other sources of risk. House price growth is also plausibly related to liquidity (Amaral et al., 2025a; Han and Strange, 2015). Our main measure of liquidity is the number of days between the *first date* a property is listed for sale and the signing of the purchase agreement. The sales time data is provided by Finance Denmark and is available at the municipality level from 2004 onward.

We also calculate the mean and standard deviation of housing returns at the municipality level from 1997 to 2019, using average prices for sold properties. The results are also robust to using publicly available house price indices, such as indices provided byFinance Denmark. Finally, we calculate measures of downside risk by counting the number of negative returns for each municipality and computing the return conditional on a negative return.

C2 Housing supply

We construct a proxy for housing supply elasticities by leveraging systematic differences in the sensitivity of local house prices to national house price variation (Guren et al., 2021). Intuitively, a larger house price response to aggregate shocks after accounting for differences in income growth indicates supply constraints.

We use national rather than regional house prices for several reasons. First, Denmark is a small, geographically compact country with only five administrative regions, making regional variation relatively coarse. Second, the Danish housing market is highly integrated: mortgage markets are national in scope, and labor market mobility across regions is facilitated by short commuting distances and well-developed infrastructure. Third, using national house prices provides a cleaner identification strategy—all municipalities are exposed to the same aggregate shock, and differences in responsiveness reflect local supply constraints rather than regional demand factors. This approach aligns with the Bartik-style logic underlying the methodology, where a common shock allows us to isolate supply-side heterogeneity from differential demand

exposure.

We estimate the sensitivity of local house prices by regressing local municipal house price growth $\Delta P_{k,t}$ on national house price growth:

$$\Delta P_{k,t} = \psi_k + \rho_k \Delta P_t^N + v_{k,t} \tag{8}$$

where $\Delta P_{k,t}$ is the annual change in municipality k's square meter house prices, ΔP_t^N is the annual change in national square meter house prices, and ρ_k is a municipality-specific coefficient. $\hat{\rho}_k$ is a proxy for the inverse housing supply elasticity in municipality k. We exclude each municipality from the sample when calculating the national house price growth.

The empirical strategy for estimating the supply elasticity resembles a difference-in-difference approach, with house price growth variation stemming from differing exposure to the boom. The key identifying assumption is that local house prices respond to aggregate shocks solely due to variations in supply constraints. However, different areas may have varying industry structures or, more generally, differential exposure to the business cycle, leading to varying levels of house price growth. To account for this, we include controls for local income growth and national income growth, allowing for municipality-specific coefficients:

$$\Delta P_{k,t} = \psi_k + \delta_k \Delta y_{k,t} + \rho_k \Delta P_t^N + \Psi_k X_{k,t} + v_{k,t} \tag{9}$$

The variation in national house price growth ΔP_t^N used to identify ρ_k is then orthogonal to changes in income, and other control variables. A higher value for ρ_k implies a greater responsiveness of house prices to national house price shocks, indicating a more supply-constrained municipality.

D1 Levered capital gains

To capture the role of leverage, we compute the annualized log capital gain on homeowner equity, defining equity invested at purchase as the household's down payment and allowing the mortgage balance to evolve according to a scheduled amortization path (abstracting from refinancing and prepayment). Let $Mortgage_{ip}$ denote the purchase-year mortgage balance (proxied by mortgage and bank debt recorded in tax data one year after the purchase year). We define equity invested at purchase as

$$Equity_{ip} \;=\; \max\big(P_{ip} - Mortgage_{ip},\, 0\big).$$

We approximate the outstanding mortgage balance at sale, $Mortgage_{is}$, using the contract amortization schedule implied by the mortgage interest rate ρ and maturity, evaluated at monthly frequency and assuming no refinancing.[16] Equity at sale is then

$$Equity_{is} \;=\; \max\big(P_{is} - Mortgage_{is},\, 0\big). \tag{10}$$

Finally, the annualized levered log capital gain is

$$r_i^{lev,\log} \;=\; \frac{\ln(Equity_{is}) - \ln(Equity_{ip})}{T_{is} - T_{ip}},$$

where $T_{is} - T_{ip}$ is the holding period in years (allowing non-integer durations given exact transaction dates). For interpretation, the corresponding annualized simple capital gain is $\exp(r_i^{lev,\log}) - 1$. We winsorize levered levered capital gains at the 1st and 99th percentile.

