Housing Capital Gains across the Income Distribution*

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Abstract

We show that high-income buyers earn higher capital gains on housing using detailed transaction data from Denmark. Geographic location statistically accounts for nearly all the difference, with little role for aggregate market timing, property type, or other buyer characteristics. This finding is consistent with income-based sorting, whereby higher-income households systematically sort into locations with persistently higher price growth. We test whether credit conditions shape access to locations with higher house-price growth and find no detectable change in buyer composition by income rank around major credit expansions and contractions.

JEL Classifications: D31, G51, R31.
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1 Introduction

Understanding why wealth accumulates differently across households requires knowing why the returns on the assets they hold differ. 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-term wealth (Benhabib, Bisin and Zhu, 2011; De Nardi and Fella, 2017). For most households, however, the dominant asset is not a financial portfolio but owner-occupied housing (Campbell, 2006; Badarinza, Campbell and Ramadorai, 2016). Housing differs from standard assets along several dimensions: it is tied to a location, it is infrequently traded, subject to borrowing constraints, and provides consumption services (Piazzesi and Schneider, 2016; Ioannides and Ngai, 2025). These features imply that the determinants of capital gains to housing and their distribution across households may differ fundamentally from those for 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 14.5 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 most of this gradient is explained statistically by systematic sorting of higher-income households into locations with persistently higher price growth.

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 rankings 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 sale capital gains and to merge buyers to the properties they actually purchase. This setup provides two key advantages: (i) we observe realized, property-level capital gains directly rather than inferring them from indices, and (ii) we can link buyer characteristics, renovations, and location to subsequent housing outcomes. We focus on unlevered returns to cleanly separate housing market effects from differences in borrowing decisions (Amornsiripanitch, Strahan and Zhang, 2026). In addition, Denmark experienced substantial housing market volatility during our sample period. The 2008 financial crisis produced price declines of similar magnitude to those in the US and UK (Bäckman and Lutz, 2025), suggesting our findings are relevant for understanding capital gains in other developed housing markets. 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 their market timing 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). In addition, richer 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 poorer households are more likely to 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 introduce buyer and property controls, as well as fixed effects. Property characteristics and buyer attributes have little explanatory power. By contrast, adding postcode fixed effects reduces the income rank coefficient by three-quarters. Further interacting postcode with timing reduces the coefficient to essentially zero. A series of robustness checks related to renovations, leverage, unsold properties, alternative geographical definitions, alternative construction of income rankings, and holding periods supports the central conclusion that the gradient is primarily about location. Where households buy, rather than what they buy, accounts for virtually the entire capital gains differential.

Motivated by these results, we examine how financial constraints, consumption needs, and local housing supply shape access to locations with high house price growth. We show that differences in location arise from sharp disparities in households' feasible choice sets. Because housing is indivisible and subject to borrowing limits and minimum consumption requirements, low-income buyers can afford only a small share of properties—especially in high-price areas with high house price growth. Buyers in the bottom third of the income distribution could feasibly purchase about 40 percent of transactions, compared to more than 60 percent for buyers in the top third, and this gap widens substantially when conditioning on consumption needs or restricting attention to areas with high house price growth. Because these areas are also high-priced, these constraints effectively shut low-income buyers out of the locations where long-term capital gains are highest.

Although credit constraints may limit access to expensive locations (Gupta, Hansman and Mabille, 2025), we find little evidence of changes in the income composition of buyers in these areas following major mortgage-market reforms. Expansions of credit, such as the introduction of interest-only loans in 2003, raised prices but left the buyer mix unchanged, consistent with inelastic supply and intense competition for scarce properties (Greenwald and Guren, 2021; Bäckman and Lutz, 2025). A macroprudential tightening in 2016 produced a similar pattern. These results indicate that persistent differences in feasible access to high-growth locations are central to explaining the income gradient.

Do the higher capital gains earned by high-income buyers simply reflect compensation for higher 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 do find that high-income buyers reside in markets with somewhat higher measured housing risk, but the differences are quantitatively small. More importantly, exposure to housing risk requires buying in precisely the high house price growth, high-price areas where low-income households face binding affordability and consumption constraints. Thus, even if higher expected capital gains are partly tied to higher risk, only households with sufficient financial resources can access these markets and bear that risk. This stands in contrast to financial assets, where all households can, in principle, invest in the same risky assets.

Fundamentally, we show that the returns to the largest asset on the household balance sheet are intricately linked to financial constraints and housing supply. If one cannot afford to buy a property in a high-return area, their individual characteristics such as risk aversion and investment skill will matter much less than in other financial markets. Our findings highlight a direct link between income, spatial sorting, and house-price dynamics, connecting the literature on the causes of spatial sorting to the consequences for wealth accumulation. Location drives the distribution of capital gains to housing, and access to markets with high house price growth is limited by borrowing constraints, consumption needs, and inelastic local supply. The implication of these results is that location translates directly into systematic differences in wealth building across the income distribution. Thus, the income gradient in capital gains to housing is consistent with persistent differences in feasible access to appreciating locations, rather than differences in market timing or property selection within locations.

Our analysis has a number of limitations, beyond external validity concerns (discussed in Section 7). First, we focus on capital gains rather than total returns, which is a more relevant component for wealth accumulation. Wealth is measured at the market value, which reflects cumulative capital gains. Nonetheless, while capital gains to housing have been the main driver of the increase in wealth-to-income ratios (Piketty and Zucman, 2014; Artola Blanco, Bauluz and Martínez-Toledano, 2021), net rental yields are unobserved in our data and may be higher in areas with low house price growth (Amaral, Dohmen, Kohl and Schularick, 2025b). This could potentially offset some of the capital gains gap we document. To assess this concern, we compute how large rental yield differentials would need to be to fully offset our estimated capital gains gap. Our baseline estimate implies a 90-10 capital gains gap of 1.36 percentage points per year. Under perfect spatial sorting, the gap between Paris (3.66%) and the rest of France (5.06%), documented in Amaral et al. (2025b), could fully offset our results.

However, spatial sorting is not perfect. Approximately 45% of buyers in the top income decile purchase in the capital region, compared to 20% 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 a 20 percentage point difference in location shares, rental yields in low-growth areas would need to exceed those in high-growth areas by approximately $1.36/[20/100] \approx 6.8$ percentage points to fully offset our results, a larger number than the gap Amaral et al. (2025b) document. Thus, while rental yield differences may partially offset our capital gains results, they are quantitatively unlikely to eliminate the income gradient in housing returns.

Second, our findings are descriptive rather than 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 isolate a single mechanism. Our contribution is documenting robust patterns in how housing shapes wealth inequality and testing specific hypotheses about the channels involved.

Third, we measure realized capital gains over 1997-2022 in Denmark rather than ex-ante expected returns. To the extent that location-based capital gain differences reflect unanticipated shocks specific to our sample period, our findings may not generalize to future wealth accumulation. We demonstrate that house price growth is strongly correlated with ex-post fundamentals, such as population and income growth, which tend to be persistent (Chodorow-Reich, Guren and McQuade, 2024). These patterns are consistent with persistent location differences in capital gains to housing, especially given limited arbitrage due to financial constraints and housing indivisibility. We further discuss external validity in Section 7.

Related literature. A prominent literature documents important differences in asset returns across the distribution (Fagereng et al., 2020; Bach et al., 2020; Kuhn, Schularick and Steins, 2020). Other papers in this literature include Blanchet and Martínez-Toledano (2023), who find that higher house-price growth in Europe was important for wealth inequality dynamics. Martínez-Toledano (2020) studies the determinants of wealth inequality during booms and busts and finds large differences in return between wealth groups. We contribute to this literature by thoroughly examining housing, the largest asset on the household balance sheet. We find evidence for several mechanisms that are distinct to housing, such as financial constraints, housing indivisibility, and supply constraints. Our main contribution is to highlight that capital gains to housing are heterogeneous across buyers and that housing has several different features that are of first-order importance for understanding heterogeneity in returns.

We also 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 et al., 2025; Diamond and Diamond, 2024), and wealth (Wolff, 2022). We extend this literature by examining how housing capital gains correlate with income rankings using transaction data, by directly examining how choice sets differ across buyers, and by examining how financial constraints and housing supply interact to limit the choice set of low-income buyers.

Our work also contributes to a large literature on spatial sorting and inequality (see Diamond and Gaubert, 2022, for a thorough overview). For instance, 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.[1] 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

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

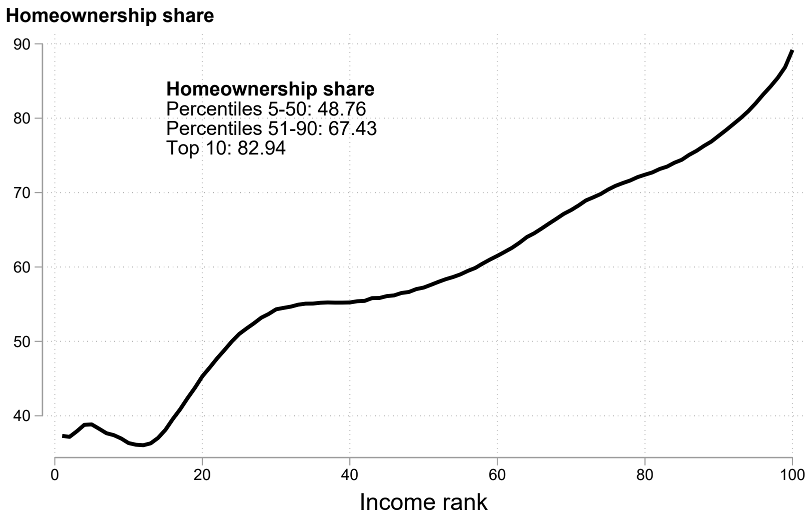


Figure 1: Homeownership rates across the income distribution

Notes: The figure plots the average homeownership rate over the income distribution. Income ranking is based on within-age, average household income over a three-year period. Income ranking is discussed in Section 3.

in productivity shocks or income growth will also generate increases in wealth inequality, as capital gains to housing accrue to existing homeowners.

