Housing Returns over the Income Distribution*

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Abstract

We show that high-income buyers earn higher financial returns to housing using detailed transaction data from Denmark. The gap in housing returns is explained by location choice, with little role for market timing, property type, buyer characteristics, or risk taking. Higher-income households purchase in areas with persistently higher house price growth but comparable risk, liquidity, and downside exposure to those chosen by lower-income households. Credit constraints and consumption needs constrain the feasible choice set of lower-income households, limiting access to high-return locations. Our results highlight how spatial sorting amplifies differences in wealth accumulation: returns on the dominant asset for most households are shaped less by risk or investment skill than by consumption needs, housing supply, and financial constraints.

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1 Introduction

Recent studies on the origin of wealth inequality have highlighted differences in returns across households (Fagereng, Guiso, Malacrino and Pistaferri, 2020; Bach, Calvet and Sodini, 2020), a mechanism fundamental to explaining the high concentration of wealth in the United States and elsewhere (Benhabib, Bisin and Zhu, 2011; De Nardi and Fella, 2017). For financial assets, it is relatively straightforward to understand differences in returns as reflecting, for instance, skill or risk-taking. Housing, however, has several unique features that require further consideration (Ioannides and Ngai, 2025). Housing is an infrequently traded idiosyncratic asset with high transaction costs, that in a majority of cases requires the household to incur debt to finance, and at the same time, represents a large share of the household consumption basket. Housing is also the largest asset on the household balance sheet (Campbell, 2006), and consequently, the returns to housing play a large role in the dynamics of inequality.

In this paper, we conduct a detailed examination of the returns to housing, and document differences in housing returns across the income distribution using detailed and accurate transaction-level data from Denmark. Our main contribution is an empirical investigation into the mechanisms that explain differences in returns related to the unique nature of housing. Summarizing our results, we find a significant positive relationship between income ranking and housing returns: households above the 90th percentile of the income distribution earn a 0.8 percent higher annualized return than households in the 10th percentile. This translates to a 8.3 percent unlevered cumulative return over a 10-year holding period and represents an economically significant difference in outcomes for what is, for most households, their most important asset. We also show that differences in returns are explained statistically by location choice, where we find a limited role for other explanations such as market timing or property type. Next, we document that there is little difference in a number of risk measures across areas where low- and high-income buyers chose to purchase. Neither the standard deviation of returns, beta with the aggregate market, market liquidity or the covariance between housing returns and income or consumption growth differ significantly between areas where low and high-income buyers locate. The only risk measure that positively correlates with income rank is idiosyncratic risk (Giacoletti, 2021). Finally, we show that higher-income buyers have a larger choice set of properties that they can potentially afford, and that consumption needs have a large impact on the set of available properties.

In our first set of empirical results, we investigate potential reasons for differences in returns between low and high-income buyers. First, richer households may purchase different types of properties that appreciate more. For instance, returns on apartments have generally outpaced the returns on single-family housing in Denmark. Second, they may be able to buy in more attractive markets. Prices in urban areas have appreciated considerably over the last 50 years (Gyourko, Mayer and Sinai, 2013; Amaral, Dohmen, Kohl and Schularick, 2021). Richer households may be more skilled at choosing locations that will appreciate, or they may buy in areas where they can limit supply growth (Ortalo-Magné and Prat, 2014). This ability to restrict supply can lead to increased house prices. Alternatively, richer households may be less constrained in their housing choices, allowing them to select more advantageous locations. Third, richer households may be able to time the market more effectively. For example, empirical evidence suggests that poorer households tend to purchase at the peak of housing booms and may be more exposed to housing market risk in downturns (Fischer, Khorunzhina and Marx, 2023). We systematically add control variables and fixed effects to assess whether these explanations account for the housing return gap. We find little impact from controls for property type (e.g., size and property type), but the introduction of municipality fixed effects renders the income coefficient close to zero and insignificant. Thus, our results indicate that the primary driver of return differences is location choice.

Beyond these factors, richer households may be more willing or able to invest in renovations and home improvements. This channel introduces a bias in the estimation of housing returns, as home improvements and renovations should be accounted for in the return but are often omitted (Nowak and Smith, 2020). While richer households are more likely to renovate, we find that controlling for renovations does not significantly affect the income rank coefficient after including other controls. We also examine other aspects pertaining to levered returns, imputed returns for unsold properties, different levels of geographic aggregation, heterogeneity across areas and holding period, and non-linearities in the relationship between income rank and housing return. Overall, these exercises consistently show that higher-income buyers earn higher returns, and that the effect is mostly explained by location choice.

