Housing Capital Gains across the Income Distribution*

Claes Bäckman† Walter D'Lima‡ Natalia Khorunzhina§

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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 this difference, with little role for aggregate market timing, property type, or buyer characteristics. Higher-income households can afford a larger share of available properties than lower-income buyers, with wider gaps in high-return areas. However, major credit expansions and contractions produced no detectable change in buyer composition across locations, suggesting inelastic supply limits access regardless of credit availability. These patterns highlight how residential sorting generates persistent differences in capital gains through differential exposure to local house price appreciation.

JEL Classifications: D31, R20.

Keywords: housing returns, location choice, market timing, wealth inequality.

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†Leibniz Institute for Financial Research SAFE. Email: claes.backman@gmail.com

‡College of Business, Florida International University, Miami, FL 33131. Ph: +1 305-779-7898. Email: wdlima@fiu.edu

§Department of Economics, Copenhagen Business School. Email: nk.eco@cbs.dk

1 Introduction

Understanding why wealth accumulates differently across households requires understanding 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, and subject to borrowing constraints, and simultaneously provides consumption services (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 1997, we find a strong positive income rank gradient: buyers at the 90th income percentile earn roughly 1.3 percentage points higher annualized capital gains on housing than buyers at the 10th percentile, a gap that cumulates to about 14 percent over a ten-year holding period. This represents an economically significant difference in outcomes for what is, for all income ranks, 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 1997 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 relative to the previous literature: (i) we observe realized, property-level capital gains directly rather than inferring capital gains from indices, and (ii) buyer characteristics, leverage, renovations, and location can be cleanly linked to subsequent housing outcomes. 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 only about 30 percent of transactions, compared to roughly 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.

Importantly, 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 the same pattern. These results indicate that persistent differences in feasible access to high-growth locations are central to explaining the income gradient.

A natural question is whether the income gradient in capital gains simply reflects 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, the main point of this paper is that the returns to the largest asset on the household balance sheet are intricately linked to financial constraints and housing supply. If you cannot afford to buy a property in a high-return area, 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 on 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 three limitations. First, we focus on capital gains rather than total returns. 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 may potentially offset some of the capital gains gap we document. While this limitation is common in the wealth inequality literature (Fagereng et al., 2020; Bach et al., 2020), readers should interpret our findings as differences in real capital gains rather than total housing returns, which also include net rental yields and other user-cost components.

Second, our findings are descriptive rather than causal in nature. 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 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.

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 in

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

2 Danish housing market

2.1 Institutional background

The Danish housing market features high homeownership, with approximately 60 precent of Danish households owning their homes. The homeownership share is stable across time (Bäckman and Lutz, 2020). The Danish housing market is also characterized by relatively high prices, par-

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

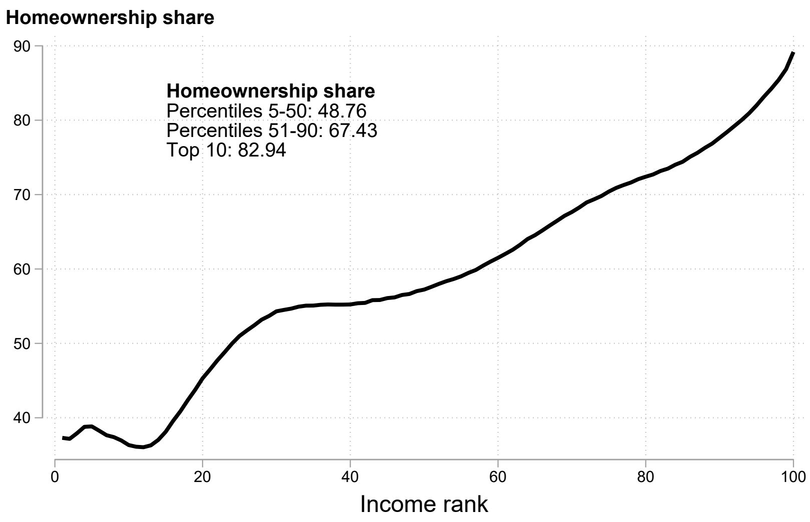


Figure 1: Homeownership rates across the income distribution

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.

ticularly in major cities such as Copenhagen and Aarhus.

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 with income. Figure 1 shows that the homeownership rate is around 50 percent in the bottom half of the income distribution, compared to a rate of 67 percent in the 51-90th percentile, and an even higher 83 percent among 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, housing wealth averaged 53.6 percent of total gross wealth, making it the most important asset for

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

all but the poorest households. 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 20-50th percentile and 86 percent for the 50-90th percentiles.[3] 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.[4]

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. There is also favorable tax treatment for multiple property ownership through an incorporated entity.

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.

[3] 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.

[4] 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).

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 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.[5]

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 municipality-level data. The average year-over-year growth rate in real house prices at the municipality 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.[6]

Compared to aggregate trends in other countries, however, Denmark is not an outlier. 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 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.

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

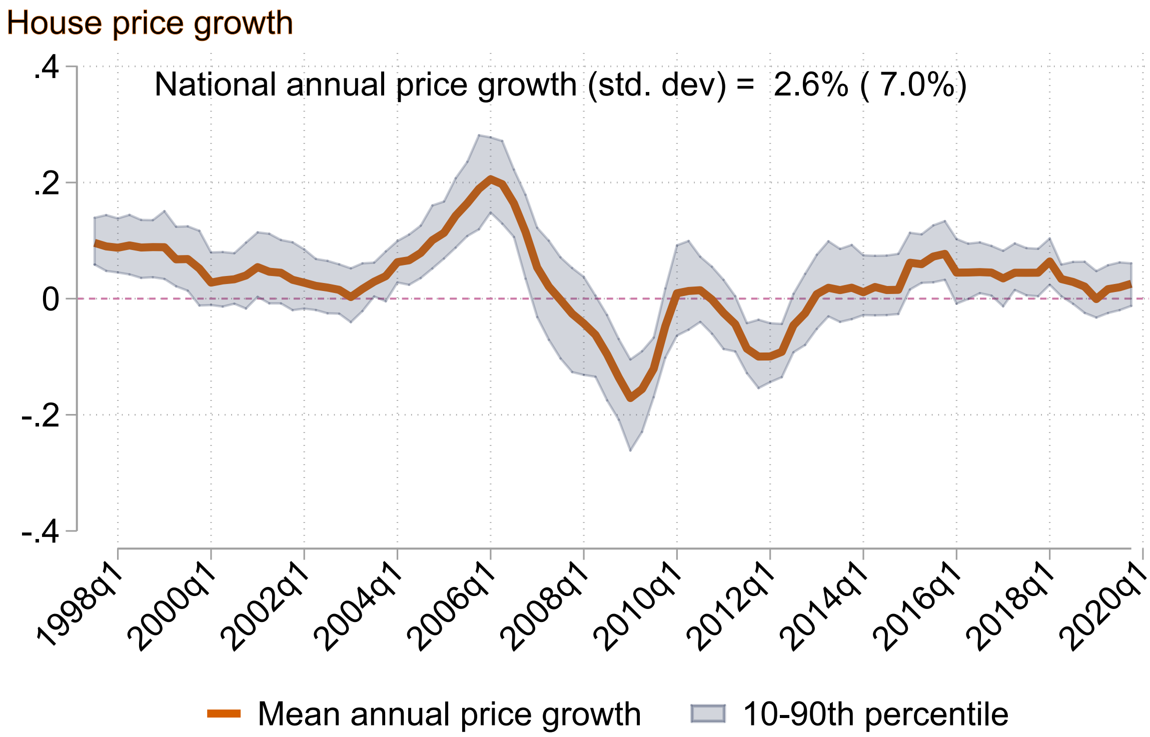


Figure 2: House price growth over time

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 level from FinansDenmark. 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.

2.4 External validity

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. The main advantage of Danish data is population-wide administrative coverage of transactions and household characteristics, which allows us to measure capital gains directly at the property level.

3 Data

3.1 Data sources

We obtain high-quality administrative data from Statistics Denmark from 1996 to 2022. The data comprises housing transaction information, underlying property characteristics, and detailed demographic and financial data linked to all individuals. The data structure consists of separate registers within Statistics Denmark that can be merged based on unique individual identifiers. We obtain comprehensive demographic and financial data from the official Danish Civil Registration System (CPR Registeret) and Danish Tax and Customs Administration (SKAT) registers. Each individual in Denmark is assigned a unique CPR number, which can then be linked to a household identifier. We use the CPR number to merge detailed individual-level demographic and financial data. Individual wealth and income data stem from the official tax records at SKAT. We also obtain demographic data such as age and place of residence, which we link to wealth data and property ownership through the individual CPR number. We then aggregate the data to the household level using household identifiers.