2 Danish housing market

2.1 Institutional background

Homeowners are subject to a range of housing-related taxes. These include property taxes, which are levied annually based on the assessed value of a property. These assessed values were effectively frozen from 2002, so property tax liabilities did not track the growth in house prices after that year.[2] Capital gains on primary residences are typically exempt, subject to specific conditions (including a lot-size threshold and a residence requirement). Most homeowners are exempt from capital gains taxes upon sale of the property. Homeowners can also deduct 30% of their mortgage interest payments from their taxable income.

Our empirical exercise focuses on capital gains to housing, an exercise that is conditional on buying a property. To help contextualize the later findings, it is essential 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. For a discussion of inequality that captures the effect of tenure choice, see Parkhomenko (2025).

Similar to many other countries, housing is the most important asset on the balance sheet for Danish 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

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

most important asset for all but the poorest households.[3] 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.[4] In Bach et al. (2020), the share allocated to residential real estate is 45 percent for the 70th to 90th percentile. 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 and other countries that have been the setting for previous studies.

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 housing investments 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. Consumption and housing investments are therefore intrinsically linked at the location level.[5]

Denmark has strict rental protection laws. To rent out a property for a limited period, the owner typically must provide a valid, legally defensible reason. Furthermore, properties constructed before 1991 are subject to rent control. If the owner has not personally resided in the property with the intent of permanent residency, they must pay a capital gains tax.

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 strict regulations and collateral requirements imposed on these institutions.

Danish borrowers can choose between a fixed-rate mortgage and a variable-rate mortgage. The maximum mortgage LTV ratio is 80%, but borrowers can add up to 15% in higher-interest bank debt. These rules were tightened in 2013. There is no single statutory payment-to-income 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 and onwards, Danish borrowers can also choose between annuity repayment plans or a 10-year

[3] Note that the data does 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.

[4] 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.

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

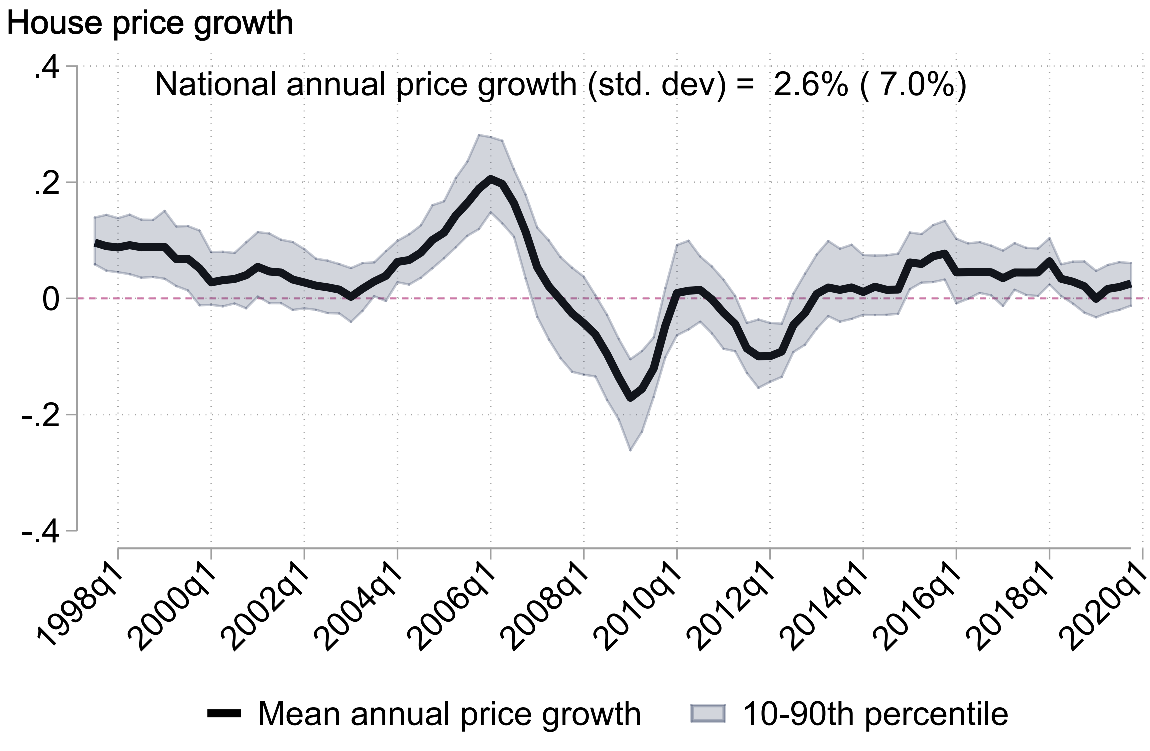


Figure 2: House price growth over time

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 is calculated as the average of the Denmark square meter price growth from 1996 to 2022.

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.[6]

2.3 Housing market dynamics

Similar to 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 was 2.7 percent, with substantial increases from 2003 to 2006 followed by a rapid decline in 2008 and 2009. The Danish housing boom from 2004 to 2007 was more pronounced in high-price areas, like Copenhagen, where the share of interest-only mortgages was higher.[7]

In line with aggregate trends in other countries, Denmark does not appear unusual. 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. These growth

[6] For more details about the mortgage market, see Bäckman and Lutz (2025).
[7] See Bäckman and Lutz (2025) for an analysis of the role of interest-only mortgages for this dynamic.

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 a single-year measure.

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 coresiding), 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 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, buyers 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 for most tests and postcodes for finer geographic comparisons. Danish municipalities are relatively small administrative areas that are situated within larger administrative regions. There are 98 municipalities in Denmark. Each municipality has an administrative function, and certain taxes are collected by the municipality. Each municipality belongs to one of five regions. For example, the capital region consists of 27 municipalities, including the central parts of Copenhagen (Copenhagen and Frederiksberg) and the outskirts. In addition, there are 605 postcodes that exist within municipalities. These have no administrative functions. We use postcodes to approximate local markets and neighborhoods. 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 is an advantage over alternative approaches that use register data, which rely instead on local house price indices combined with property types to infer housing returns (e.g., Fagereng et al., 2020; Bach et al., 2020).

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

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

where $T_{is} - T_{ip}$ is the holding period. We deflate transaction prices using the consumer price index. Because we observe exact transaction dates, we allow T_{ip} and T_{is} to be non-integers. Our

[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.

results are also robust to using a geometric mean of the above formula instead. We remove outliers by winsorizing $r_i^{u,\log}$ at the 1st and 99th percentile. Appendix D1 presents analogous results for levered returns, which account for mortgage financing but require additional assumptions about amortization schedules.

To assess whether selection into repeat sales affects our results, we also impute unrealized capital gains for properties that are observed only once in our transaction data (i.e., not resold within the sample period). We use municipality-level apartment and house price indices from Finance Denmark and match each purchase to the corresponding municipality $\times$ property-type index at 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; equivalently, the imputed annualized capital gain is the annualized growth rate of the matched index from the purchase quarter to 2022Q4. This imputation abstracts from property-specific quality changes and within-municipality price heterogeneity, and we therefore use it as a robustness check rather than a main outcome.

3.3 Conceptual remarks

A limitation of the capital gain measures noted above is that they overlook dividends in the form of net rents. Properly accounting for the total return to housing would entail measuring rents after user costs on a similar property (Kermani and Wong, 2024). 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 house (Fagereng et al., 2020; Bach et al., 2020) or to impute rents using market-level rent indices (Kermani and Wong, 2024; Amaral et al., 2025b; Lyons, Shertzer, Gray and Agorastos, 2025). Statistics Denmark provides statistics for imputed rents, calculated as a percentage of the value of the property. However, this is an accounting construct only and not a true measure of the dividends from homeownership. We find that the imputed rent rate varies little across income ranks. Consequently, adding this imputed dividend has little effect on the estimated income gradient in capital gains. Since this is an accounting artifact, this 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. Imputing rents using market-level indices is therefore not an option. We discuss how to interpret our results in light of the lack of data on net rents in the conclusion section. With these caveats in mind, we interpret our results as differences in real capital gains rather than comprehensive 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 it is not clear which model is appropriate for housing given infrequent trading, substantial idiosyncratic risk, and borrowing constraints. We therefore emphasize realized capital gains as a model-free measure directly relevant for wealth accumulation.

Table 1: Descriptive statistics

	All	Income groups		
	(1)	(2)	(3)	4
Purchase price	1,188,338	938,998	1,022,745	1,341,782
Sales price	1,431,182	1,089,687	1,190,506	1,650,698
Purchase year	2005	2004	2004	2005
Year between transactions	8	8	8	8
Total capital gain (%)	24.6	20.3	20.9	27.8
Annualized real return (%)	3.4	3.0	2.9	3.7
Returns by urbanization level (%)				
Capital	5.1	5.5	5.2	5.0
City	3.5	3.9	3.4	3.6
Countryside	2.7	2.1	2.5	3.0
Province	2.5	1.7	2.1	2.9
Rural	2.1	1.6	1.8	2.5
Property characteristics				
Apartment	0.30	0.34	0.24	0.34
Floor number	2	2	2	2
Rooms	4	4	4	4
Size m^2	112	102	112	113
Building age	55	59	55	55
Buyer characteristics				
Total income, pre-purchase	320,624	124,959	219,095	421,874
Mortgage, pre-purchase	453,573	240,582	279,420	606,697
Wealth rank	46	50	39	50
Renovation indicator	0.33	0.25	0.29	0.38
Renovation amount (DKK)	9,528	5,651	7,154	11,779
Age	41	46	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	0.37	0.54
Repeat sale share	0.27	0.31	0.27	0.26
N	202,955	18,466	74,300	110,189

Notes: The table presents the summary statistics for the final estimation sample. The sample includes only repeat sales transactions. We divide the sample into low-, middle-, and high-income based on their income ranking. 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. Education and age are calculated as the maximum variable among the buyers.