What explains differences in returns at the aggregate level? One explanation is that higher-income households live in riskier housing markets and require greater compensation for this risk. We investigate several proxies for housing market risk, but find little evidence of higher risk among high-income buyers. Areas where high-income buyers live have a *lower* covariance with income or consumption growth, in contrast to standard asset-pricing explanations for return differences. Moreover, these areas have higher liquidity, experienced fewer negative returns, and had less negative returns, conditional on a downturn. The only risk measure that positively correlates with income ranking is idiosyncratic housing risk (Giacoletti, 2021), although the difference is minor. Thus, richer households reside in areas with higher returns but do not appear to face higher risk. While the lack of correlation between risk and returns in housing markets may seem puzzling, ex-ante, the applicability of the risk-return relationship to housing markets is unclear. Han (2013) provides evidence of a negative correlation between risk and return—the opposite of predictions from standard models in finance— and shows that this finding can be rationalized in markets with large hedging demand and constrained supply. Danish data reveal the same result: in the cross-section of housing returns, return and risk are *negatively* correlated.

Instead, we find that higher house price growth in the cross-section is correlated with income growth and growth in the working-age population. These results are reminiscent of the literature on spatial sorting, where changes in the return to skill have led to increased income inequality (Diamond, 2016; Baum-Snow, Freedman and Pavan, 2018). We also document that richer households live in areas that are more supply constrained using the method from Guren, McKay, Nakamura and Steinsson (2021) to calculate supply-elasticities across municipalities. Our results show that changes in income are capitalized into house prices, which primarily benefit higher-income homeowners.

Having established the importance of location for housing returns, we examine why households locate in different areas. Notably, 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.[1]

We investigate how location choice is shaped by consumption needs, financial constraints, and

[1]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).

social networks across the income distribution by examining the share of transactions unavailable to a given buyer. Credit constraints may prevent poorer households from purchasing in expensive locations (Gupta, Hansman and Mabille, 2022a). The amount of housing consumption together with financial resources determines households' location choice by dictating the amount of housing they can consume. For example, a family of two adults and a child will likely need at least two bedrooms. The consumption needs, together with the financial resources, then determine where the household can locate and constrain feasible location choices. Certain locations are inaccessible to some households, since the consumption price in that area is too high. This restriction on the choice set differs from that for other financial assets, where there are typically few restrictions on the *amount* of an asset that the buyer needs to purchase. For stocks, for example, regardless of income, households can invest in any stock they believe will outperform in the future. Higher-income investors will naturally invest more than low-income investors, but both rich and poor are (mostly) able to purchase the same stocks.

We show that the choice set is smaller for low-income households. The share of transactions that buyers could potentially afford is linearly increasing in income rank. Quantitatively, buyers in the bottom third of the income distribution could afford around 30 percent of all transactions, whereas buyers in the upper third could afford around 60 percent. If we restrict the choice set to properties in high-return areas, the choice set is significantly reduced, although the gradient in income rank is similar. If we condition both on high-return areas and consumption needs, defined as buyers being able to purchase similarly sized properties, the choice set for low-income buyers is reduced from around 30 percent of all transactions to 8 percent.

Our results highlight the link between changes in income, spatial sorting, and house prices, thereby providing a link between the large literature on the causes and consequences of spatial sorting and wealth inequality. This paper's main contribution is to highlight that location choice is the main driver of returns to housing, the most important asset on the household balance sheet. Because of housing's prominence as an asset, differences in location choice thus have a first-order impact on both returns and wealth inequality. We show that differences in risk are not likely to be a strong contributor to differences in housing returns. Instead, our results suggest that housing returns, and consequently wealth building, are shaped in part by both financial constraints, housing supply, and consumption needs, factors that are distinct from attitudes to risk or skill in investment.

Related literature. We contribute to recent literature leveraging detailed administrative data to examine differences in asset returns across households. Recent papers have examined how housing returns correlate with gender (Goldsmith-Pinkham and Shue, 2023; Girshina, Bach, Sodini and Team, 2021), race (Kermani and Wong, 2024; Gupta et al., 2022a; Diamond and Diamond, 2024), and wealth (Wolff, 2022). We extend this literature by examining how housing returns correlate with income rankings using transaction data and by directly examining how choice sets differ across buyers.