Our main variable of interest pertains to the income ranking. For each year, we calculate the within age-cohorts rank of all households in Denmark, based on average total income in $t-1$, t and $t+1$ to reduce transitory noise in income. The income variables measures total income, including labor income, transfers, and capital income. Our results are robust to alternative definitions of income, including the use of only pre-purchase income rank or a single year to construct the ranking. We use the average income within the household to account for differences in the number of buyers. We also ensure that households consist of at most two adults, to avoid having adult children living at home influencing the results. To match each property transaction to buyers, we calculate buyers (at most two) using individual income data and match that income to the corresponding position in the household income distribution.[7] Since we later focus on homebuyers over age 25, we also remove individuals under age 25 in this step. Andersen, Johannesen and Sheridan (2020) notes that young households with low income are usually students who receive transfers from their parents, making their own income an unreliable measure of their financial resources.

We acquire detailed administrative data on ownership and characteristics of all registered properties in Denmark's housing stock, and all transactions for those properties, from 1996 to 2022 from the SKAT register and the Danish housing register (Bygnings-og Boligregistret, BBR). We restrict our analysis to properties for which the buyer's ID is known, to match housing transactions to income data. We exclude transactions that Statistics Denmark flags as anomalous, and transactions where the buyer is not an individual. Since we are interested in housing

[7] 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 sum up the individual incomes and match to the household income distribution.

capital gains, we focus on properties with at least two observed transactions. We also include transactions with at most two buyers. This represents a substantial majority of all transactions. Lastly, we restrict our attention to residential dwellings that serve as primary homes, excluding summer houses or investment properties from the analyses. We identify primary homes based on the address where the individual is legally residing. This partially restricts our ability to study the highest deciles of the distribution, where ownership of multiple properties is more common. However, ownership of multiple properties is generally limited in Denmark for tax reasons. This is discussed in more detail in Section 2.

We generate a sample of repeat sales and merge the income ranking information of the buyer(s) one year before purchase. We also merge relevant property characteristic variables, such as number of rooms and living area. The final sample consists of about 218,000 repeat sales transactions. We also collect data on single transactions, a dataset that contains 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 today. Each municipality has an administrative function, and certain taxes are collected by the municipality. A municipality reform in 2007 reduced the number of municipalities from 315 to 98. We use unique identifiers provided by Statistics Denmark to assign properties before 2007 to the new municipality codes. 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 for 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 represents 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).

Unlevered capital gains. 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 results are also robust to using a geometric of the above formula instead. We remove outliers by winzoring $r_i^{u,\log}$ at the 1st and 99th percentile.

Levered capital gains. Most households in Denmark buy their property with debt. 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 in 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.[8] Equity at sale is then

$$Equity_{is} = \max\big(P_{is} - Mortgage_{is}, 0\big). \tag{2}$$

[8]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.

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 $\exp(r_i^{lev,\log}) - 1$.

Single transactions. To assess whether selection into repeat sales affects our results, we impute unrealized capital gains for properties that are observed only once in our transaction data (i.e., not resold within the sample period). 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 significant limitation of the capital gain measures 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). Denmark Statistics 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. 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 (Fagereng et al., 2020).

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. The rank variable is constructed based on all households in Denmark. We define low, middle, high income groups as terciles of the income-rank distribution (0–33, 34–66, 67–100). Note that these are rankings based on all households, and so are not equally weighted in the transactions data.

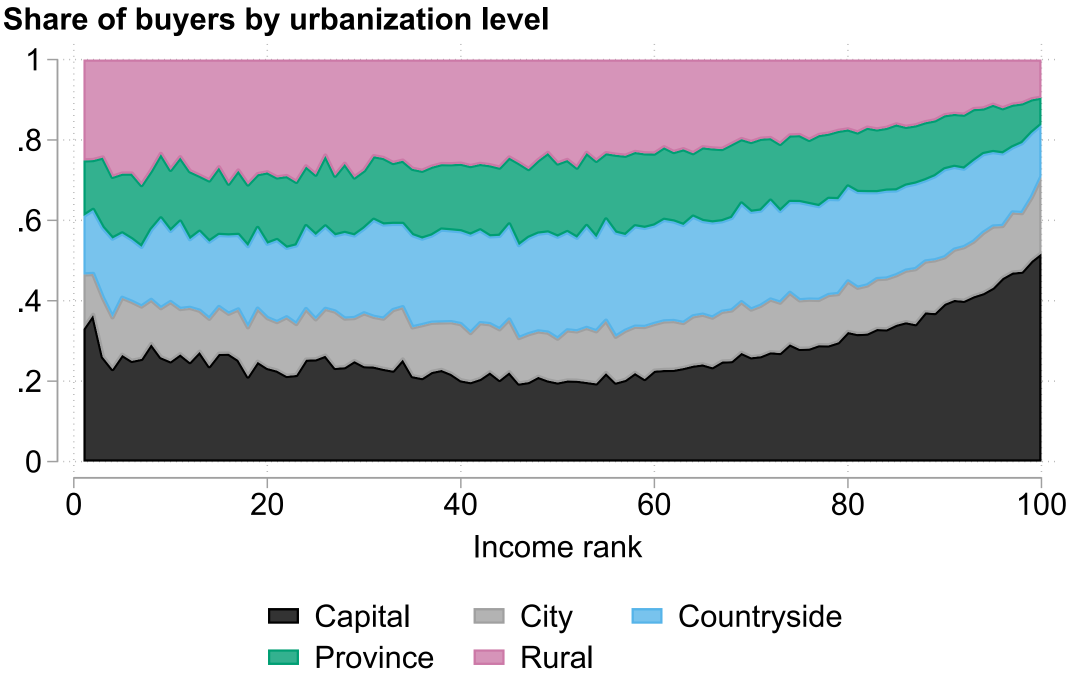
There is little difference in years between transactions (i.e., holding period) and the purchase year between income groups. High-income buyers (column 4) achieve both higher total capital gains on housing and have higher annualized returns compared to low-income buyers (column 2) and middle-income buyers (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 spend more money on renovations on average. 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 trans-

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.

actions 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 total transactions. The share of transaction within each income group that appears more than once (a repeat sale) is somewhat higher for the low income group (31%),



*

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 Denmark Statistics based on urbanization level. Income rankings are adjusted for age and are described in Section 3.

but is similar between middle income and high income buyers (27% vs 26%).

Because 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 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 also 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

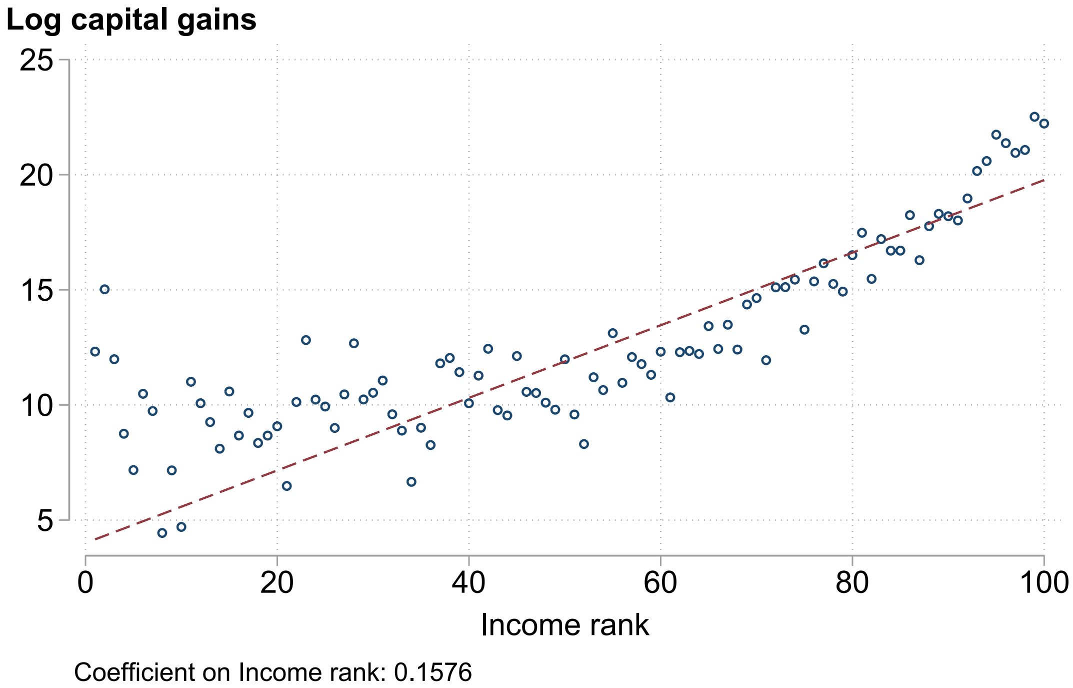


Figure 4: Capital gains to housing by income ranking

Notes: This figure plots income rank against the capital gain on housing, calculated as $\ln(P_{is}) - \ln(P_{ip})$. Income rankings are adjusted for age and are described in Section 3.