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, 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 returns 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. Richer 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 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. High-income buyers (top tercile) of the income distribution account for 54 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 between 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. Overall, we note that the income ranking is similar for single and repeat sales. Single transactions have a slightly higher purchase price, which derives from differences in purchase year and, to some extent, to small differences in location and from differences in property characteristics, especially an apartment indicator. Overall, the differences across 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. Further, 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 locating increases with income rank after the 40th income percentile. These are also the areas with the highest housing capital gains, as documented in Table 1. Conversely, lower- and middle-income buyers are more concentrated in province 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

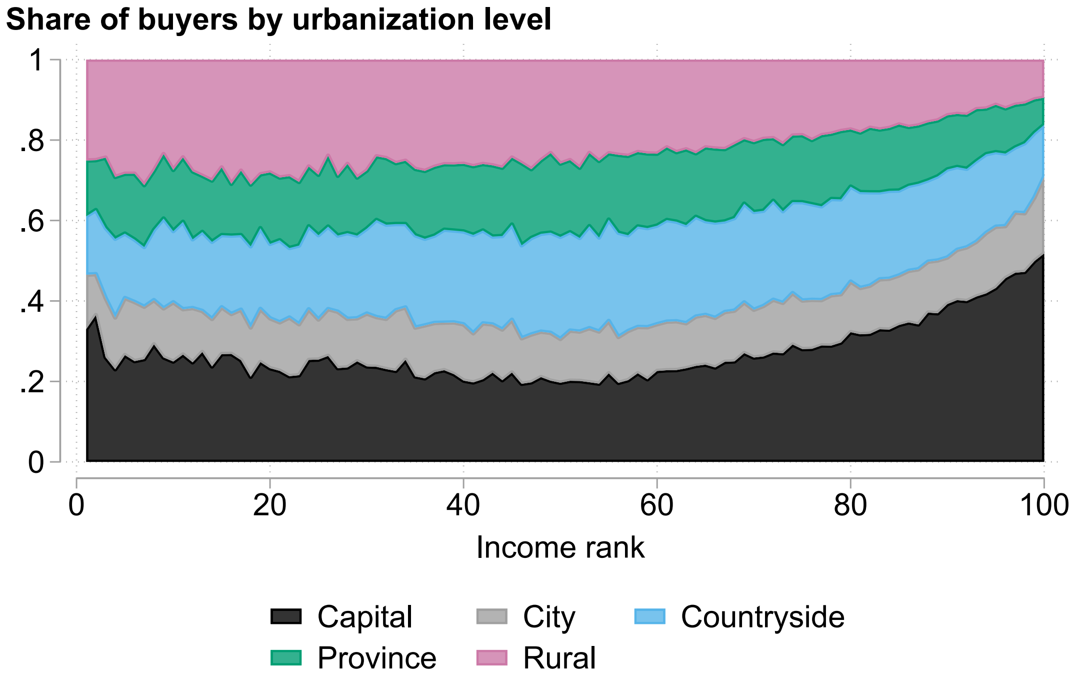


Figure 3: Share of buyers by urbanization level

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 urbanization level. Income rankings are adjusted for age and are described in Section 3.

average returns by income rank and shows a strong, approximately linear gradient. We relate annualized real capital gains to buyers' income rank and then decompose the gradient by successively controlling for property characteristics, buyer characteristics, market timing, and local market fixed effects. The central finding is that higher-income households realize higher capital gains on housing, but this gap is explained almost entirely by where households buy (and, to a smaller extent, when they transact within local markets), rather than by differences in observable 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 in value, or undertake more renovations and maintenance 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 simple 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 returns to account for variation in

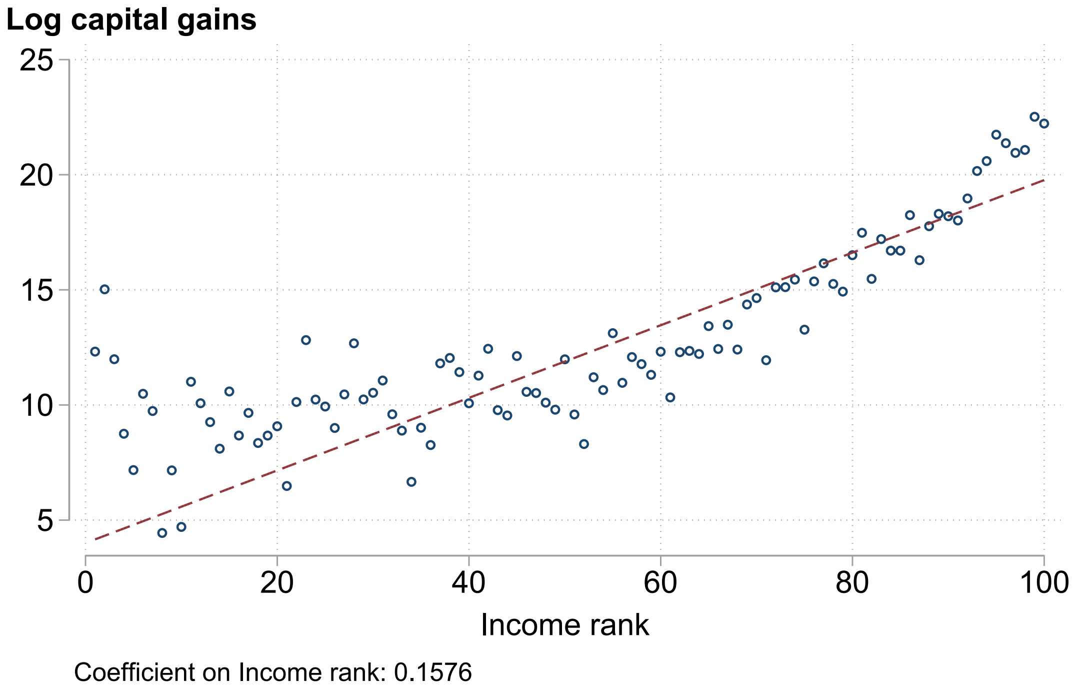


Figure 4: Capital gains to housing by income ranking

Notes: This figure plots income rank against the total (non-annualized) capital gain on housing, calculated as $\ln(P_{is}) - \ln(P_{ip})$. The subsequent regression analysis uses annualized returns to account for variation in holding periods. Income rankings are adjusted for age and are described in Section 3.

holding periods across buyers:

$$Y_i = \beta_0 + \beta_1 Income\ Rank_i + X_i\Gamma + \mu_i + \epsilon_i \tag{2}$$

The specification regresses the outcome Y_i, the unlevered annualized log capital gain r_i^u on the main variable of interest, $Income\ Rank_i$, and vectors of control variables X_i capturing homeowner and property characteristics. We scale income rank from 0 to 100. The outcome Y_i is the annualized log return $r_i^{u,\log}$ multiplied by 100, so that a coefficient of 1 corresponds to one percentage point per year. We also include different sets of fixed effects in μ_i. The methodology is similar to that of Goldsmith-Pinkham and Shue (2023) and Kermani and Wong (2024), who study the difference in housing returns based on gender and race, respectively. $Income\ Rank_i$ is the income ranking of the buyer(s) in the year before purchase. We progressively introduce controls and fixed effects to assess the extent to which observed factors explain the coefficient on $Income\ Rank_i$. This approach absorbs both causal effects and selection (Kermani and Wong, 2024).

Figure 5 graphically plots the magnitude of the coefficient on $Income\ Rank_i$, and the corresponding 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 positive and 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 return. To assess the

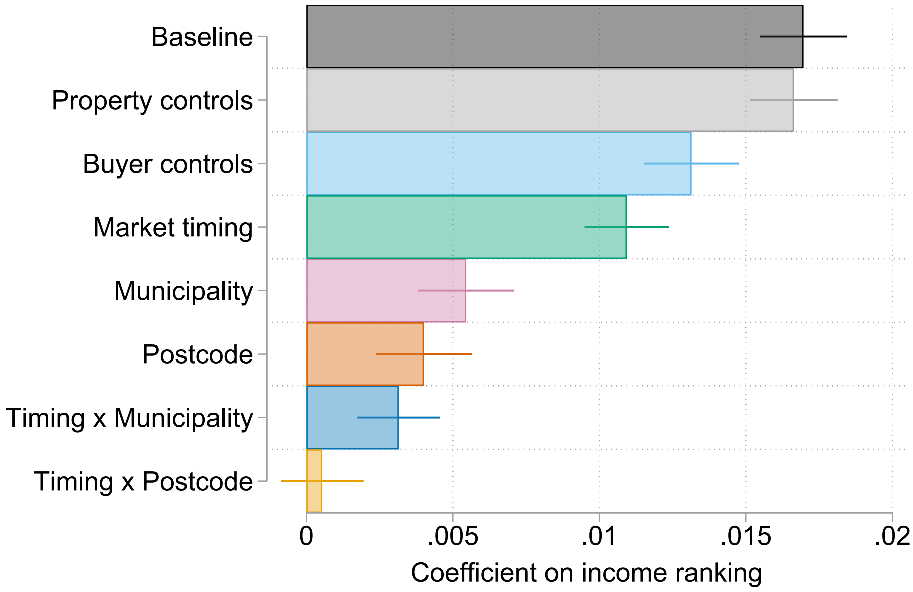


Figure 5: Income-rank gradient in housing capital gains across specifications

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. *Postcode* adds fixed effects for postcodes, leaving out municipality. *Municipality* adds fixed effects for municipality, leaving market timing controls out. *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.

economic significance, we compute the differential effects across income ranks. The estimated coefficient implies a 90-10 annualized gap of $\Delta r^{\log}(\%) = \beta(90-10) = 80\beta$. With $\beta = 0.017$, this equals 1.36 percentage points per year. Over a 10-year holding period, the implied cumulative gap is $\exp\left(\frac{H\cdot\Delta r^{\log}(\%)}{100}\right) - 1 = \exp(0.136) - 1 \approx 14.5\%$.