A related literature documents differences in asset returns across the distribution (Fagereng et al., 2020; Bach et al., 2020; Kuhn, Schularick and Steins, 2020). We contribute to this literature by thoroughly examining housing returns, the largest asset on the household balance sheet. Although the mechanism for why richer households get higher housing returns is not yet established, one channel explaining higher returns for wealthy households are differences in risk aversion. We find little evidence that risk drives housing returns, consistent with previous evidence in Han (2013). The importance of housing *consumption* suggests that housing should be studied less as an investment and more as a consumption good.

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 (2021) documents that rising house prices causes middle-income US households to move out of cities because they cannot afford to purchase a home.[2] 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 two-thirds of Danish households owning their homes. The homeownership share has been relatively stable across time (Bäckman and Lutz, 2020). The market is generally perceived as well designed and

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

regulated (Campbell, 2013), with low speculative activity and high transparency. The Danish housing market is also characterized by relatively high prices, particularly in major cities such as Copenhagen and Aarhus.

Homeowners are subject to a range of housing-related taxes. These include property taxes, levied annually based on property value, and capital gains taxes on profits from home sales. Capital gains taxes are waived if the owner has resided in the property for a specified period during ownership and if the lot size is below a threshold. Most homeowners are exempt from transaction taxes upon sale of the property. Homeowners can also deduct 30% of their mortgage interest payments from their taxable income. This applies to both primary residences and summer houses.

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 all but the poorest households. The housing share of gross wealth appears lower than that reported in Fagereng et al. (2020), 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. Kuhn et al. (2020) report similar statistics for the United States, where 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 similar in Denmark and other countries that are in focus in previous studies.

Most Danes own housing on their personal balance sheet for consumption purposes. The share of owners with multiple properties has increased from 14 percent in 1996 to nearly 18 percent in 2016. Excluding summer houses, the share was 9 percent in 2016, increasing to just over 10 percent in 2020. About 250,000 Danes own summer houses, corresponding to approximately 5 percent of the population. Ownership of multiple properties is concentrated in the highest income deciles, with 25.43 percent of the top 10 percent owning multiple properties. Excluding summer houses, the share is 15.52 percent. This likely stems from the strict rental protection laws in Denmark. 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

[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.

to rent control. If the owner has not personally resided in the property with intent of permanent residency, they must pay capital gains tax. There is also favorable tax treatment for multiple property ownership through an incorporated entity.

Danish house prices have shown considerable volatility over the last twenty years. Figure 1 plots the average house price growth over time, along with the 25th and 75th percentiles, based on zip-code level data. There have also been sizable differences across areas and property types, with large cities and apartments generally appreciating more. The average year-over-year growth rate in real house prices at the zip-code level from 1996 to 2016 was 3.1 percent, with substantial increases from 2003 to 2006 followed by a rapid decline in 2008 and 2009.[4] However, despite a large decline in prices in 2007, foreclosures and defaults remained low. For example, at most, slightly more than 600 homes per quarter were repossessed, on an outstanding stock of 2.5 million properties.

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 year-over-year return in Denmark was 2.7% from 1997 to 2019. These growth rates are comparable to the United States (2.1% real growth) and slightly above the Euro-area average of 1.5%. Denmark experienced lower real house price growth than France (3.1%), the United Kingdom (3.9%), Norway (4.4%), and Sweden (5.5%), but higher than Germany (0.004%). The standard deviation of returns in Denmark over the same period was 7.4%, which is comparable to the United States and the United Kingdom (both 7.3%), but is more volatile than in the other countries mentioned.

Overall, the Danish housing market is broadly comparable to other previously studied countries. Housing market dynamics, the importance of housing wealth for most households, the home-ownership rate, and the tax system are broadly similar to those in other countries, suggesting external validity for our results.

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

[4] See Bäckman and Lutz (2025) for an analysis of the role of interest-only mortgages for this dynamic.

are typically issued with a fixed interest rate and a maturity of up to 30 years. They are highly rated by credit rating agencies due to strict regulations and collateral requirements imposed on these institutions.