rural municipalities, where capital gains is 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 margins account for them. Using repeat-sales transactions, Figure 4 plots 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 spell i:

$$Y_i = \beta_0 + \beta_1 Income\ Ranking_i + X_i\Gamma + \mu_i + \epsilon_i \tag{3}$$

The specification regresses the outcome Y_i, the unlevered annualized log capital gain r_i^u on the main variable of interest, $Income\ Ranking_i$, and vectors of control variables X_i capturing homeowner and property characteristics. We scale income rank from 0 to 100 and express Y_i in log-percentage-points 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. $Income\ Ranking_i$ 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 $Income\ Ranking_i$. This approach absorbs both causal effects and selection (Kermani and Wong, 2024).

Figure 5 graphically plots the magnitude of the coefficient on $IncomeRanking_i$, the corresponding regression results are detailed in Appendix in 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 and implies that a one-unit increase in rank is associated with a 0.017 log point increase in log annualized capital gains. To assess the 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 log-percentage-points per year. Over a 10-year holding period, the implied

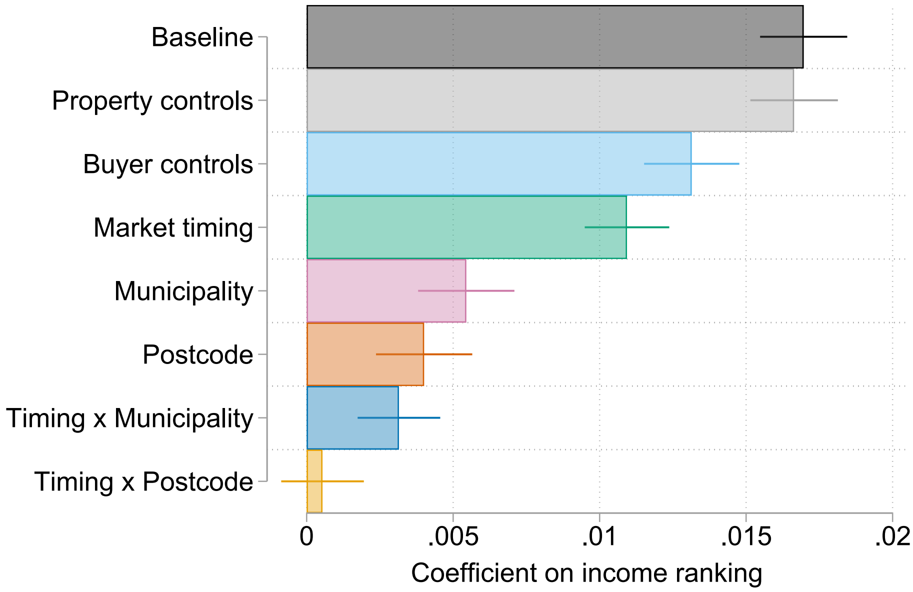


Figure 5: Income-rank gradient in housing capital-gains across specifications

Notes: The figure plots the coefficient on Income Rank on the x-axis from estimating Equation (3) 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* adds fixed effects for year-of-sale, year-of-purchase and municipality. *Market timing* × *Postcode* adds fixed effects for year-of-sale, year-of-purchase and postcode.

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 (3) helps to capture differences in capital gains generated by these characteristics. For instance, the prices for apartments generally grow faster than the prices 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 slightly smaller in magnitude but 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 even slightly decreases the coefficient on income rank to 0.014. We conclude that differences in property or homebuyer characteristics explain little of the variation in returnsover 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 Appendix shows including market timing indicators increasing the adjusted R^2 from 0.04 when controlling only for property and buyer characteristics to 0.25 with fixed effects for market timing. The coefficient on income rank changed only little from 0.014 in the specification controlling for property and homeowner characteristics to 0.011, showing no 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 return 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 postal codes, which are smaller neighborhood units within municipalities.Including fixed effects for municipalities in the fifth line of Figure 5, the coefficient on income rank reduces to 0.006, whereas controlling for the finer geography of the postcode reduces the coefficient on income rank further to 0.004. 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 the coefficient on income rank becomes even smaller, and, on the last line on Figure 5 with the controls for postcode interacted with the market timing it reduces even closer to 0 to become statistically insignificant. Once differences in location and market timing are accounted for, there is little evidence that high- and low-income households realize systematically different returns on comparable housing investments. This indicates that the higher returns of higher-income buyers are explained by 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.

Comparison to the literature Our findings on the differences in returns between low- and high-income buyers in Denmark are largely comparable to those in the previous literature. For example, Table 6 of Bach et al. (2020) reports that historical housing returns range from 4.19% for the bottom decile to 5.43% for P90-P95, a gap of 1.24 percentage points. Figure OA.16 in Fagereng et al. (2020) shows that the returns to housing for individuals in the 10th and 90th percentile is approximately 4.3 and 5 percent, respectively. The gap is therefore 0.7 percentage points. Note that these two papers report results for all households, whereas we report results for homebuyers only. [10]

4.1 Robustness and extensions

Differences in levered returns. Our results are corroborated by using levered returns. Table B3 reports the results, again summarizing different regression specifications. The coefficient on income rank is now larger at 0.017 in the baseline specification, consistent with the intuition that leverage magnifies returns. The baseline coefficients imply that buyers in the 90th percentile would earn 13.6 percent higher returns than buyers in the 10th percentile over a 10-year holding period. Controlling for property and buyer characteristics as well as market

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

[10]The relationship between housing returns and wealth ranking in Fagereng et al. (2020) is also non-monotonic, and appears approximately flat above the median.

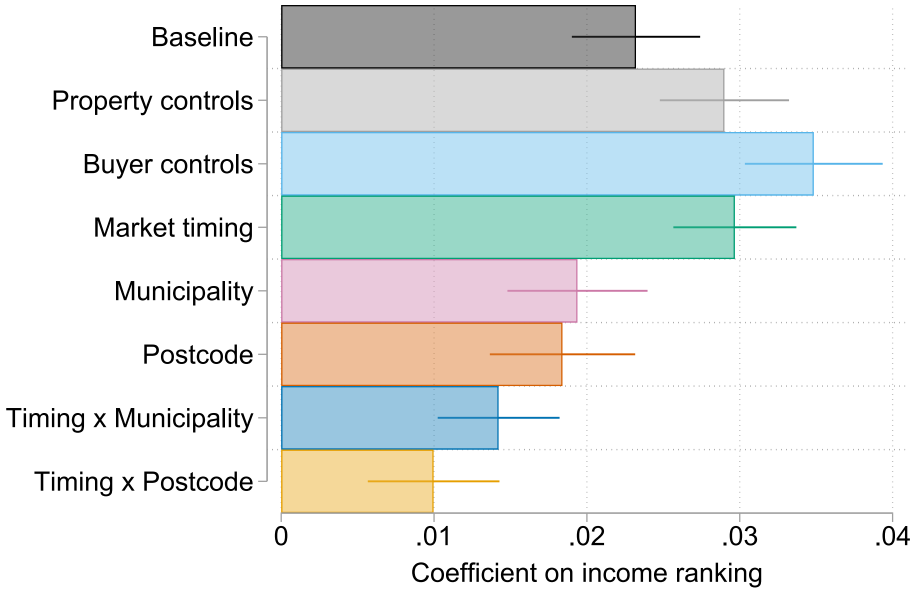


Figure 6: Levered housing capital gains and income rank

Notes: The figure plots the coefficient on Income Rank on the x-axis for various specifications. The outcome variable is the annualized levered log returns. We calculate the levered returns using the mortgage debt of the household one year after purchase. The *baseline estimate* includes no control variables and corresponds to the slope of the line in Figure 4(a). *Property controls* includes controls for floor number, number of rooms, square meter size of the property, an apartment indicator, and building age. *Buyer controls* include controls for wealth rank, gender, education, and family size. *Market timing* adds fixed effects for year of purchase and the year of sale. *Municipality* adds fixed effects for municipality, leaving market timing cotrols out. *Market timing, Municipality* adds fixed effects for year-of-sale, year-of-purchase and municipality.

timing strengthens the relationship between income and housing capital gains. The coefficient on income rank nearly doubles once buyer characteristics and the year of purchase and sale fixed effects are added, 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 0.008 in the last column of B3 remains statistically significant, and implies a cumulative difference in returns of 6.7 percent over a 10 year holding period.