We now proceed to analyze the statistical drivers of differences in capital gains. We begin with property and buyer characteristics. Then we move on to market timing and location. Our repeat sales measure already controls for time-invariant property characteristics, but note that time-varying property characteristics, the price for 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 grow faster than the price for single-family housing in Denmark.

Property and homebuyer characteristics. The characteristics of the property explain a small part of the difference in capital gains. The second line in Figure 5 presents an estimate of the effect of income rank on capital gains, controlling for property age and type (apartment or single family house), size and floor number. The coefficient is unchanged and remains statistically significant and economically meaningful. Next, we add controls for homebuyer characteristics (age, gender, net wealth, 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 time between transactions. Figure 2 already showed that 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 the 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 changed 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 richer and poorer buyers experience similar exposure to aggregate market conditions.

Geographical location. Adding geographical location fixed effects explains a large part of the income gap in housing capital gains. We use identifiers for municipalities and postcodes, which are smaller neighborhood units within municipalities. With fixed effects for municipalities included (the fifth line of Figure 5), the coefficient on income rank reduces to 0.005, whereas controlling for the finer geography of the postcode reduces the coefficient on income rank further to 0.003. We later return to the interpretation of this result in detail, and we do not suggest the effect is necessarily causal. Controls for municipality and postcode capture both causal effects and selection: the locality fixed effects capture both buyer characteristics within a given area (likely reflecting their income, wealth, employment, and social ties) and the locality's causal effect. Similar concerns arise in other studies exploring differences in housing returns that control for location (e.g. Goldsmith-Pinkham and Shue, 2023; Kermani and Wong, 2024).

While Denmark experienced a large housing boom-bust cycle between 2003 and 2009, both the boom and the bust varied across areas and time.[9] If different locations experienced booms and busts at different times (Ferreira and Gyourko, 2023), controls for nationwide trends in house-price dynamics as above cannot fully capture the local boom and bust effects. The second to last line of Figure 5 shows, with controls for both market timing and municipality, that the coefficient on income rank becomes even smaller. On the last line in Figure 5, within postcodes and conditional on timing, the income gradient disappears. The aggregate income-return relationship thus reflects differential exposure to local markets, not differential performance within them. This indicates that the higher capital gains of higher-income buyers are explained by

[9]See Bäckman and Lutz (2025) for a discussion of the causes of the housing boom between 2003 and 2007.

systematic differences in where and when they buy and sell, rather than by the better performance within a given local market. This finding also suggests that the income gap in housing capital gains appears to be largely compositional rather than causal.

The decomposition in Figure 5 addresses whether the income gradient reflects where households buy versus how they perform within a given local market. When postcode-time fixed effects reduce the income coefficient to near zero, this shows the gradient is a compositional effect of location exposure rather than within-market outperformance. 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 returns, ruling out within-market mechanisms (e.g., superior negotiation or property selection within neighborhoods) as drivers of the aggregate gradient.

We can go one step further and examine the income gradient in capital gains *within* local markets. Appendix Table B3 shows that there is a negative coefficient on income ranking within different levels of urbanization. This reflects compositional heterogeneity: the aggregate positive gradient arises because high-income households sort into high-return urban locations. *Within* these urban markets, however, the gradient is slightly negative under saturated controls. The coefficient of -0.004 for the capital-city area implies a 90-10 gap of -0.32 percentage points per year, smaller in absolute value than the aggregate 1.36 percentage point gap. 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. Importantly, this within-urban pattern does not overturn the location-sorting story: the aggregate gradient remains driven by differential sorting *across* locations, not differential returns *within* locations.

Comparison to the literature. Our findings on the differences in capital gains on housing between low- and high-income buyers in Denmark are comparable to those in the previous literature. Table 6 of Bach et al. (2020) reports housing returns range 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 the returns to housing for individuals in the 10th and 90th percentile in Norway are approximately 4.3 and 5 percent, respectively. The gap is therefore 0.7 percentage points. These studies report results for all households, whereas we report results for homebuyers only.

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 returns 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 ranking variable. The first bar shows our baseline specification. The second bar, labeled "Range, pre-purchase," uses only income 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 all Danish households.

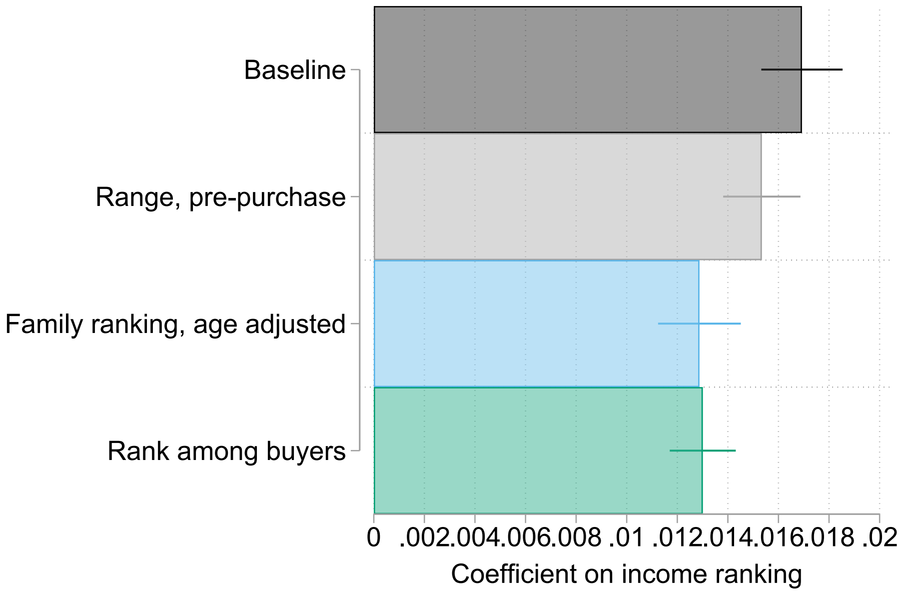


Figure 6: Income-rank gradient under alternative ranking definitions

Notes: The figure plots the coefficient on income rank from estimating Equation (2) using alternative definitions of the income ranking variable. "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.

The results are reassuringly stable across all specifications. 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 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, however, the results are stable across different specifications.

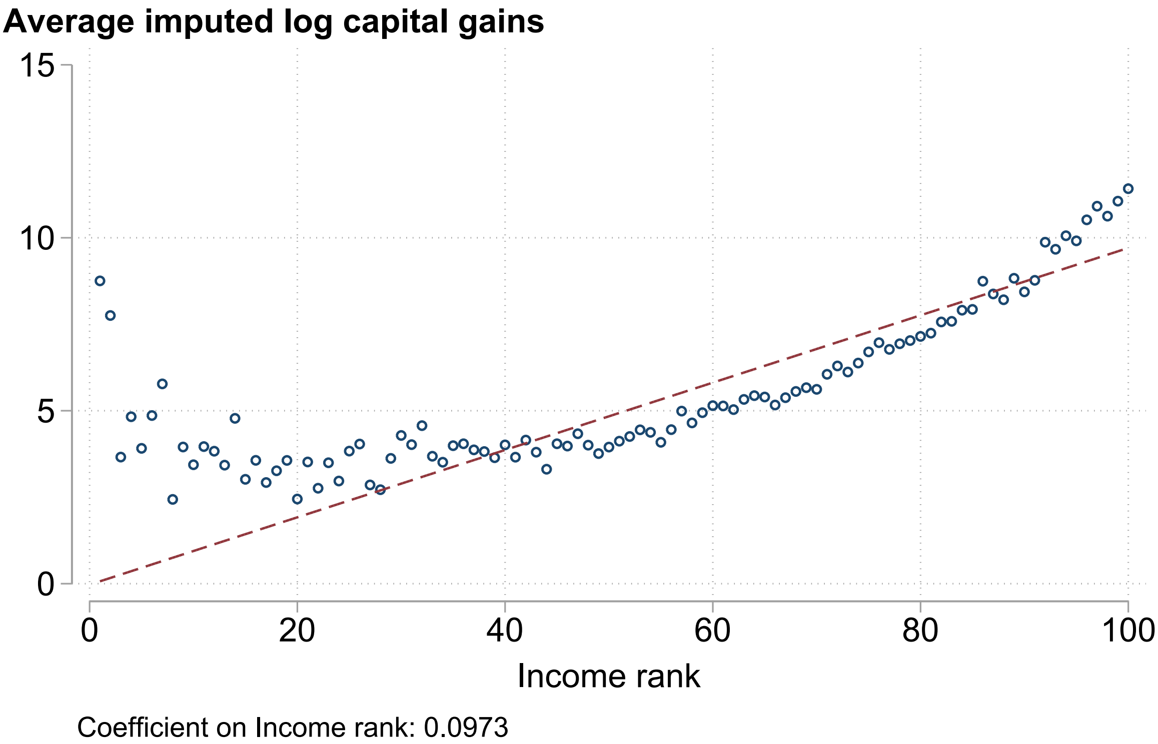


Figure 7: Imputed housing capital gains and income rank for single transactions

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.

Imputing returns for single-transactions. Because we focus on repeat sales, many ownership spells are right-censored: properties purchased during the sample period but not resold by 2022 have no observed subsequent transaction price, and are therefore excluded. To investigate how the censoring due to incomplete spells affects our findings, we impute capital gains for single-transaction properties using municipality-level house-price indices.