Table D1 reports the results, summarizing different regression specifications. The coefficient on income rank on levered capital gains is now larger at 0.023, compared to 0.017 in the baseline specification. This is consistent with the intuition that leverage magnifies capital gains. Controlling for property and buyer characteristics as well as market timing strengthens the relationship between income and housing capital gains, suggesting that unobserved differences in buyer composition and aggregate market conditions attenuate the income gradient in levered capital gains. Fixed effects for municipality reduce the magnitude of the coefficient considerably, and even more so while controlling for both market timing and location. However, the coefficient on income rank of 0.009 in the last column of Table D1 remains statistically significant, and implies a cumulative difference in levered capital gains of 7.5 percent over a 10-year holding period.[17]

[16] We observe mortgage and bank debt at the individual level but cannot link liabilities to specific properties. This introduces measurement error, particularly for households holding multiple properties. We assess robustness by restricting the levered capital gains analysis to households owning a single property.

[17] The cumulative difference is calculated as the difference in log capital gains between the 10th and 90th percentile over a 10-year holding period using the coefficient on income ranking. Over a 10-year holding period, the implied cumulative gap is $\exp\Big(\frac{H \cdot \Delta r^{\log}(\%)}{100}\Big) - 1 = \exp(0.072) - 1 \approx 7.5\%$.

Table D1: Levered housing capital-gains and income rank

	(1) Baseline	(2) Property	(3) Buyers	(4) Timing	(5) Mun.	(6) Post.	(7) Timing x Mun.	(8) Timing x Post.
Income rank	0.023***	0.029***	0.035***	0.030***	0.019***	0.016***	0.014***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Apartment		0.334*	0.419**	-0.186	-0.779***	-1.231***	-1.804***	-2.389***
		(0.190)	(0.191)	(0.168)	(0.194)	(0.199)	(0.168)	(0.181)
Floor number		0.718***	0.684***	0.758***	0.237***	0.180***	0.217***	0.131**
		(0.053)	(0.053)	(0.047)	(0.059)	(0.063)	(0.051)	(0.055)
Rooms		0.316***	0.214***	0.191***	0.157**	0.142**	0.095	0.093
		(0.066)	(0.066)	(0.060)	(0.066)	(0.066)	(0.058)	(0.061)
Size m^2		-0.037***	-0.033***	-0.027***	-0.022***	-0.021***	-0.015***	-0.014***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Building age		0.033***	0.030***	0.025***	0.024***	0.024***	0.021***	0.020***
		(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Age			-0.142***	-0.082***	-0.125***	-0.123***	-0.066***	-0.063***
			(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Number of buyers			-0.295**	-0.173	-1.098***	-1.211***	-0.902***	-1.013***
			(0.130)	(0.118)	(0.132)	(0.133)	(0.117)	(0.124)
Wealth rank			-0.040***	-0.017***	-0.050***	-0.052***	-0.017***	-0.021***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female			-0.503***	-0.458***	-0.808***	-0.871***	-0.715***	-0.768***
			(0.149)	(0.133)	(0.149)	(0.149)	(0.129)	(0.134)
Education			-0.058***	0.140***	-0.156***	-0.194***	0.044**	-0.029
			(0.022)	(0.020)	(0.022)	(0.022)	(0.019)	(0.020)
Family size			0.017	0.098**	-0.019	-0.016	0.096**	0.127**
			(0.054)	(0.049)	(0.054)	(0.054)	(0.048)	(0.050)
Adjusted R-squared	0.001	0.016	0.030	0.233	0.039	0.044	0.314	0.393
Observations	165,122	165,122	165,122	165,122	165,122	165,122	165,041	160,998