Imputing returns for single-transactions. Our focus on repeat sales generates many censored ownership spells, because the final transaction price is unobserved for unsold properties. To investigate how the censoring of returns due to incomplete spells affects our findings, we impute returns for single-transaction properties using municipality-level house-price indices.

Figure 7 shows a linear relationship between imputed returns and income rank similar to the one on Figure 4 for the repeat-sales returns. The regression involving imputed returns on income

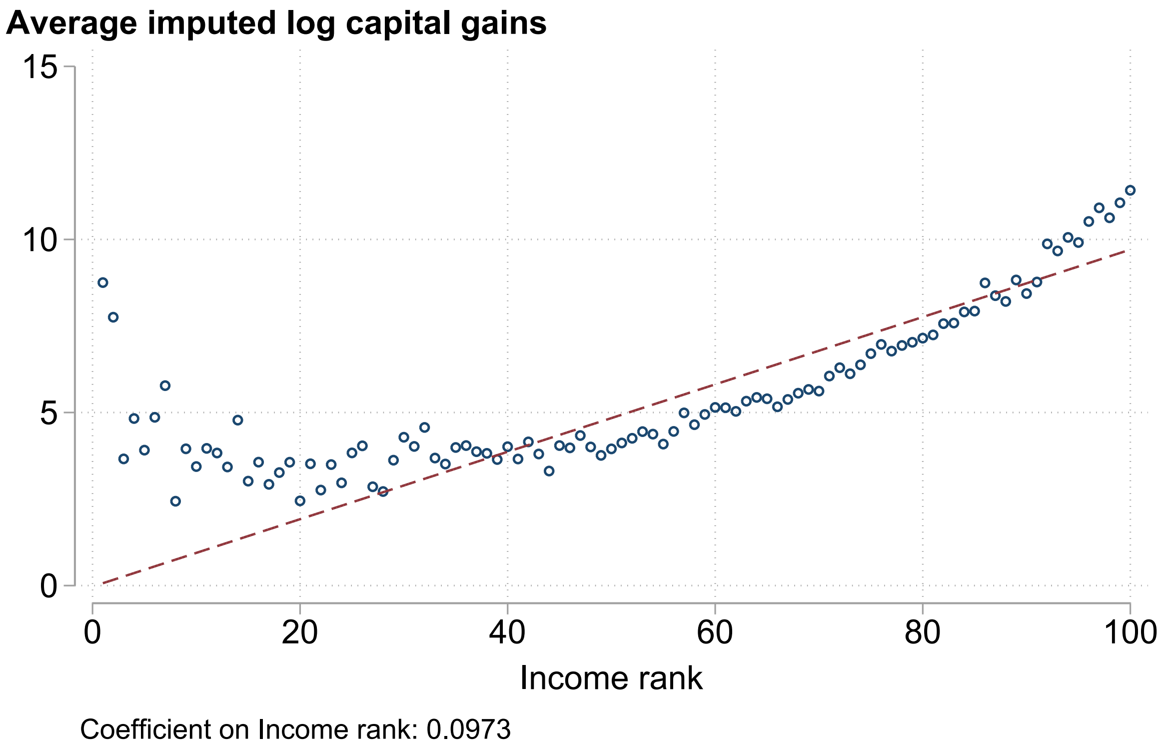


Figure 7: Imputed housing capital gains and income rank for single transactions

Notes: The figure plots the average imputed returns against income ranking. Income rankings are adjusted for age and are described in Section 3. Imputed returns 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.

rank yields a coefficient of 0.017, which is also similar to the baseline estimate in Table B2. Selection into selling does not appear to be a large driver of the income gradient in returns.

It is reassuring that the share of repeat transactions are similar across the income distribution, and that the coefficients on income rank for the imputed returns and repeat-sales returns are similar. Return censoring due to incomplete spells is particularly concerning if there are differences in censoring by income rank. Summary statistics in the bottom of Table 1 shows this difference is not substantial.

Also note that imputing returns for each buyer is similar to the approach in Bach et al. (2020) and Fagereng et al. (2020), with the disadvantage that there is little reason to estimate how much of the difference in imputed returns is explained by the market and buyer characteristics. By design, location will explain the differences in returns. Indeed, using repeat transactions instead of municipality-level returns is the key advantage of our analysis, as it allowed us to study the individual-level variation in housing investment performance.

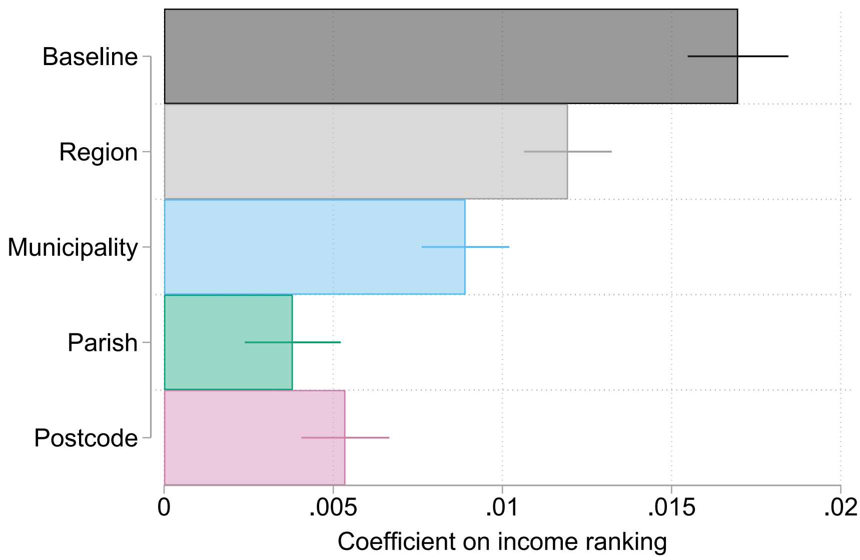


Figure 8: Level of geographical aggregation

Notes: The figure plots the coefficient on income rank on the x-axis from estimating Equation (3) for various levels of geographic aggregation. The outcome variable is annualized log returns. Income rankings are adjusted for age and are described in Section 3. The results show the coefficient on income rank using region, municipality and postal code fixed effects.

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 aggregation level balances the preservation of sufficient observations and captures the local aspect of housing markets. We now also examine how other geographical levels affect the estimated coefficient on income rank.

Denmark is divided into 98 municipality, where each municipality belongs to one of the five regions.

Figure 8 shows region fixed effects explain about half of the difference in returns over 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. The regions are therefore akin to a Metropolitan Statistical areas 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. Especially in larger cities, postcodes capture smaller neighborhoods better than municipalities. There is considerable

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

	Baseline, no controls				All controls and FE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Income rank	0.0280***	0.0252***	0.0255***	0.0246***	0.0037***	0.0018**	0.0008	0.0009
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Ren. indicator		0.9786***				0.8388***		
		(0.0433)				(0.0399)		
Ren. count			0.1691***				0.2219***	
			(0.0066)				(0.0065)	
Ren. amount (DKK)				0.0000***				0.0000***
				(0.0000)				(0.0000)
Buyer/property controls	No	No	No	No	Yes	Yes	Yes	Yes
PurchaseYear x PostCode.	No	No	No	No	Yes	Yes	Yes	Yes
SalesYear x PostCode.	No	No	No	No	Yes	Yes	Yes	Yes
Adjusted R-squared	0.007	0.011	0.010	0.011	0.353	0.356	0.357	0.358
Observations	139,617	139,617	139,617	139,617	122,424	122,424	122,424	122,424

Notes: This table presents the regression results that relate housing capital gains and income ranking when we control for renovations. The outcome variable is the annualized log housing capital gains. The sample is limited to include only sales occuring 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 break applied for between purchase and sale, and *Ren. amount (DKK)* is the total sum of the tax break in DKK. Columns 1-4 do not include controls or fixed effects. Columns 5-8 include all controls and fixed effects for postcodes × markett timing. *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.* adds fixed effects for year-of-purchase, year-of-sale and municipality. *Timing x Post.* adds fixed effects for year-of-purchase, year-of-sale and postcode.