Danish borrowers can choose between a fixed-rate mortgage and a variable-rate mortgage. 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. 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]

3 Data

3.1 Data sources

We obtain high-quality administrative data from Statistics Denmark. 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 their total income that year. We use the average income within the household to account for differences in family size. We also ensure that households consist of at most two adults. Children over 18 are assigned the

[5]For more details about the mortgage market, see Bäckman and Lutz (2025).

same household identifier as their parents. To match each property transaction to buyers, we calculate the average income of the buyers (at most two) using individual income data and match that income to the corresponding position in the household income distribution.[6] 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 2019 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 returns, 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. 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) at the time of purchase using the household identifier. If there are multiple buyers, we verify whether the household identifier is consistent across buyers. This represents 80% of two-buyer transactions, and in such cases we use the income ranking of the household. In the remaining 20% of cases where household identifiers differ, we use the average ranking. We use the income ranking in the year prior to the housing purchase as the main variable of interest. We also merge relevant property characteristic variables such as number of rooms and living area. The final sample consists of 174,759 repeat sales transactions.

[6] 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.

3.2 Measuring housing returns

We calculate housing returns 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). We calculate the unlevered rate of return r_i^u for owner i using the following formula:

$$1 + r_i^u = \left(\frac{P_{i1}}{P_{ib}} \right)^{\frac{1}{T_{is} - T_{ip}}}, \tag{1}$$

where P_{ip} and P_{is} are the purchase and sale prices, and $T_{is} - T_{ip}$ is the length of ownership in years (i.e., holding period). Both transaction prices and dates are recorded in the data, facilitating the calculation of accurate unlevered returns. Since we observe the exact dates, we allow T_{is} and T_{ip} to be nonintegers to better measure the exact holding period.

A key limitation of the unlevered return is that most households in Denmark buy their property with debt. Similar to homebuyers in the United States, 30-year mortgages imply that Danish homebuyers maintain high levels of leverage over time. Danish mortgages are either 30-year annuity contracts that mainly pay interest up front, or, since 2003, have also included interest-only mortgages. To capture the effect of leverage, we follow Goldsmith-Pinkham and Shue (2023) and calculate the levered housing return. We use the total debt for buyers recorded in tax data for the year of purchase to calculate the leverage ratio for each property.[7] Using the mortgage interest rate ρ from Finans Danmark, we calculate the share of principal repaid at every monthly duration, assuming no refinancing, and calculate the hypothetical mortgage at time of sale, $Mortgage_{is}$. The mortgage rate in Denmark is set by the market, not by mortgage banks, and buyers typically cannot negotiate it. We use the amount repaid to calculate home equity at the time of sale s as $Equity_{is} = \max(P_{is} - Mortgage_{is}, 0)$. Again following Goldsmith-Pinkham and Shue (2023), we then calculate the net present value of equity at time b as the sum of the downpayment plus the discounted value of principal repayment: $Equity_{ib} = D_{ib} + \sum_{\tau=b}^{s} w_{i\tau}/(1+\rho_b)^{\tau-b}$. The leveraged annualized return is then:

$$1 + r_i^{lev} = \left(\frac{Equity_{is}}{Equity_{ib}} \right)^{\frac{1}{T_{is} - T_{is}}} \tag{2}$$

[7] We measure mortgage and bank debt for each individual in the data, but we cannot link the mortgage to specific properties. This presents a problem only for individuals who own more than one property, which we can also observe in the data.

To account for unrealized capital gains, we also impute house price gains for all buyers using municipality house price indices. We use apartment and house price indices from Finans Danmark, matched to the purchase for each unsold property. We then calculate returns on the municipality-level index from the purchase quarter to the fourth quarter of 2019. The return for each unsold property is then simply the initial purchase price times the change in the municipality-price index for a given property type.

3.3 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.

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 middle-income buyers, but there are relatively minor differences in property characteristics such as building age and size. The higher purchase price is therefore likely not driven by property characteristics. High-income buyers are more likely to live in the capital region and are much less likely to live in rural areas. 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 hold relatively large amounts of wealth. Low income buyers are also considerably older compared to middle- and high-income buyers. Finally, the bottom of the table calculates the share of total transactions and the share of repeat sale transactions by income group. For the repeat-sale share, we calculate this as the share of all transactions where we can match the buyer to a property. The number of transactions among low income buyers is considerably lower, with only 11 percent of total transactions. High income buyers in the top third of the income distribution accounts for 55 percent of total transactions. These numbers match the homeownership share among the different groups. The repeat sale share is very similar across groups, especially when comparing middle income and high income buyers.

Table A1 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 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 status. 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 later impute returns for single transactions using municipality-level data and find very similar results.