Figure 7 shows a relationship between imputed capital gains and income rank similar to the one in Figure 4 for the repeat sales capital gains. The regression involving imputed capital gains on income rank yields a coefficient of 0.0973. Note that we are plotting the total capital gain instead of the annualized gain. Selection into selling does not appear to be a large driver of the income gradient in capital gains.

It is also reassuring that the share of repeat transactions is similar across the income distribution. Censoring due to incomplete spells is particularly concerning if there are differences in censoring by income rank. Summary statistics at the bottom of Table 1 show this difference is not substantial.

Note that imputing capital gains for each buyer using aggregated location-level house-price indices is similar to the approach in Bach et al. (2020) and Fagereng et al. (2020). In that setting, it is not possible to assess how much of the variation in imputed capital gains is at-

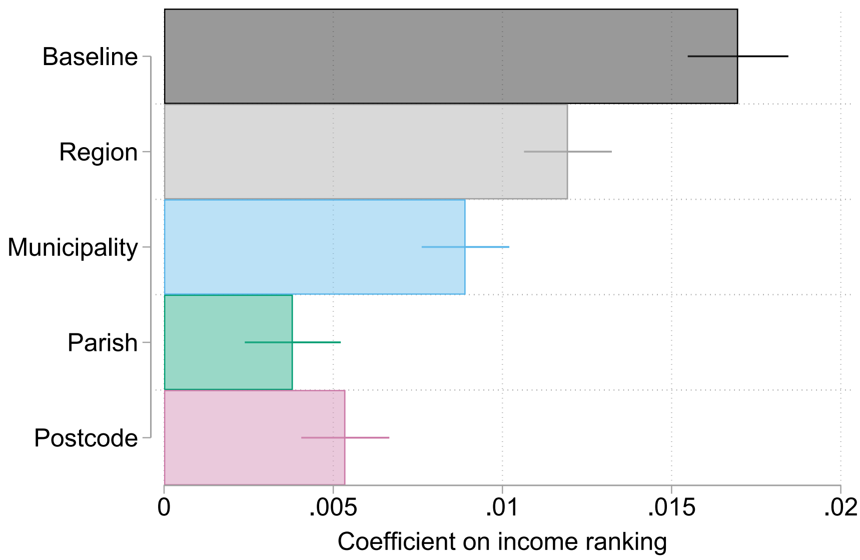


Figure 8: Level of geographical aggregation

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 returns. 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.

tributable to market-wide movements versus buyer and property characteristics. By design, location will explain the differences in capital gains. Indeed, using repeat transactions instead of municipality-level capital gains is the key advantage of our analysis, as it allows us to study the 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 about half 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. Traveling from central Copenhagen to one of the municipalities located the furthest away, Halsnæs, is estimated to take 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 municipalities. There is considerable variation in house price growth at the postcode level not captured by the broader geographical regions. A regression of postcode level house price return on $Municipality \times Year\ Quarter$ has an R-squared of 34 percent. Note that these estimates are larger than those reported in Table B2 because the specifications now include *only* income rank and geographic fixed effects, whereas Table B2 progressively adds property, buyer, and timing controls.

Renovations. The observed relationship between income rank and housing return 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. In Denmark, homeowners can refinance or take out supplementary loans against their property, meaning that local house-price growth directly relaxes borrowing constraints 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 value-enhancing improvements. The renovation channel is therefore not independent of location. Low-income households, who face tighter credit limits and lower liquid wealth, may be unable to make value-enhancing improvements even after purchasing a property. 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 count of tax breaks utilized by each buyer between purchase and sale dates. Since 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 and are all preserved. 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).

Figure A3 shows higher-income buyers are more likely to utilize 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 sample only covers transactions with a sales year after 2011. 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 *total* returns should equalize across locations, leaving investors indifferent between cities (Amaral et

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.

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, 2021). In principle, these wedges can sustain persistent cross-city differences in expected returns, even after adjusting for risk. Since we lack data on rents, we focus on the capital gains component of housing returns and 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 as in Giacoletti (2021), and housing market liquidity (Amaral et al., 2025a). The details on how we construct these measures are available 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 map this volatility difference

Table 3: Regressions of housing risk measures on income rank.

	(1) Std.dev	(2) Beta region	(3) Beta Denmark	(4) Sum negative	(5) Return if negative
Panel A: First set of risk measures					
Income rank	0.000094***	0.000994***	0.002956***	-0.012720***	-0.000137***
	(0.00000)	(0.00002)	(0.00004)	(0.00017)	(0.00000)
Adjusted R-squared	0.0144	0.0124	0.0285	0.0240	0.0113
Observations	217,926	217,926	217,926	217,926	217,926
	(1) Sales time	(2) Cov. Cons	(3) Cov. Inc	(4) Id. Risk	(5) Id. Risk unscaled
Panel B: Second set of risk measures					
Income rank	-0.303815***	0.000008***	0.000002***	0.000012***	0.000763***
	(0.00372)	(0.00000)	(0.00000)	(0.00000)	(0.00003)
Adjusted R-squared	0.0321	0.0227	0.0143	0.0016	0.0027
Observations	217,926	217,926	217,926	201,297	201,297

Notes: The table reports univariate regressions of each municipal risk measure on buyers' income rank. We describe how we calculate housing risk measures in Appendix 8. We merge the municipality-level measures to each buyer based on the location of their purchased property.

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 $0.0072 \times 0.36 = 0.002592$, 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. This calculation should be viewed as an upper bound. The empirical relationship between risk and house price growth is weak and sometimes negative (Han, 2013). In Denmark, the cross-sectional relationship between the standard deviation of house-price growth and average house-price growth is weak (see Figure A2). A plausible explanation is that in markets with inelastic supply, part of the variation in risk reflects hedging motives: households may be willing to accept lower expected capital gains in exchange for owning a property that better hedges future housing consumption (Han, 2013). Hence, differences in the standard deviation of house-price growth can account for at most a modest share of the observed capital gain gap.

We next examine other indicators of risk. The coefficients in Columns 4 and 5 indicate that 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. Further, higher-income buyers tend to live in areas where house-price growth covaries more strongly with income and consumption growth. Again, the magnitudes are small. Finally, Eichholtz, Korevaar, Lindenthal and Tallec (2021) find that housing risk is dominated by idiosyncratic variation, particularly at shorter holding period horizons. Similarly, we find higher-income buyers take on more idiosyncratic risk, though the difference remains small.

Overall, our findings suggest that the income gradient in housing capital gains is not primarily compensation for higher risk. A key difference from financial assets is that housing is an indivisible, location-specific asset that also provides consumption benefits, 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. The next section studies how these borrowing constraints shape location choice and access to high-growth areas.

6 Determinants of location

Higher-income buyers earn systematically higher capital gains on their housing investments, largely because they sort into locations with high capital gains. There is also some evidence that higher-income buyers take on more risk, although the evidence is mixed. These patterns raise a central question for understanding return inequality and, by extension, wealth 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 (Ioannides and Ngai, 2025), and the choice set is restricted by mortgage-market rules and the indivisibility of dwellings. These distinctions are crucial for understanding the origins of differences in capital gains to housing. To clarify how these factors translate into differences in capital gains, it is helpful to contrast housing with other financial assets. For equities, households face essentially no minimum-investment constraint. 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 an investment return. When a household buys a home in location j, it obtains a flow of consumption services s_j (based on size, amenities, schools, or commuting distances) and an expected financial return g_j.

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

$$M \leq \theta_H P.$$

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

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

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

where $p(M, r, t)$ is the mortgage payment, which directly implies a maximum mortgage loan $\bar{M}^{PTI}$ as a function of income and contract terms. 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 income-inelastic (Gaubert and Robert-Nicoud, 2025), this minimum size constraint binds more tightly for low-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 price on the property. To test this prediction, we document how property size affects the choice set below. Second, if borrowing constraints are the primary force keeping low-income households out of high-return areas, loosening these constraints (higher LTVs, lower PTI limits, interest-only mortgages) should raise P^{max}, widen $\mathcal{J}(M^{max})$, and allow some low-income households to enter high-return 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. The prediction is that lower-income buyers would be able to buy housing if they could meet a required purchase price, which corresponds to an elastic supply of owner-occupied housing. 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. Our main empirical prediction is that relaxing borrowing constraints should increase the share of low-income buyers in high-return areas if supply of owner-occupied housing is elastic.

However, 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 high-return areas. Greenwald and Guren (2021) 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. If a lower-income buyer sought to purchase housing in an expensive area where the supply of properties is limited, they would be competing against higher-income buyers with more purchasing power. In that case, increased demand from lower-income households may be capitalized into higher prices, because higher-income buyers can still win those homes. Anticipating this, lower-income buyers may not wish to compete in markets where they expect to be unable to buy after a competitive bidding process. This alternative mechanism delivers the opposite prediction from above: credit expansions raise prices in high-return areas 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 a loan-to-value or a payment-to-income 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, therefore we test whether the results are sensitive to alternative numbers and we find that they are not. We use income measured one year prior to purchase to compute the maximum amount of income the buyers could make, 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 to fund their downpayment for them. Although the two measures are similar, the model-implied borrowing capacity maps more directly into the conceptual framework and to the later credit

[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 is 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.