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 $Municipality \times YearQuarter$ has an R-squared of 34 percent.

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. We can 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 the properties sold after 2011. Restricting the sample to the properties sold after 2011 does not change the overall sample composition substantially. In the restricted sample we lose only a part of transactions with the shorter holdings for the properties bought after 1998 and sold before 2011, but we keep many remaining shorter-term transactions and all transactions with the longer holding periods (above 14 years).

Figure A2 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 ranking is mostly unaffected by controls for renovations. The first column replicates the baseline result, showing that there is a strong income gradient in annualized log capital gains. The coefficient is larger than in the baseline table, as the sample only covers transactions with a sales year after 2011. However, including different proxies for renovations only leads to a small reduction in the coefficient. Finally, columns 5-8 shows that if we include renovation proxies plus all controls from the baseline regressions along with fixed effects for postcode $\times$ market timing, the results still show that the coefficient on income ranking is close to zero.

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 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 whether the higher capital gains earned by high-income buyers can be explained, at least in part, by their exposure to higher housing risk. This section studies 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 C1. 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: Regressions of housing risk measures on income rank.

	(1) Mun return	(2) Sharpe	(3) Std.dev	(4) Beta region	(5) Beta Denmark	(6) Sum negative
Income rank	0.00009***	0.00067***	0.00009***	0.00078***	0.00243***	-0.01052***
	(0.00000)	(0.00001)	(0.00000)	(0.00001)	(0.00002)	(0.00008)
Adjusted R-squared	0.021	0.015	0.013	0.007	0.020	0.017
Observations	1,082,022	1,082,022	1,082,022	1,082,022	1,082,022	1,082,022
	(1) Return negative	(2) Sales time	(3) Cov. Cons	(4) Cov. Inc	(5) Id. Risk	(6) reg12
Income rank	-0.00015***	-0.19252***	0.00001***	0.00000***	0.00000***	0.00040***
	(0.00000)	(0.00165)	(0.00000)	(0.00000)	(0.00000)	(0.00002)
Adjusted R-squared	0.012	0.013	0.016	0.013	0.000	0.001
Observations	1,082,022	1,082,022	1,082,022	1,082,022	254,526	254,526

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 C1. We merge the municipality-level measures to each buyer based on the location of their purchased property.

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 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 A1). 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 return gap.

We also examine other indicators of risk. The coefficients in Columns 6 and 7 indicate that the probability of experiencing a period of negative house price growth is lower the further up in the income ranking the buyer is located, but also that, conditional on a negative outcome, the magnitude of negative growth is larger. Higher-income buyers are also buying properties in more liquid markets, as measured by the time-on-market". Further, higher-income buyers live in areas with higher covariance between house price growth and income/consumption growth. Again, however, the magnitudes are small. Finally, Eichholtz, Korevaar, Lindenthal and Tallec (2021) estimate that idiosyncratic risk is the largest risk component of housing, especially at shorter holding periods. We find that richer buyers take on more idiosyncratic risk, but the difference is again small.

Overall, the risk evidence suggests that the income gradient in housing capital gains is not primarily due to compensation for higher risk. The key difference from financial assets is that housing is an indivisible, location-specific asset that also provides consumption benefits, so households cannot cheaply buy 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-return areas.

6 Determinants of location

Higher-income buyers earn systematically higher capital gains on their housing investments, largely due to sorting into high capital gains locations. There is also some evidence that higher-income buyers take on more risk, although the evidence is mixed. In Appendix C3, we show that higher municipality-level house price growth is driven by income and population growth. 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, 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 understand how these factors influence differences in capital gains, it is helpful to compare housing with other financial assets. For equities, households face almost no constraints on the minimum amount they must invest. A low-income household can buy any individual stock, even if only a small amount. Differences in returns on financial portfolios, therefore, reflect differences in skill, risk tolerance, or information—not differences in access. Housing is fundamentally different: households cannot buy a "fraction" of a high-return neighborhood (Parkhomenko, 2025). Consistent with this, most Danish households hold only one property, and investment-only housing is concentrated among the wealthiest 10%.[11] 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 returns. 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 feasible choice set: the set of properties a household can finance and that satisfy its minimum consumption 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 M to a fraction of the property price

$$M \leq \theta_H P.$$

This constraint is wealth-based and requires buyers to have sufficient equity. 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. Taken together, the minimum of these constraints generates an upper bound of $M^{\max} = \min(\bar{M}^{LTV}, \bar{M}^{PTI})$ on maximum borrowing (Bäckman and Khorunzhina, 2024), and consequently limits the maximum purchase price to the sum of maximum borrowing plus their net wealth, $P^{\max} = M^{\max} + NetWealth$.

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

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

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 this amount, so location j is feasible only if $P_j(q) \leq P^{\max}$. The feasible set is therefore

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

In other words, entire locations drop out of the choice set when the cheapest dwelling that meets consumption needs is already too expensive.

This structure yields two clear 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, then 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. Essentially, 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, if supply is inelastic, it is unclear whether lower-income buyers can out-compete higher-income buyers for the limited number of objects available in high-return areas. Greenwald and Guren (2021) show that with inelastic supply, any change in credit will affect house prices instead of the homeownership rate. Imagine, for example, that a lower-income buyer sought to purchase housing in an expensive area. If the supply of properties is limited, they would be competing against higher-income buyers with more purchasing power. Higher demand for lower-income households may simply lead to higher prices paid by higher-income buyers, and 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. This is what we test below.

6.2 The feasible set and financial constraints

We construct a simple proxy for each household's feasible choice set. We use a 25% random sample of transactions, and collect all properties sold in the same year as the buyer's actual purchase. A property is considered to be within the feasible set if its transaction price is at or below the maximum borrowing for the buyer. 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 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. There is no legal guidance on maximum PTI limits in Danish law, and so we test whether the results are sensitive to alternative numbers. They are not. We use the income one year before the purchase and calculate the maximum amount of income the buyers could spend on the mortgage payments. We then use an 30-year annuity schedule to find the loan size that corresponds to the maximum payments. As a robustness check, we also construct a measure based on the actual purchase price paid by the household (Appendix Table B6). This measure represents a conservative lower bound for what buyers can afford, and guarantees feasibility based on observed behavior. 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 maximum borrowing constraint maps more directly into the conceptual framework and to the later credit reforms.

Figure 9 shows the share of affordable transactions (based on maximum borrowing) by income rank.[12] 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 B5 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 results show that

[12]Table B5 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.

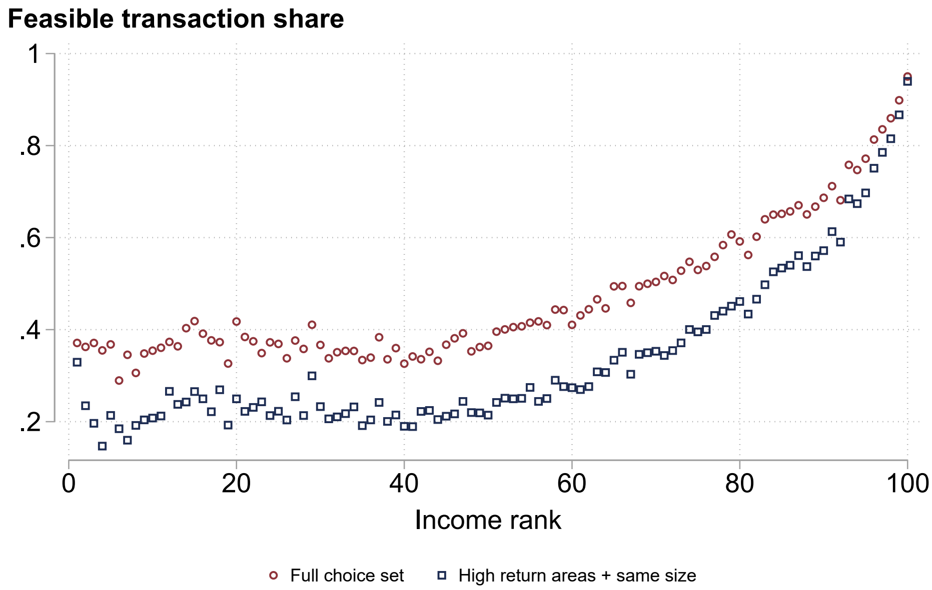
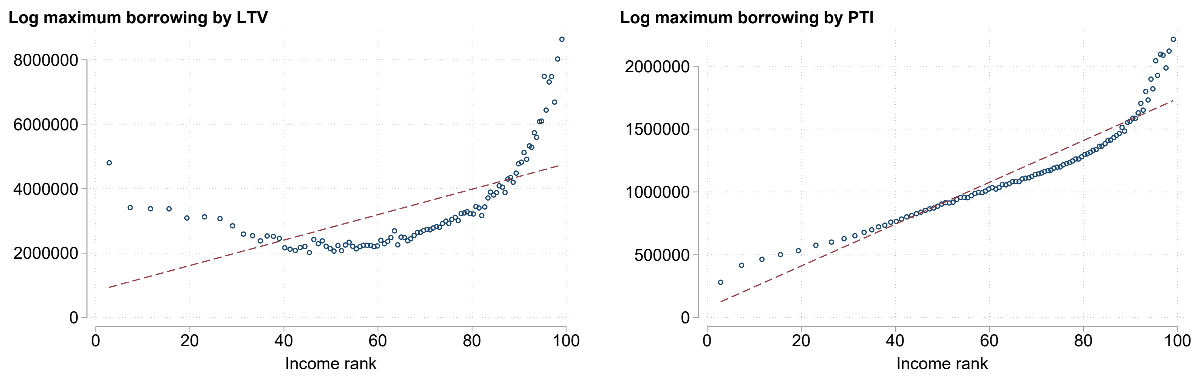