4 Income Gaps in Housing Returns

We now present evidence of substantial income gaps in housing returns and explore their determinants. The analysis begins with a non-parametric examination of annualized returns and income rank in Figure 2. The figure depicts a positive and linear relationship between income rank and the average annualized return (panel a), and reveals a similar positive relationship for the total return (panel b). We present summary statistics for three unequally sized groups based on income rank in Table 1. The average annualized unlevered returns are 3.283% for low-income buyers, compared to 3.493% for middle income buyers and 3.872% for high income buyers. Few differences exist in the standard deviation of returns across income groups, suggesting that higher returns for high-income buyers do not compensate for risk. Indeed, the standard deviation of returns is lower for high-income buyers. We present a more detailed discussion pertaining to house price risk later.

Differences in returns may stem from many underlying factors. For example, higher-income households may purchase properties with characteristics that appreciate more in value. A salient recent 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, 2022b). Similarly, richer households may better time the market, purchase in areas that later appreciate more in value, or undertake more renovations and maintenance due to their income, wealth, or credit availability. Differences in these factors across the income distribution could plausibly explain the income gaps in returns.

To analyze the importance of these factors, we employ a simple linear regression framework to estimate the relationship between income rank and annualized return, controlling for a wide range of factors:

$$Y_{it} = \beta_0 + \beta_1 Income\ Ranking_{it} + X_{it}\Gamma + \mu_i + \epsilon_{it} \tag{3}$$

The specification regresses the outcome Y_{it}, either the unlevered return r_i^u or the levered return r_i^{lev} on the main variable of interest, $Income\ Ranking_i$, and vectors of control variables X_{it} and fixed effects μ_i capturing homeowner and property characteristics.[8] $Income\ Ranking_i$ is the average 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 these gaps. This approach absorbs both causal effects and selection (Kermani and Wong, 2024).

Figure 3 presents the results, with corresponding detailed regression results in Table 2. The baseline specification, shown in the first line, does not include any control variables. The coefficient of 0.0112 on $Income\ Ranking$ is positive and statistically significant at the 1% level and implies that a one-unit increase in rank is associated with a 0.1 percentage point increase in returns. To assess the economic significance, we compute the differential effects across income ranks. The estimate implies that households above the 90th percentile earn $(0.0100 * (90 - 10) = 0.8\%$ higher returns compared to households in the 10th percentile The cumulative difference in unlevered returns to housing between the 10th and 90th percentile over 10 years is $(1 + 0.0100 * (90 - 10)/100)^{10} - 1 = 8.3\%$. This cumulative return corresponds well to the total realized returns, which show a 9.1 percentage point difference between the bottom 10% and the top 10%. This implies (and the data confirms) that the holding period is similar between rich and poor households.

We can compare the differences in returns of 0.8% between low and high-income buyers in Denmark to the previous literature. Bach et al. (2020) use an asset pricing model with property and location types to calculate returns using Swedish data. Table 6 of Bach et al. (2020) reports housing returns ranging from 4.19% for the bottom decile to 6.14% for the top 0.01 percent. Using data from Table 6 in Bach et al. (2020) and regressing historical housing returns on wealth deciles yields a coefficient of 0.1345 on the wealth group for the bottom 90 percent, comparable to our estimate 0.1 in the baseline specification of Figure 3.[9] Overall, our estimates are similar to the most comparable paper, and suggest that differences in returns across high

[8]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.

[9]We use the bottom 90% because the top 10% is more finely divided. Using returns for all groups reported in Table 6 of Bach et al. (2020) yields a coefficient of 0.16.

and low income buyers are important.

We now proceed to analyze the statistical drivers of differences in returns. We begin with property and buyer characteristics, before moving on to market timing and location.

Property and homebuyer characteristics.

Property characteristics explain a small share of the returns. The second line in Figure 3 presents an estimate of the effect of income rank on returns, controlling for property type (apartment or single family house), property size in square meters, and the number of floors. 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 lowers the coefficient on Income Rank to 0.00688, but the estimate remain large and statistically significant. We conclude that differences in property or homebuyer characteristics explain some of the variation in returns, but that a sizable component remains.

Market timing.

Next, we introduce controls for market timing and the time between sale. Figure 1 shows 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 returns. To assess this hypothesis, the fourth line in the figure incorporates fixed effects for $Year^P \times Year^S$ (year of purchase interacted with year of sale). Using year-quarters instead does not alter the result. This specification accounts for the general house price trend between the purchase and sale years and provides a clearer understanding of the importance of market timing. The coefficient on *Income Rank* is reduced from 0.00688 in the baseline specification to 0.00614, indicating that market timing does not explain the difference in returns.