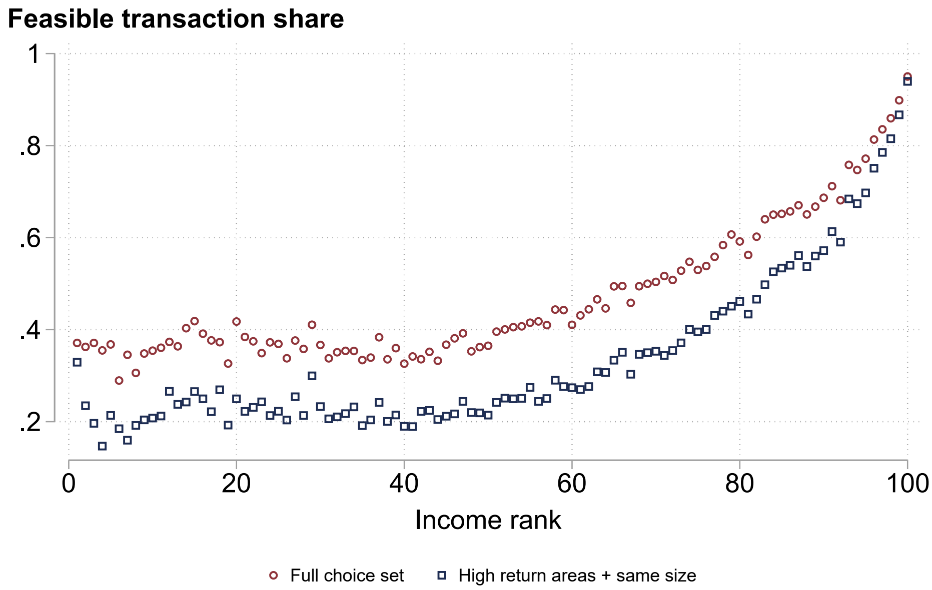


Figure 9: Choice set over income rank

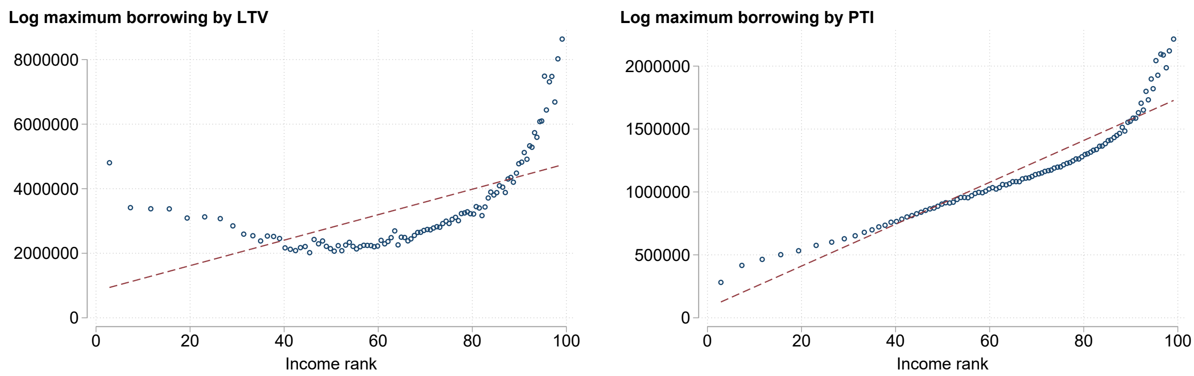
Notes: The figure plots income rank and choice set for each buyer. We first compute each buyer's maximum borrowing $M^{\max}$ as the minimum of the LTV- and PTI-implied loan ceilings, then add available wealth to obtain maximum purchase price $P^{\max}$. The choice set denotes the share of transactions 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-return areas where the property size is within 10% of the chosen size. High-return 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.

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 similar for both the full choice set and for high-return areas with a fixed house size: higher-income households face a systematically larger set of potential purchases. Table B4 shows that the slope is similar across other subsets of the choice set. Second, conditioning on high-return areas and a similar size, the choice set is considerably smaller for all income groups. This pattern reflects the higher purchase price in high-return areas. Together, these findings suggest that consumption needs limit access to high-return areas, and that higher-income buyers generally have a larger set of available properties.

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 lower of these constraints naturally determines their borrowing capacity (see also Grodecka, 2020). 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.

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



(a) Loan-to-value

(b) Payment-to-income

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. 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.

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 low-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, Tang-Andersen Martinello, Hviid and Sinding Bentzen (2022) find that LTV restrictions disproportionately affect younger and less wealthy households, while DTI and DSTI limits primarily affect buyers in the largest cities and low-income buyers.

The choice-set calculations are by construction partial-equilibrium: they evaluate affordability at current prices. For example, Figure 9 shows that buyers in the 40th percentile have a feasible set covering around 20% of properties in high-return areas in the same size category. In equilibrium, prices in high-return, supply-constrained areas would not remain fixed if low-income buyers suddenly received more borrowing capacity. Because high-income buyers have higher ability-to-pay, they would bid up scarce homes and continue to win them 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-return areas or mainly raises prices paid by the winners.

6.3 Loosening financial constraints and location choice

We now ask whether mortgage reforms that expand borrowing capacity alter the income composition of buyers in high-return areas. In Denmark, several major mortgage-market reforms directly altered payment-to-income and down-payment 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-return municipalities of Copenhagen and Aarhus. The empirical analysis below tests whether these policy changes increased the presence of low-income buyers in high-return municipalities. We show the share of low-income buyers remains remarkably stable across all reforms.

Introduction of interest-only mortgages in 2003. This reform arguably led to a major loosening of payment-to-income constraints (Bäckman and Lutz, 2025, 2020), but, consistent with the inelastic-supply mechanism, had little impact on the ability of low-income households to buy in high-return areas. We show this formally by estimating the following regression for buyer i in municipality m in year t:

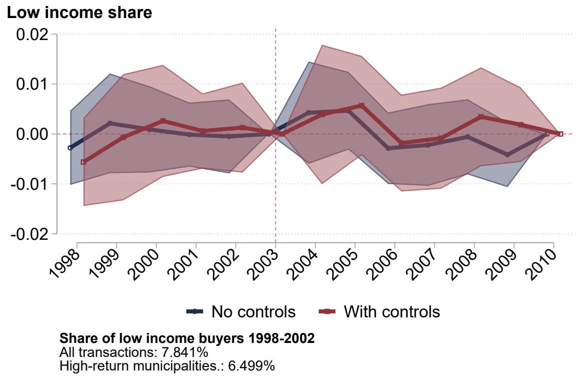
$$Y_{imt} = \alpha_m + \gamma_t + \sum_{k=1998}^{2010} \beta_k (HighReturn_m \times \mathbf{1}_{t=k}) + X_{it}\Gamma + \epsilon_{imt} \tag{3}$$

where the dependent variable Y_{imt} is either the log purchase price or a binary variable that indicates if the buyer income rank is in the bottom half of the income distribution. $HighReturn_m$ 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 return municipalities over the entire sample period. We also include a vector of control variables in X_{it}, along with municipality and year fixed effects in α_m and γ_t, respectively. These are the same controls as in the baseline returns regressions. We cluster standard errors at the municipality level. The sample includes all transactions instead of only repeat transactions to increase statistical power.

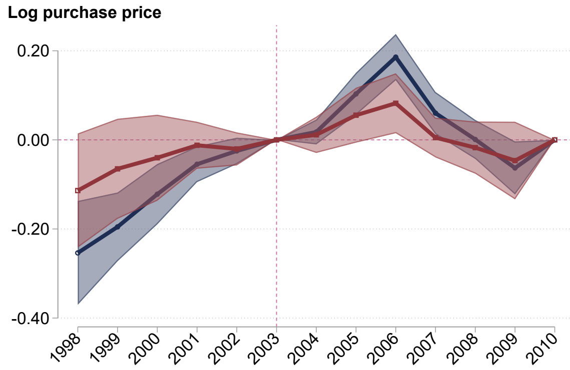
Figure 11(a) shows that the share of low-income buyers is not statistically different before and after interest-only mortgages were introduced, and remains relatively stable over time. A similar finding is reported in Bäckman and Lutz (2020) for the homeownership rate, rather than transactions. These results are even more striking once we consider that interest-only mortgages affect the payment-to-income constraint, which represented the binding constraint for most low-income buyers. In addition, it is not the case that interest-only mortgages were restricted to high-income buyers or that they were not popular: 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).

Figure 11(b) shows that house prices rise with the introduction of interest-only mortgages. This result replicates the findings in Bäckman and Lutz (2025) that the introduction of interest-only mortgages led to higher prices, and is consistent with the mechanism in Greenwald and Guren (2021) in which credit expansions are primarily reflected in prices when supply is tight. High-return locations have less elastic supply, as measured by the supply-elasticity measure in Guren, McKay, Nakamura and Steinsson (2021); we describe its construction in Appendix C3. These areas are also characterized by high price levels.

Credit growth guidance. 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 specifically to Copenhagen and its surrounding



(a) Share of low-income buyers



(b) Log house prices

Figure 11: Introduction of Interest-only mortgages and housing market outcomes for high-return areas

Notes: The figures plots the coefficients on β_k estimating Equation (3). The outcome variable in panel a) is the share of low-income buyers. The outcome variable in panel b) is log house prices. The omitted year is 2003. The data are at the municipality 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). Standard errors are clustered at the municipality level.

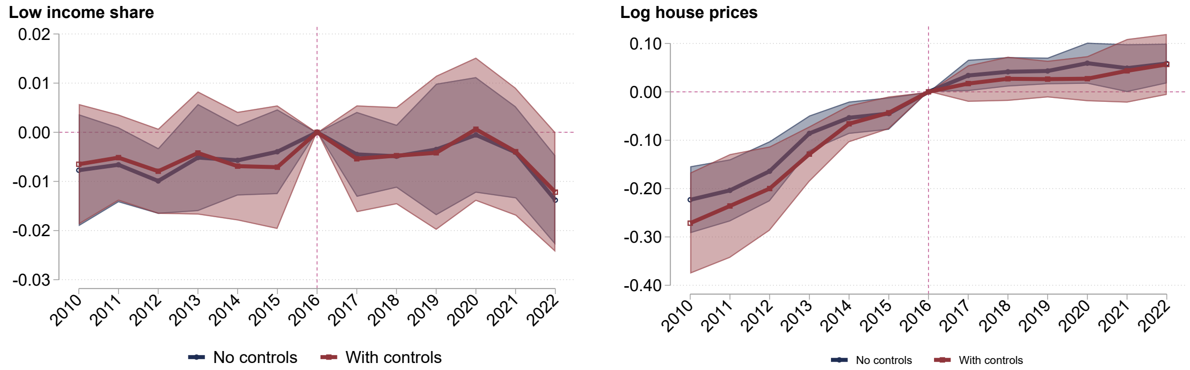
municipalities, as well as Aarhus, Denmark's second-largest city. The guidance was motivated by rapidly rising house prices in these areas, combined with historically low interest rates, which raised concerns about excessive credit risk among financially vulnerable borrowers. The FSA instructed banks 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 factors, or thin liquidity 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 payment-to-income (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 low-income households are predominantly PTI-limited, the guidance should reduce their ability to purchase in treated municipalities. Importantly, these are also municipalities with high house price growth. In our partial-equilibrium choice-set framework, holding prices fixed, the guidance implies a decline in the share of low-income or financially vulnerable buyers in these locations following its introduction.