Figure 9: Choice set over income rank

Notes: The figures plots income rank and choice set for each buyer. The choice set is defined using the actual purchase price for each buyer pairs and denotes the share of transactions for each buyer that is below their actual purchase price. 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 in 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.

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 also examine which financial constraints bind maximum borrowing. Recall that if households face two financial constraints, then the lower of these constraints naturally determines their borrowing capacity (see also Grodecka, 2020). Figure A3 plots the binding constraints by income rank. Over the income distribution, the share of households bound by the LTV constraint is U-shaped in income, with a low share of buyers bound by the LTV constraint at both the top and the bottom of the income distribution. The U-shaped pattern is stable across years, and is present in both high- and low-return municipalities. On average, slightly above 50% of borrowers are bound by the PTI limit. Figure 10(a) shows that the maximum borrowing according to the LTV constraint is relatively similar between high- and low-income buyers. Instead, the main difference in maximum borrowing comes form the PTI constraint, shown in panel b), where higher-income buyers have a considerable advantage. Consistent with these results, Rhode Nissen, Tang-Andersen Martinello, Hviid and Sinding Bentzen (2022) find that LTV restrictions impact young and less wealthy households more, adn that limits on the DTI ratio and the DSTI



(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.

ratio impact primarily housing buyers in the largest cities and low-income buyers.

The choice-set calculations are inherently partial-equilibrium: they evaluate affordability at current prices. For example, buyers in the 40th percentile could afford around 15% of properties in high return areas in the same size category. In equilibrium, however, 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 systematically higher ability-to-pay, they would bid up scarce properties and continue to win them, even if prices rose. In that case the allocation of properties across income groups would remain essentially unchanged, but transaction prices would increase. Our empirical test below exploits variation in credit conditions to examine exactly this channel: whether relaxing borrowing capacity alters who buys in high-return areas or instead mainly raises prices paid by the eventual winners.

6.3 Loosening financial constraints and location choice

Having shown that lower-income households face a smaller choice set, especially in high-return areas, we now ask whether expanding borrowing capacity through mortgage reforms increases their presence in these locations. In the Danish setting, 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 a credit-assessment guidance in 2016 that tightened mortgage credit rules specifically in the high-return areas in Copenhagen and Aarhus.

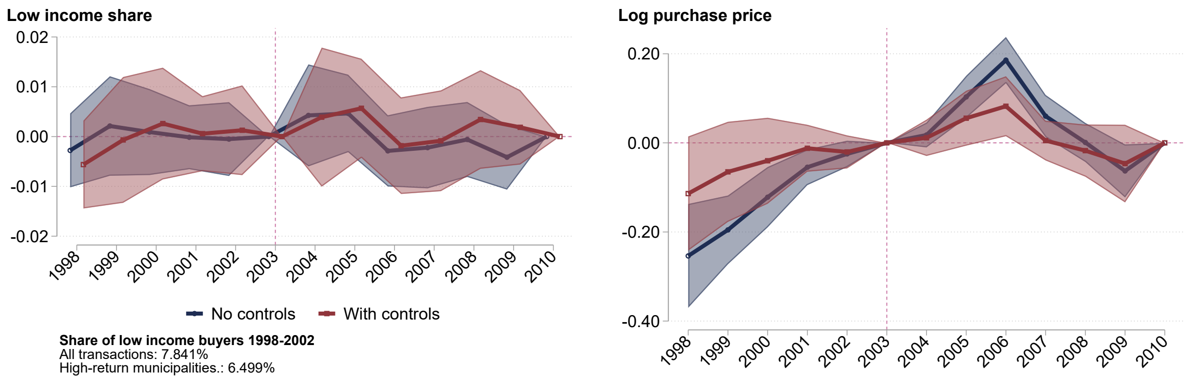
The empirical analysis below tests whether these policy changes increased the presence of low-income buyers in high-return municipalities. As we show, the share of low-income buyers remains remarkably stable across all reforms.

Introduction of interest-only mortgages in 2003. We start with the 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:

$$LowIncome_{imt} = \alpha_m + \gamma_t + \sum_{k=1998}^{2010} \beta_k (HighReturn_m \times \mathbf{1}_{t=k}) + X_{it}\Gamma + \epsilon_m \tag{4}$$

where $LowIncome_{imt}$ is a dummy equal to one if the buyer income rank is in the bottom half of the 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 on the municipality level. The sample includes all transactions instead of only repeat transactions to improve statistical power.

Figure 11, panel a), shows that the share of low-income buyers is not statistically different before and after interest-only mortgages were introduced, and indeed follows a relatively stable share over time. The pre-trends are not statistically different form zero, and while there is a slight uptick in the share of low-income buyers in 2004 and 2005, the estimates are not statistically significant at conventional levels and the coefficients are again close to zero in 2006. A similar finding is reported in Bäckman and Lutz (2020) for the homeownership rate, rather than transactions. These results are even more striking once you 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 by above 60% for buyers of all income declines (Bäckman and Lutz, 2020). The share of



(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 figure plots the coefficients on β_k estimating (4). The omitted year is 2003. The data is on the municipality level. High return municipalities are defined as municipalities in the top quintile of average house price growth between 1997 and 2018. *Property controls* includes controls for floor number, number of rooms, square meter size of the property, an apartment indicator, and building age. *Buyer controls* include controls for wealth rank, gender, education, and family size. *Market timing* adds fixed effects for year of purchase and the year of sale. *Municipality* adds fixed effects for municipality, leaving market timing controls out. *Market timing, Municipality* adds fixed effects for year-of-sale, year-of-purchase and municipality.

interest-only mortgages is also considerably higher in areas with high price levels (Bäckman and Lutz, 2025). Instead, panel b) shows that house price growth increased 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, consistent with the inelastic supply setup in Greenwald and Guren (2021).

Credit growth guidance. We also examine another instance of credit tightening: in February 2016, the Danish Financial Supervisory Authority (FSA) introduced a credit-assessment guidance (*Vejledning om forsigtighed i kreditvurderingen ved belåning af boliger i vækstområder*) that applied specifically to Copenhagen, its surrounding municipalities, and Aarhus, the second largest city in Denmark. 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.[13]

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. Equivalently, the theory predicts a decline in the share of low-income or financially vulnerable buyers in these locations following the introduction of the guidance.

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

$$LowIncome_{imt} = \alpha_m + \gamma_t + \sum_{k=2010}^{2019} \beta_k (Treated_m \times \mathbf{1}_{t=k}) + X_{it}\Gamma + \epsilon_{imt}, \tag{5}$$

where $Treat_i$ equals one for municipalities covered by the 2016 guidance. The rest of the specification and the control variables are the same as in Equation (4).