The limited explanatory power of market timing warrants further consideration. While Denmark experienced a large housing boom-bust cycle between 2003 and 2009, both the boom and the bust varied across areas and time (see, for e.g., Bäckman and Lutz, 2025, for a discussion of the causes of the housing boom between 2003 and 2007). If different locations experienced booms and busts at different times, controls for market timing alone may fail to capture the effect. We return to this issue below.

Geographical location.

Next, we show that geographical location alone (statistically) explains the entire income gap in housing returns. We later return to the interpretation of this result in detail, and we do not suggest that the effect is necessarily causal. Controls for municipality capture both causal effects and selection: the municipality fixed effects capture both buyer characteristics within a given area (likely reflecting their income, wealth, employment, and social ties) and the municipality'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).

Danish municipalities are relatively small administrative areas that are situated within larger administrative regions. For instance, the capital region consists of two municipalities in central Copenhagen (Copenhagen and Frederiksberg), and a further 27 municipalities on the outskirts.[10]

Including fixed effects for municipalities in the fifth line of Figure 3, the coefficient on $IncomeRank$ reduces to almost zero. Because housing markets may experience booms and busts at different times (Ferreira and Gyourko, 2023), we additionally include interactions between municipality and time dummies, that is, Sale Time $\times$ Purchase Time $\times$ Municipality. With controls for timing and location, the coefficient on income rank becomes slightly larger, but is still close to zero.

Differences in levered returns

We also replicate our results using levered returns. Figure 4 plots the results, again summarizing different regression specifications. The corresponding results are presented in Table 3. The coefficient on income rank is now larger at 0.03 in the baseline specification, consistent with the intuition that leverage magnifies returns. The baseline coefficients imply that buyers in the 90th percentile would earn 25 percent higher returns than buyers in the 10th percentile over a 10-year holding period. Controls for property and buyer characteristics and market timing explain little of the variation, but fixed effects for municipality reduce the magnitude of the coefficient considerably. However, the coefficient on income rank of 0.0119 remains statistically significant, and implies a cumulative difference in returns of 10 percent over a 10 year holding

[10] Each municipality has an administrative function, and certain taxes are collected by the municipality. There are 98 municipalities in Denmark today. A municipality reform in 2007 reduced the number of municipalities from 315 to 98. We use unique identifiers provided by Denmark Statistics to assign properties before 2007 to the new municipality codes.

period.

Summarizing the results.

The results of the sequentially estimated regressions suggest that the entire difference in returns across the income distribution can be explained by location and market timing. Richer buyers can purchase properties in areas that appreciate more in value at opportune times, explaining their greater housing returns. After exploring robustness and heterogeneity in these results we later explore differences in returns and risk across location, and study why households live where they live.

4.1 Robustness and heterogeneity

We next turn to several important robustness checks, including imputed returns for unsold properties, accounting for renovations, and using different levels of geographical aggregation.

Imputed Returns for Unsold Properties.

Our focus on repeat sales generates many censored ownership spells, as the final transaction price is unobserved for unsold properties. To account for this, we impute returns for single-transactions using municipality-level house price indices. Imputing returns for each buyer is similar in principle 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 location or property characteristics. By design, location will explain all of the differences in returns. Indeed, this is one of the main advantages of using repeat transactions instead of municipality-level returns.

We impute returns for single transactions using municipality-level house price indices, and explore how returns differ across the income distribution. Figure 5 shows a similar linear relationship between imputed returns and income rank as before. The regression involving imputed returns on income rank yields a coefficient of 0.01, which is identical to the baseline estimate in Table 2. It is reassuring that the share of repeat transactions are similar across the income distribution, and that the coefficients on *Income Rank* are similar.

Return censoring due to incomplete spells is particularly concerning if there are differences in censoring by income rank. Although this is a plausible concern, summary statistics in Table

1 shows that, empirically, this difference is not substantial. While the share of repeat sales transactions is slightly higher for low-income buyers, these constitute a small fraction of total transactions. Comparing middle-income buyers to hig-income buyers, there is only a negligible difference in the share of transactions with a repeat sale.

Renovations

The observed relationship between income rank and housing return may stem from higher-income households renovating more due to greater financial ability or differential consumption preferences. As a result, the sale price may be higher, thereby leading to greater returns. We examine the impact of renovations on housing returns using data from a renovation tax break available since 2011.[11] 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. First, we show that higher-income buyers are more likely to utilize the tax break and, on average, apply for a larger amount, as Figure 6 shows. However, including renovations does not substantially impact the coefficient on income rank after we account for other variables. In unreported results, we find that including renovations does not significantly alter the coefficient on income rank after we include other controls.