We test this prediction using a municipality–year panel and the following event-study specification:

$$Y_{imt} = \alpha_m + \gamma_t + \sum_{k=2010}^{2019} \beta_k (Treated_m \times \mathbf{1}_{t=k}) + X_{it}\Gamma + \epsilon_{imt}, \tag{4}$$

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



(a) Share of low-income buyers (b) Log house prices

Figure 12: Growth guidance and housing market outcomes

Notes: The figures plots the coefficients on β_k estimating Equation (4). The outcome variable in panel a) is the share of low-income buyers. The outcome variable in panel b) is log house prices. The omitted year is 2016. The data are at the municipality level. High-return municipalities are defined as municipalities in the top quintile of average house price growth between 1997 and 2018. 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.

where the dependent variable is either the share of low-income buyers or log house prices. $Treated_m$ equals one for municipalities covered by the 2016 guidance. The rest of the specification and the control variables are the same as in Equation (3).

Figure 12 shows the income composition of buyers remains stable before and after 2016. The event-study coefficients for buyer composition 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 high-return locations. Instead, the 2003 interest-only reform is associated mainly with higher prices without a compositional shift toward low-income buyers, and the 2016 guidance likewise appears to have operated primarily through prices rather than by shifting the composition of buyers.

6.4 Why Credit Reforms Do Not Shift Buyer Composition

Taken together, the Danish mortgage-market reforms provide a series of empirical tests of the hypothesis that credit constraints limit access to high-return areas. If borrowing constraints were the main barrier preventing low-income households from accessing high-return locations, then the introduction of interest-only mortgages in 2003 should have expanded the feasible set for constrained buyers and increased their presence in high-return municipalities. Instead, we find no measurable change in the income composition of buyers in these areas.

Borrowing constraints still shape who can afford to buy in high-return locations at prevailing prices, as documented in Section 6. The reforms suggest, however, that easing credit in supply-constrained markets is largely absorbed by prices rather than by increased entry of low-income households. Instead, when credit expands, prices adjust to maintain the existing spatial sorting. The persistent income gradient in housing capital gains therefore reflects 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 high-return locations.

Our findings have several important implications. Most importantly, our findings indicate that loosening mortgage payment constraints do not help low-income households access high-return areas. Even when borrowing capacity expands, the effective affordability of properties in these locations remains unchanged for low-income buyers. This finding is consistent with a setting in which supply in high-return locations is inelastic and buyers competition is strong: when credit constraints loosen, higher-income households can outbid lower-income households for the limited stock of available properties, leaving the income composition unchanged.

Some final caveats are worth mentioning. The literature on spatial sorting has suggested several other mechanisms for why households locate in certain areas (see e.g., Diamond and Gaubert, 2022). A long-standing observation in this literature is that mobility among low-income workers to greater economic opportunities 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 in their place of birth (Diamond, 2016), may face high search or moving costs (Bergman, Chan and Kapor, 2020; Badarinza et al., 2024), 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 to capture higher housing returns 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 high-return areas.

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. We document in Appendix E1 that municipalities with higher income and population growth experience systematically 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 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 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. While we show that municipalities with higher capital gains also feature higher income and population growth, we do not 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.

7 External validity

Our analysis uses administrative data from Denmark, raising the natural question of how broadly our findings extend beyond this specific institutional setting. Importantly, the mechanisms that we highlight are not unique to Denmark. Instead, our findings speak to general equilibrium forces that arise whenever housing markets combine (i) persistent spatial heterogeneity in economic growth, (ii) borrowing constraints and housing indivisibility, and (iii) limited supply adjustment. We now discuss how the key parts of the results generalize to other settings.

A key feature underlying our findings 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 features are common to owner-occupied housing markets in most advanced economies, including the United States, the United Kingdom, and much of continental Europe. Further, 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 et al., 2025; Amaral et al., 2025b). Importantly, higher house-price growth in high-price areas, a key feature of our analysis, is also present in other countries like the United States. To illustrate this, Figure 13 plots house price indices over time for different price groups in the United States using data from Zillow. To construct the figure, we use the longest time series available that includes price levels. We rank zip codes by house prices in 2000, the first year of the sample, and form price 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.

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

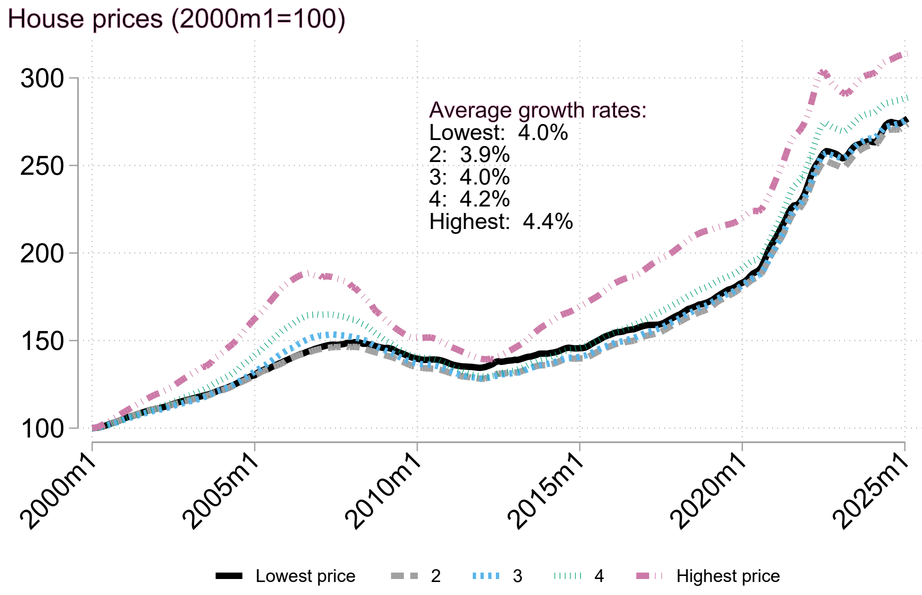


Figure 13: House price growth by price level in the United States

Notes: The figure plots indexed house prices over time for five groups using data from Zillow. 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.

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. While specific mortgage products such as interest-only loans are specific to Denmark, similar products are also present in the United States, Sweden, the Netherlands, and elsewhere (Scanlon, Lunde and Whitehead, 2008). More importantly, even if the institutional setup in Denmark is somewhat unique, the broader mechanism is not. 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 for a limited stock of homes. The same logic applies in high-demand urban housing markets in many countries.

At the same time, our results are not intended to apply universally. The mechanisms we document 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). Similarly, countries with high recurring property taxation or substantial capital gains taxation on owner-occupied housing may exhibit different incentives and return patterns. Moreover, our analysis focuses on realized capital gains over a specific historical period. While we show that these gains are strongly correlated with persistent local fundamentals, we cannot rule out that the magnitude of location-based return differences may vary across periods or institutional regimes.

Taken together, our findings suggest that housing amplifies wealth inequality through spatial exposure, rather than through differential skill, timing, or risk-taking within local markets.

This mechanism is not unique to Denmark, but its quantitative importance will depend on the degree of spatial inequality, borrowing constraints, and housing supply rigidity in a given economy. Where these forces are strong, residential location choice is likely to play a central role in shaping differences in wealth accumulation across households.

8 Conclusion

This paper documents substantial differences in housing capital gains across the income distribution. We show location statistically accounts for the entire income gradient in realized capital gains on housing. Differences in risk-taking have little explanatory power for these capital gains, and differences in returns at the municipality level are closely related to income and population growth. Finally, 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.

Our results relate closely to the literature on spatial sorting and inequality (see Diamond and Gaubert, 2022), which has mostly focused on *income inequality*. Our results suggest that increased spatial sorting will not only generate income inequality, but also wealth inequality through changes in house prices. This channel builds on top of the persistent differences in wealth-building opportunities afforded by greater income prospects in better areas.