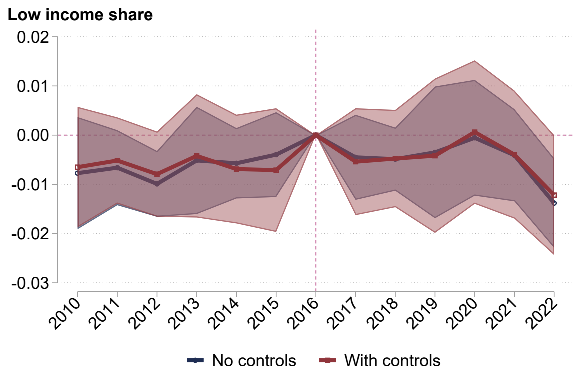
Figure 12 shows that despite a policy explicitly aimed at restricting credit to vulnerable households in high-price markets, the income composition of buyers remains stable before and after 2016. The event-study coefficients for buyer composition are small and statistically indistinguishable from zero, with no detectable break at the time of the policy.

These findings reinforce the conclusion from the previous subsection: adjustments in credit conditions, whether through national reforms or targeted guidance, have limited impact on who buys in high-return locations. Instead, the 2016 guidance appears to have operated primarily through prices rather than through changes in buyer composition.

6.4 Interpreting the Null Effect of Credit Reforms

Taken together, the Danish mortgage-market reforms provide a series of sharp empirical tests of the idea 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 loosening of credit conditions, most notably the introduction of interest-only mortgages in

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



(a) Share of low income buyers

Figure 12: Growth guidance and housing market outcomes

Notes: The figure plots the coefficients on β_k estimating (4). The omitted year is 2003. The data is on the municipality level. High return municipalities are defined as municipalities in the top quintile of average house price growth between 1997 and 2018. *Property controls* includes controls for floor number, number of rooms, square meter size of the property, an apartment indicator, and building age. *Buyer controls* include controls for wealth rank, gender, education, and family size. *Market timing* adds fixed effects for year of purchase and the year of sale. *Municipality* adds fixed effects for municipality, leaving market timing controls out. *Market timing, Municipality* adds fixed effects for year-of-sale, year-of-purchase and municipality.

2003, should have expanded the feasible set for constrained buyers and increased their presence in high-return municipalities. Instead, we find no measurable shift in the income composition of these areas. The share of low-income buyers in high-return municipalities remains essentially unchanged across all major reforms. These results are consistent with credit shocks affecting house prices instead of access to housing. Thus, the persistent income gradient in housing capital gains we documented earlier is not driven by differential access created by credit constraints, but by persistent sorting in an environment where prices rather than composition adjust to credit conditions.

This null result has several important implications. Most importantly, the results indicate that financial constraints related to payment constraints are not the binding margin for most low-income households when it comes to accessing high-return areas. Note that the credit reforms that we analyze target the payment constraint, which is a different constraint from the LTV constraint analyzed in Gupta et al. (2025). Even when borrowing capacity expands, the effective affordability of properties in these locations remains unchanged for low-income buyers. This result is consistent with a setting in which supply in high-return locations is inelastic and 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.

A final caveat is 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). These frictions matter for our setting because, as we document in Appendix C3, municipalities with higher income and population growth experience systematically higher house price growth. Limited mobility, therefore, implies that households that remain in less advantaged areas also forgo higher capital gains. We do not investigate these frictions here.

7 Conclusion

The effect of inequality is a central topic in contemporary academic and policy debates. This paper explores the relationship between income ranking and housing capital gains, contributing to the recent literature on differences in the returns to wealth (Bach et al., 2020; Fagereng et al., 2020; Kuhn et al., 2020). Using detailed administrative data from Denmark, which characterizes household income ranking and tracks purchase and sale transactions, we find that households with a higher income ranking earn higher unlevered returns. Furthermore, the results suggest that location choice explains the entire difference in returns across the income distribution. Differences in risk-taking have little explanatory power for capital gains to housing, and differences in returns at the municipality level are driven by income and population growth. Finally, we investigate how financial constraints and preferences drive location choice and, in the end, contribute to differences in returns. Our results underscore the importance of understanding location choice when studying differences 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.

Ultimately, this paper documents differences in realized returns and not differences in expected returns. An important question is whether the patterns in housing capital gains 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 result that differences in returns are driven by location implies a clear 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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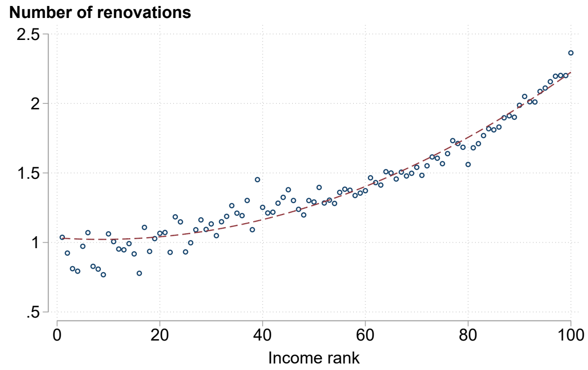
INTERNET APPENDIX

FOR ONLINE PUBLICATION

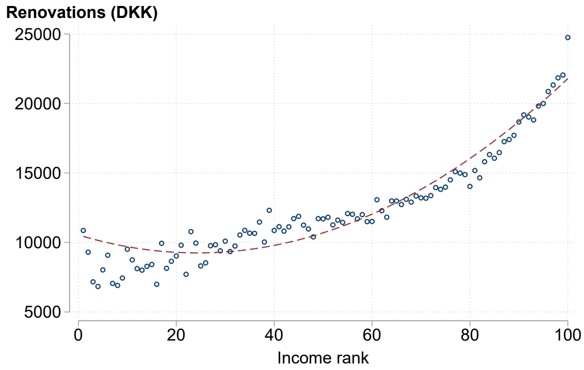
Appendix: Figures

Figure A1: 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 is collected from FinansDanmark.



(a) Renovation Usage and Income Rank



(b) Renovation Amount and Income Rank

Figure A2: 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.

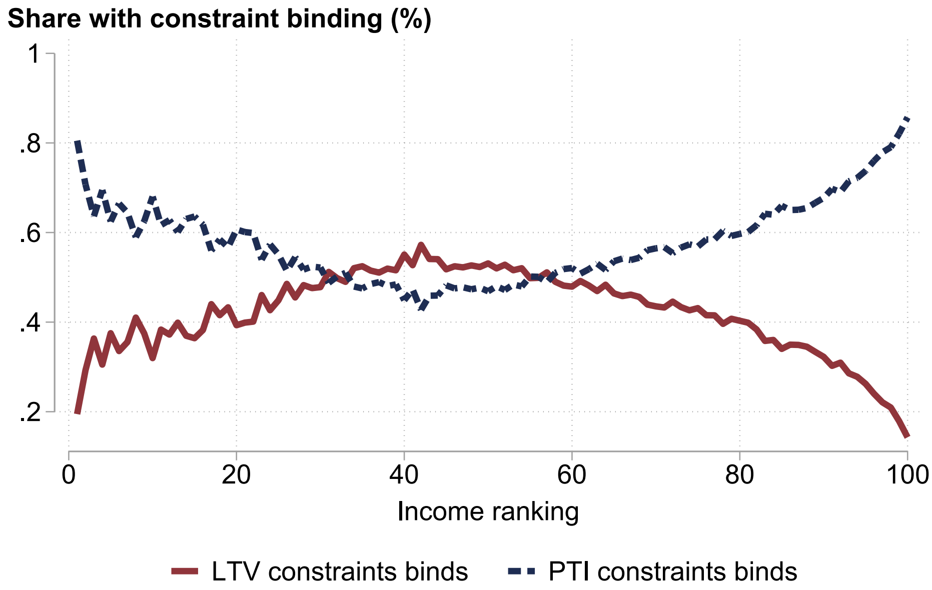


Figure A3: Binding constraints by income rank

Notes: The figures 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.

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.