Notes: This table presents the regression results that relate levered annualized housing capital-gains and income ranking. The outcome variable is the annualized levered log housing capital gains. We calculate leverage using the household's mortgage debt one year after purchase. *Baseline* includes no control variables. *Property* includes controls for floor number, number of rooms, square meter size of the property, an apartment indicator, and building age. *Buyers* include controls for age, wealth rank, gender, education, and family size. For buyer pairs, we calculate the maximum age and education level. *Timing* adds fixed effects for year of purchase and year of sale. *Mun.* adds fixed effects for municipality. *Timing x Mun.* includes purchase-year × municipality and sale-year × municipality interaction fixed effects. *Timing x Post.* includes purchase-year × postcode and sale-year × postcode interaction fixed effects. Standard errors in parentheses, clustered at the municipality level. *** p¡0.01, ** p¡0.05, * p¡0.10.

E1 Determinants of house price growth

Our results indicate that higher-income households have larger capital gains on their housing, a result statistically explained by high-income households being located in areas with higher house price growth. This raises the question of why persistent differences in house price growth exist across locations. In spatial economic models, changes in prices across locations are derived from the present value of housing:

$$P_{m,t} = \mathbb{E}_t \sum_{j=1}^{\infty} \left(Rent_{m,t+j} \cdot \left(\frac{1}{1+r_t} \right)^j \right), \tag{11}$$

where $P_{m,t}$ is the price in location m at time t, $\sum_{j=1}^{\infty} Rent_{m,t+j}$ represents the stream of future rents, and r_t is the real interest rate. House prices are affected by changes in economic conditions, such as local income, through rents (Loewenstein and Willen, 2023). We measure changes in the determinants of housing demand using administrative data.

The existing literature suggests that supply plays a key role in understanding differences in returns across locations. To see the intuition, suppose that there is an increase in demand in certain locations, for instance, due to increased urbanization, skill-biased technological change, or some other factor. If supply is elastic, any change in demand will result in new construction and a muted response in either rents or house prices (Greenwald and Guren, 2025). Van Nieuwerburgh and Weill (2010) construct a spatial dynamic equilibrium model, demonstrating that local wage shocks combined with inelastic supply lead to higher dispersion in prices. Gyourko et al. (2013) constructs a similar model where the demand shock originates from population growth, which again interacts with housing supply.

We estimate variants of the following equation:

$$\Delta P_{kt} = \alpha + X'_{kt}\beta + \gamma_t + \gamma_r + \epsilon_{kt} \tag{12}$$

where the dependent variable is the year-over-year difference in log prices for municipality k in region r in year t. The vector X_{kt} includes measures of local economic conditions—population, disposable income, and employment—entered either in levels or as year-over-year changes, along with the housing supply elasticity and, in some specifications, interactions between income and supply. Table E1 reports results for different combinations of these variables: columns (1)–(3) use level measures, columns (4)–(7) use changes, and columns (3), (6), and (7) add income-supply interactions. Since we are interested in cross-sectional differences, we control for year fixed effects γ_t and, in certain specifications, region fixed effects γ_r. We standardize all variables to have zero mean and unit standard deviation, so each coefficient measures the change in house price growth for a one-standard-deviation increase in the variable. Standard errors are clustered at the municipality level.