We document differences in realized capital gains and not 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 that affected housing markets in the last 30 years. With noisy asset returns, a long time series is needed to estimate an asset's population return from its sample mean (Merton, 1980). Our results indicate that income and population growth are primary drivers of capital gains, and there is limited evidence that capital gains are driven by risk. If differential growth in income across locations is capitalized into house prices, our finding that differences in returns are driven by location implies a link between spatial sorting, house-price growth, and wealth inequality. As long as trends in income growth and population growth 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

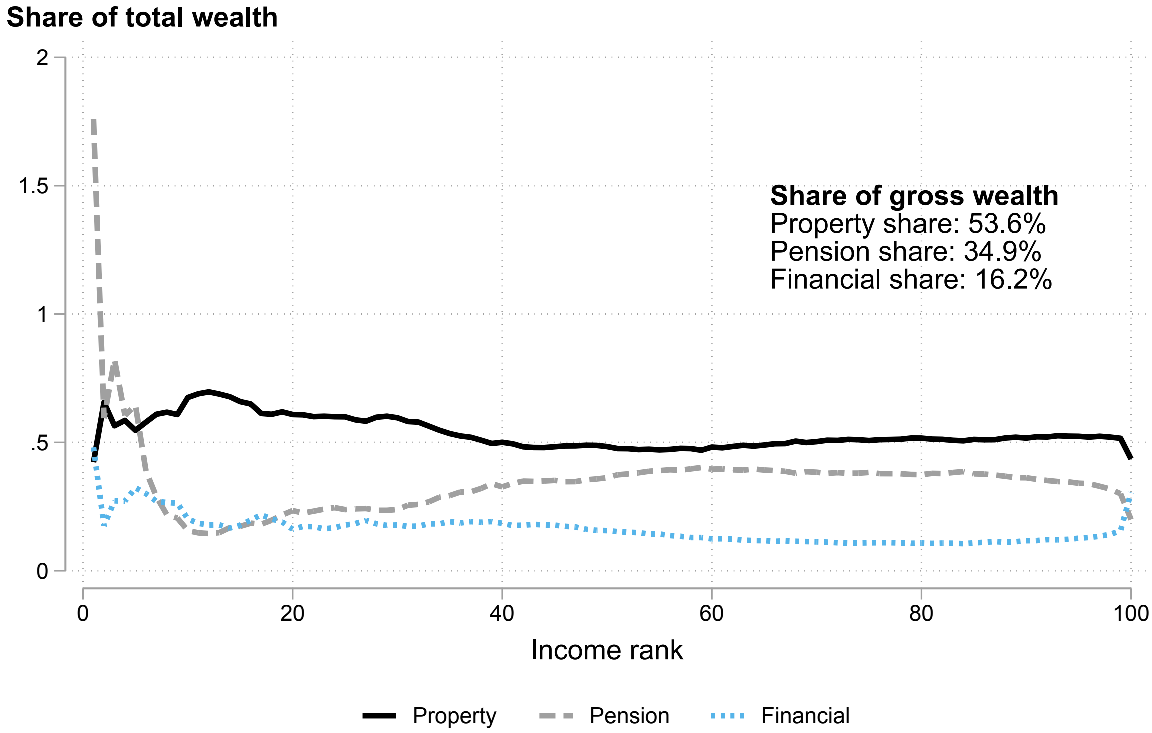
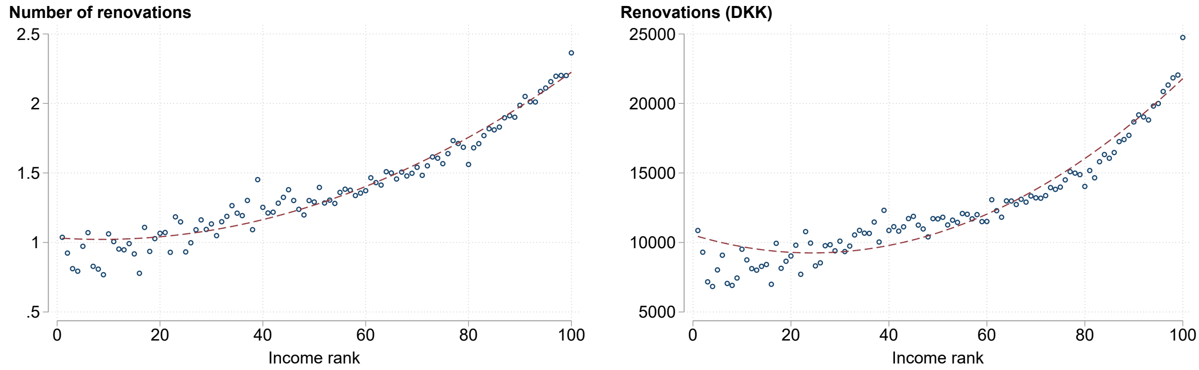


Figure A1: Asset allocation by income rank

Notes: The figure plots the share of wealth invested in different assets by income rank in 2014. 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. 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.

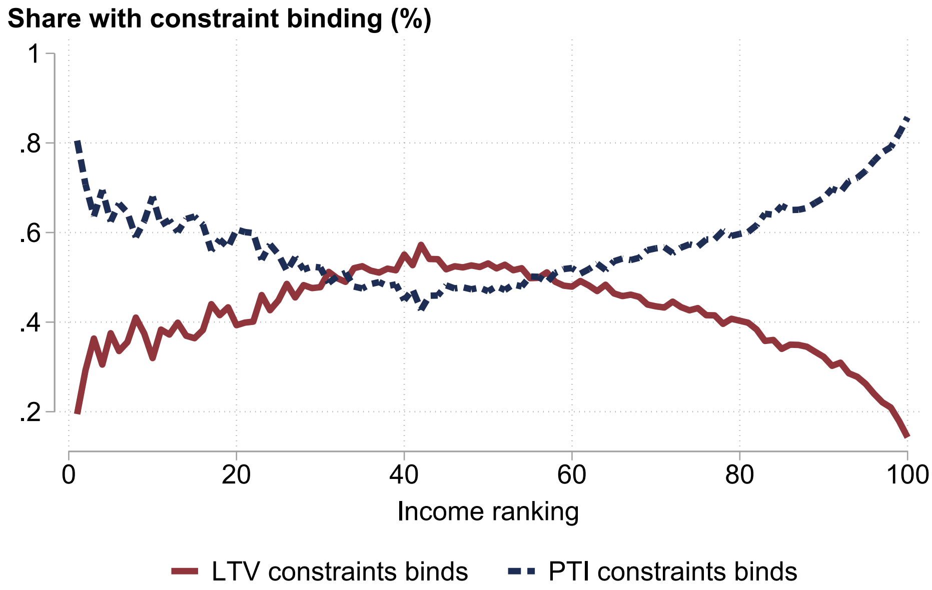


Figure A4: Binding constraints by income rank

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	68	67	69
Repeat sale	0.31	1.00	0.00
Purchase price	1,325,589	1,290,162	1,341,374
Purchase year	2009	2005	2011
Apartment indicator	0.19	0.27	0.15
Floor number	2	2	1
Rooms	4	4	4
Building m^2	217	255	200
Size m^2	113	104	117
Building age	54	52	55
Capital	0.22	0.26	0.20
City	0.11	0.12	0.10
Countryside	0.21	0.20	0.21
Province	0.19	0.17	0.19
Rural	0.28	0.25	0.29
Share of all transactions		0.308	0.692
N	1,076,778	331,897	744,881

Notes: This table presents the summary statistics comparing single and repeat sales.

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 ranking. 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 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.

Table B3: Housing capital gains and income ranking 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 ranking for various urban classifications. The outcome variable is the annualized log returns. All regressions control for property characteristics, buyer characteristics, year-of-purchase, year-of-sale and postcode fixed effects. Major cities are København, Aarhus, Odense, Aalborg, and big cities add Esbjerg, Randers, Horsens, Kolding, Vejle and Roskilde to the major cities.

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. 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).

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.

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:

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

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 local returns 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 housing returns.[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 returns 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 $P_{i,t}$ and $P_{i,T}$ denote the purchase and resale prices of house i.The LME is defined as:

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

[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 $R^{\text{Mun}}_{t,T}$ 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:

$$\frac{\log(1 + \text{LME}_i)}{\sqrt{\tau_i}} = X_i'\beta + \alpha_{\text{Mun}(i)} + \alpha_{p(i)} + u_i, \tag{7}$$

where τ_i 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 $\alpha_{\text{Mun}(i)}$ and $\alpha_{p(i)}$ 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 $\sqrt{hp_i}$ 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. Housing returns are 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 Finance Denmark. Finally, we calculate measures of downside risk by totaling the number of negative returns for each municipality and computing the return conditional on a negative return.

C2 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

$$Equity_{is} \;=\; \max\big(P_{is} - Mortgage_{is},\, 0\big). \tag{8}$$

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 returns at the 1st and 99th percentile.

C3 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:

$$\Delta P_{k,t} = \psi_k + \gamma_k \Delta P_t^N + v_{k,t} \tag{9}$$

where ΔP_t^N is the annual change in national house prices and γ_k is a municipality-specific coefficient. $\hat{\gamma}_k$ is a proxy for the inverse housing supply elasticity in municipality k.

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

[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.

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 employment, allowing for municipality-specific coefficients:

$$\Delta P_{k,t} = \psi_k + \delta_k \Delta y_{k,t} + \gamma_k \Delta P_t^N + \Psi_k X_{k,t} + v_{k,t} \tag{10}$$

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

D1 Levered returns

Table D1 reports the results, again summarizing different regression specifications. The coefficient on income rank on levered returns is now larger at 0.023, compared to 0.017 in the baseline specification, consistent with the intuition that leverage magnifies returns. 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 had previously attenuated the income gradient. 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 returns of 7.5 percent over a 10-year holding period.[17] In conclusion, differences in borrowing and leverage decisions amplify the income gradient in housing capital gains.

[17] The cumulative difference is calculated as the difference in log returns 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 $\exp\left(\frac{H\cdot\Delta r^{\log}(\%)}{100}\right) - 1 = \exp(0.072) - 1 \approx 7.5\%$.

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 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.

E1 Determinants of house price growth

Our results indicate that richer households earn higher returns on housing because they reside in areas experiencing higher growth in house prices. 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:

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

where $P_{i,t}$ is the price in location i at time t, $\sum_{j=1}^{\infty} Rent_{i,t+j}$ 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. We focus on variables used in the previous literature: changes in population and income growth.

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, 2021). 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:

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

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 housing returns are 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, like in Equation (11), a higher income level in a location would be associated

Table E1: Housing return 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 housing returns. 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. We calculate changes as the year-over-year log difference by municipality. Housing supply elasticities are measured using the methodology in Guren et al. (2021) and are described in Appendix C3.

with higher price levels but not necessarily with higher returns. 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 income on changes in house prices 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 explain over half of the cross-sectional variation in returns 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.