Appendix: Tables

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***	0.016***	0.014***	0.011***	0.006***	0.004***	0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Apartment		0.330***	0.101	-0.118**	-0.676***	-0.937***	-1.019***	-1.291***
		(0.062)	(0.063)	(0.054)	(0.064)	(0.066)	(0.053)	(0.057)
Floor number		0.284***	0.301***	0.335***	0.035**	0.008	0.042***	0.013
		(0.016)	(0.016)	(0.014)	(0.017)	(0.018)	(0.013)	(0.015)
Rooms		0.139***	0.156***	0.138***	0.105***	0.088***	0.079***	0.072***
		(0.024)	(0.024)	(0.021)	(0.024)	(0.024)	(0.021)	(0.021)
Size m^2		-0.017***	-0.013***	-0.011***	-0.007***	-0.007***	-0.005***	-0.004***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Building age		0.012***	0.010***	0.010***	0.009***	0.009***	0.009***	0.009***
		(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Age			-0.047***	-0.030***	-0.033***	-0.032***	-0.018***	-0.017***
			(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Number of buyers			-1.679***	-1.516***	-2.049***	-2.108***	-1.836***	-1.840***
			(0.045)	(0.040)	(0.046)	(0.046)	(0.040)	(0.041)
Wealth rank			-0.010***	0.000	-0.015***	-0.016***	-0.002***	-0.003***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female			-0.384***	-0.328***	-0.555***	-0.586***	-0.497***	-0.522***
			(0.052)	(0.046)	(0.052)	(0.052)	(0.044)	(0.044)
Education			0.004	0.087***	-0.054***	-0.074***	0.030***	0.000
			(0.007)	(0.007)	(0.007)	(0.008)	(0.006)	(0.007)
Family size			-0.012	0.008	-0.007	-0.005	0.004	-0.003
			(0.019)	(0.017)	(0.018)	(0.019)	(0.016)	(0.016)
Adjusted R-squared	0.002	0.023	0.038	0.254	0.054	0.059	0.335	0.412
Observations	202,955	202,955	202,955	202,955	202,955	202,954	202,921	200,407

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.* adds fixed effects for year-of-purchase, year-of-sale and municipality. *Timing x Post.* adds fixed effects for year-of-purchase, year-of-sale and postcode.

Table B3: 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	0.017***	0.024***	0.034***	0.029***	0.017***	0.015***	0.012***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Apartment		1.019***	1.245***	0.522***	0.040	-0.356*	-1.242***	-1.775***
		(0.187)	(0.187)	(0.154)	(0.189)	(0.194)	(0.151)	(0.165)
Floor number		0.743***	0.709***	0.833***	0.166***	0.079	0.171***	0.086*
		(0.051)	(0.051)	(0.042)	(0.055)	(0.059)	(0.043)	(0.048)
Rooms		0.394***	0.239***	0.195***	0.185***	0.164***	0.082	0.098*
		(0.062)	(0.061)	(0.053)	(0.061)	(0.062)	(0.051)	(0.055)
Size m^2		-0.042***	-0.039***	-0.030***	-0.026***	-0.025***	-0.016***	-0.015***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Building age		0.036***	0.032***	0.029***	0.025***	0.024***	0.025***	0.024***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Age			-0.176***	-0.095***	-0.159***	-0.157***	-0.077***	-0.074***
			(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Number of buyers			0.565***	0.580***	-0.308**	-0.385***	-0.397***	-0.488***
			(0.121)	(0.104)	(0.123)	(0.123)	(0.102)	(0.109)
Wealth rank			-0.048***	-0.019***	-0.058***	-0.060***	-0.022***	-0.024***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female			-0.381***	-0.409***	-0.727***	-0.770***	-0.773***	-0.874***
			(0.145)	(0.122)	(0.144)	(0.145)	(0.116)	(0.123)
Education			-0.140***	0.116***	-0.237***	-0.268***	0.017	-0.045**
			(0.020)	(0.017)	(0.020)	(0.021)	(0.017)	(0.018)
Family size			-0.063	0.051	-0.104**	-0.103**	0.049	0.060
			(0.050)	(0.043)	(0.050)	(0.050)	(0.041)	(0.044)
Adjusted R-squared	0.000	0.024	0.050	0.333	0.063	0.067	0.422	0.482
Observations	149,287	149,287	149,287	149,287	149,287	149,286	149,244	145,693

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. The *Baseline* includes no control variables and corresponds to the slope of the line in Figure 4(a). *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.* adds fixed effects for year-of-purchase, year-of-sale and municipality. *Timing x Post.* adds fixed effects for year-of-purchase, year-of-sale and postcode. The cumulative difference is calculated as the difference in returns between the 10th and 90th percentile over a 10-year holding period using the coefficient on income ranking. The formula is: $(1 + Coefficient * (90 - 10)/100)^{10} - 1$.

Table B4: 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 B5: Choice set and income rank using maximum borrowing

	All areas				High return areas			
	(1) All	(2) Same size	(3) Same rooms	(4) All	(5) Same size	(6) Same rooms	(7) c7	(8) c8
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 income rank on the choice set for each buyer. Choice set is defined using maximum borrowing plus any equity for each buyer pairs 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 1-3 use all transactions within the choice set, and columns 4-6 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.

Table B6: 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 income rank on the choice set for each buyer. Choice set is defined using the actual purchase price for each buyer pairs 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 1-3 use all transactions within the choice set, and columns 4-6 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) show that for a utility-maximizing household allocating resources between consumption and investments, the following equation holds:

$$\ln E[R_{t+1}] - \ln R_f = \gamma \operatorname{Cov}\left[\ln\left(\frac{C_{t+1}}{C_t}\right), \ln R_{t+1} - \ln R_f\right], \tag{6}$$

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.[14]

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.

[14]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.

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:

$$\text{LME}_i = \frac{P_{i,T}/R_{t,T}^{\text{Mun}} - P_{i,t}}{P_{i,t}}, \tag{7}$$

where $R_{t,T}^{\text{Mun}}$ 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:

$$\frac{\log(1 + \text{LME}_i)}{\sqrt{\tau_i}} = X_i'\beta + \alpha_{\text{Mun}(i)} + \alpha_{p(i)} + u_i, \tag{8}$$

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 (8), 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 *the first date* a property is listed for sale and the signing of the purchase agreement. The sales time data is provided by Finans Danmark and is available on the municipality level from 2004 and 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 Finans Danmark. 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 Housing supply

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

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

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

where $\Delta P_{r,t}$ is the annual change in regional 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 shocks solely due to variations in supply constraints. However, different areas may have varying industry structures or, more generally, differential exposure to the business cycle, leading to varying levels of house price growth. To account for this, we include controls for local income growth and employment, allowing for municipality-specific coefficients:

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

The estimate of 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 regional house price shocks, indicating a more supply-constrained municipality.

C3 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 the following equation:

$$\Delta P_{kt} = \alpha + \beta_1 Income + \beta_2 Employment + \beta_3 Supply + \gamma_t + \gamma_r + \epsilon_{krt} \tag{12}$$

where the dependent variable is the year-over-year difference in log prices for municipality k in region r in year t. The variables of interest are income and employment (either in levels or in growth rates). Since we are interested in cross-sectional differences, we control for year fixed effects in γ_t. We also control for region fixed effects γ_r in certain regressions. Finally, we standardize all variables to have zero means and standard deviations of 1, to allow for easy interpretation of the coefficients. Each coefficient measures the change in housing returns for a municipality for a one standard deviation increase in the variable. Finally, we cluster standard errors at the municipality level.

Table B7 shows that housing returns are higher in areas with higher population and income

Table B7: 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	No	Yes	Yes	No	Yes	Yes	Yes
_cons	Yes	No	No	Yes	No	No	No
region	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 FinansDanmark 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 household, that 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 C2.

levels. In addition, areas with high income and inelastic supply experienced higher housing returns, as shown by the interaction between income levels and housing supply in column 3. Interpreting these results and focusing on income, 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 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. The R-squared in column 7 is 0.57, meaning that year-fixed effects and changes in income and population explain over half of the variation in house price growth.

Finally, we investigate whether income growth has larger effects in supply-constrained areas.

According to standard supply and demand, the *responsiveness* to income or interest rate shocks should be higher in a more constrained area (Louie, Mondragon and Wieland, 2025). We can directly estimate this by including an interaction between supply and shocks. Similar to Louie et al. (2025), we do not find that the impact of income growth is larger in areas that are more constrained. The implication is that supply is not important for explaining the *reaction* of house price growth to income growth or interest rates in Denmark. For an equivalent demand shock, house prices react similarly in areas with high and low supply elasticities. Instead, differences in *income growth across locations* explain why certain areas experience higher house price growth.

The aggregate statistics are also informative. The Danish population grew by 11% from 1996 to 2019, and Danish income inequality has increased steadily over the past 30 years.[15] An increase in population or top income shares would increase demand in expensive areas, which, combined with inelastic supply, would increase house prices (Howard and Liebersohn, 2025), in particular since population and income growth are higher in Copenhagen (International Monetary Fund, 2016).

[15] Data from Denmark Statistics show that the Gini coefficient has increased from 22.83 in 1996 to 30.61 in 2023. Data is available from Denmark Statistics, Table IFOR41. Data on population growth is also taken from Denmark Statistics, Table BEFOLK1.