Table E1 shows that house price growth is higher in areas with higher population and income levels. Areas with higher income *levels* experience higher *growth* rates in house prices. In a spatial equilibrium, as in Equation (11), a higher income level in a location would be associated

Table E1: House price growth predictors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Population	0.0606***	0.0476***	0.0483***				0.0433***
	(2.82)	(3.24)	(3.28)				(2.77)
Disposable income	-0.0189	0.0497***	0.0633***				0.0785***
	(-0.98)	(2.66)	(2.82)				(3.63)
Employment rate	0.188***	0.0318	0.0330				0.0269
	(8.10)	(1.24)	(1.29)				(1.05)
Disposable income x Supply			-0.0303				-0.0153
			(-1.20)				(-0.61)
Change in Population				0.0348	0.0767***	0.0558***	0.0533***
				(1.55)	(3.96)	(2.84)	(2.75)
Change in Disposable income				0.461***	0.181***	0.162***	0.145***
				(22.42)	(5.59)	(4.65)	(4.03)
Change in Employment rate				-0.186***	0.00829	0.0152	0.00488
				(-6.90)	(0.28)	(0.52)	(0.16)
Change in disposable income x Supply						0.00790	0.0118
						(0.25)	(0.37)
Housing supply elasticity	0.122**	-0.0291	-0.0226	0.0210	0.0396	-0.0448	0.0472
	(2.14)	(-0.81)	(-0.61)	(0.42)	(1.21)	(-1.30)	(1.29)
Year Fixed Effects	No	Yes	Yes	No	Yes	Yes	Yes
Region fixed effects	No	Yes	Yes	No	No	Yes	No
Adjusted R-squared	0.0375	0.575	0.575	0.174	0.570	0.580	0.574
Observations	2532	2532	2532	2530	2530	2530	2530

Notes: The table presents predictors of house price growth. The outcome variable is the municipality-level, annual, log difference in house prices, where we use data from Finance Denmark on average square meter prices for apartments and houses at the municipality level. We use the number of transactions for apartments and houses in each municipality as weights when calculating property prices. Transactions are available from 2004. Prior to 2004 we use the average share of apartments in 2004. Return predictors are calculated using register data for all households, which we then aggregate to the municipality level. All variables standardized to zero mean and unit standard deviation. We calculate changes as the year-over-year log difference by municipality. Housing supply elasticities are described in Appendix C2. Standard errors in parentheses, clustered at the municipality level. *** p¡0.01, ** p¡0.05, * p¡0.10.

with higher price levels but not necessarily with higher house price growth. Instead, changes in prices should derive from changes in either incomes or amenities. We can understand this result by noting that if we sort municipalities by income levels in 1996, there is a strong positive relationship between income levels and income growth. Moreover, when we regress changes in house prices on changes in income in columns 3-4, we find that changes in disposable income and working-age population predict higher house price growth. Column (7) combines both level and change measures in a single specification. Changes in disposable income and population remain the strongest predictors of house price growth, with an adjusted R-squared of 0.57, indicating that local economic conditions account for over half of the cross-sectional variation in house price growth after controlling for year fixed effects.

Several important mechanisms remain unmeasured in our analysis. First, our results document a correlation between spatial sorting and housing capital gains, but we cannot fully disentangle the two-way relationship between location choice and returns. If spatial sorting is driven by other factors—such as homophily, social networks, or preferences for local amenities like schools—then the observed relationship between income and housing returns may reflect both the direct effect of location on capital gains and the indirect effect through differential income growth. In particular, if high-income households systematically locate in areas that also experience

faster income growth (as documented for college-educated workers in the United States since the 1980s), then spatial sorting contributes to both income inequality and wealth inequality through multiple channels. While we show that municipalities with higher capital gains also feature higher income and population growth, we cannot measure the extent to which location choice itself amplifies income growth trajectories. Second, our analysis focuses on housing capital gains but does not capture differential returns to human capital accumulation. In many countries, including the United States and the United Kingdom, high-price areas often feature better schools and educational opportunities (Diamond and Gaubert, 2022). If households in high-return locations also benefit from superior human capital investments—through better schools, peer effects, or access to high-skill employment networks, then spatial sorting generates wealth inequality not only through differential housing returns but also through differential returns to human capital (Ioannides and Ngai, 2025). This mechanism represents an important propagation channel that amplifies the inequality effects we document but remains outside the scope of our analysis.