Level of geographical aggregation

We have shown that municipality fixed effects statistically explain the differences in returns across the income distribution. Our analysis of geographical location has focused on municipalities, as this aggregation level balances the preservation of sufficient observations with the capture of the local aspect of housing markets. An alternative approach is to use either a smaller geographical unit like zip codes that capture neighborhoods, or a larger unit that capture aggregate regional factors. We now provide results for different levels of geographical aggregation to investigate whether the location effect we find are driven by neighborhoods or regions. To do so, we run the same regression as before but include fixed effects for different levels of geographical aggregation. We begin by discussing how we measure these.

Denmark is divided into 98 municipality, where each municipality belong to one of 5 regions.[12]

[11] The same tax break for renovations was previously used in Andersen, Badarinza, Liu, Marx and Ramadorai (2022).

[12] A municipality-reform in 2007 consolidated Denmark into 98 municipalities and 5 regions. We use unique geo-

The regions are larger administrative areas that capture 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. We also have identifiers for ZIP-codes and for church parishes, which are smaller geographical units.

The results are provided in Figure 7. Region fixed effects explain almost 70 percent of the differences in returns, whereas municipality fixed effects explain the rest. Using ZIP-code or parish fixed effects adds little beyond municipality fixed effects.

A Copenhagen Effect?

A natural question is whether the findings so far reflect a Copenhagen effect. House price growth has been higher in Copenhagen than in the rest of Denmark over our sample period. Buyers in Copenhagen represents about a third of the final sample, which is very close to the population share of the region. Buyers in the Copenhagen region have a higher average income rank than buyers in other regions, suggesting that there is sorting based on income to the region. Notably, the *average* return for buyers in the Copenhagen region is also considerably higher.

Focusing only on buyers in the Copenhagen region, the coefficient on income rank is negative. Inside the Copenhagen region, it is low income buyers that earn a higher return. If we instead focus on other regions, we find the familiar positive coefficient on income rank in the same range as in the main estimation. Differences in returns across the income distribution are therefore driven by Copenhagen versus the rest of Denmark.

To further explore the importance of Copenhagen versus the rest of Denmark, we estimate the regression specification from Column (5) of Table 2 for each different municipality classification in Figure 8. We use a classification from Denmark Statistics that sorts municipalities into broader categories, such as Capital region and Cities, Provincial cities, Countryside, or Rural. Overall, the coefficient on income rank approaches zero in the capital region, suggesting little difference in housing returns between high- and low-income buyers in the Greater Copenhagen region. Conversely, we find a positive coefficient on income rank in provincial cities.

graphical identifiers provided by Denmark Statistics to match transactions prior to 2007 to new municipalities.

Non-linearities

Next, we explore non-linearities in the relationship between income rank and housing return. We divide buyers into 10 groups according to their income rank, and estimate separate coefficients for each group. Figure 9 presents results from both the baseline specification and the specification including all controls and municipality, time-between sales, purchase year and sales year fixed effects. The baseline estimates with no control variables reveal a U-shaped relationship between income rank and returns. This specification is marked in orange, and measures the difference in average returns for each group relative to the median income group. Relative to the middle-income group, the coefficient for buyers in income groups 1 to 4 is positive and significant in the baseline specification. The highest-income buyers in group 10 have an average return 1.2 percentage points higher than buyers in the lowest income group. With the introduction of controls, the difference in returns becomes statistically insignificant at the 5 percent level and approaches zero for all groups except the 9th decile. Most of the difference in returns between households across the income distribution can be explained by detailed control variables for market timing and location.

Heterogeneity by holding period.

The holding period may vary across income ranks for households due to differential constraints and objectives. Figure 10 depicts the coefficients from the baseline specification and the specification with all controls and fixed effects (from Figure 9) for subsets based on holding period length (the period between purchase and sale dates). Without including controls or fixed effects, shorter holding periods are associated with larger coefficients on income rank. With the introduction of controls, the coefficients are slightly smaller in magnitude but the overall pattern remains. Higher-income households earn higher returns on properties with short holding periods but lower returns on properties with long holding periods. However, the average holding period across high and low-income buyers is very similar, suggesting that differences in holdings periods are not driving differences in returns.

5 What explains differences in returns across municipalities?

Our results indicate that richer households earn higher returns on housing because they reside in areas experiencing higher house price growth. This raises the question of why persistent differences in house price growth exist across locations. In spatial economic models, changes in prices across locations are derived from the present value of housing:

$$P_{i,t} = \sum_{j=1}^{\infty} \mathbb{E}\left(Rent_{i,t+j} \cdot \left(\frac{1}{1+r_t}\right)^j\right), \tag{4}$$

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. 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.

We construct a proxy for supply elasticities using the methodology in Guren et al. (2021), described in detail in Appendix C1. 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:

$$\Delta P_{kt} = \alpha + \beta_1 Income + \beta_2 Employment + \beta_3 Supply + \gamma_t + \gamma_r + \gamma_k + \epsilon_{krt} \tag{5}$$

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 also control for year fixed effects in γ_t. We also control for region fixed effects in γ_k and 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 4 shows that housing returns are higher in areas with higher population and income 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 (4), 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), however, 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.[13] 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, for e.g., Copenhagen (International Monetary Fund, 2016).

[13]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.

6 Housing risk

In an asset market equilibrium with rational expectations, risk-adjusted returns should equalize across cities, rendering investors indifferent to location.[14] Differences in returns may thus stem from richer households' exposure to higher risk. This section examines the housing-related risks households face and how these risks vary across the income distribution.

We study several sources of risk plausibly priced in housing returns: covariance of consumption and income with housing returns, idiosyncratic risk as in Giacoletti (2021), and housing market liquidity (Amaral, Toth and Zdrzalek, 2025). The details on how we construct these measures are available in Appendix C1. Overall, we find little evidence that higher-income households live in areas with riskier housing markets. We also explore why the risk-return relationship does not hold in the Danish housing market.

We aggregate our risk data to the municipality level to explore housing-related risk, and merge municipality-level data with each buyer based on their primary residence. For this analysis, we consider both single and repeat buyers, although all results are consistent if we focus on repeat transactions. In unreported results, we have also examined results across all households (not just buyers). Overall, we find little evidence that higher housing returns for high-income buyers relate to risk.

Table 5 provides summary statistics on risk for 10 groups of buyers. Both Sharpe ratios and average returns by municipality are positively related to income rank. Consistent with the repeat-sales evidence, buyers with higher income rank live in areas that experience higher returns. However, there is little evidence that these higher returns are associated with measures of risk: the standard deviation of housing returns, the covariance of consumption or income growth with housing returns. Sales times and measures of downside risk are all lower for higher income buyers. Univariate regressions on income rank and risk in Table 6 confirms these results: the coefficient on income rank is negative in all regressions except for idiosyncratic risk.

Idiosyncratic risk is the only variable positively related to income rank. The coefficient on income rank in Table 6 suggests that high-income buyers take on more idiosyncratic risk. If we

[14] In theory, investors should equalize the *total* return to investing across locations (Amaral et al., 2021). The lack of data on long-term rents across locations forces us to only consider differences in capital gains. If housing markets are segmented, as suggested by search behavior (Badarinza, Balasubramaniam and Ramadorai, 2024) and the response of the homeownership rate to credit shocks (Greenwald and Guren, 2021), the returns to owner-occupied housing should also equalize across locations.

regress idiosyncratic risk on housing returns to get a measure of how idiosyncratic risk is priced, we can get an estimate of how much idiosyncratic risk is priced in returns. We can represent this by parameter $\beta^{Idio.}$ The difference in returns attributed to idiosyncratic risk between the bottom and top third of the income distribution will then be equal to $\beta^{Idio.} \times (\sigma^{Idio.}_{top} - \sigma^{Idio.}_{bottom})$, which represents around 39 percent of the difference in returns. Obviously, this example is incomplete as we are only considering one source of risk, whereas all risks should be priced.

In light of the traditional relationship between risk and return, these findings may seem puzzling and is not limited to high-income buyers. Figure B1 in the Appendix shows that housing returns and risk are also *negatively* correlated in the cross-section of municipalities. However, this finding is not unique to the Danish housing market; for instance, it has also been observed in some US housing markets. A plausible explanation for this negative relationship is inelastic supply combined with hedging demand, as the current house hedges against future housing consumption (Han, 2013).

7 Determinants of location choice

Richer households earn higher financial returns on their housing investments, with these returns statistically explained by location choice. This section discusses the determinants of location choice for rich and poor households. We first discuss how financial constraints shape location choices before exploring the effect of housing consumption and social networks. This section closely relates 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.

The key concept we explore is the *choice set*: what possible other transactions are available for each buyer? We define the choice set as all other transactions occurring in the same time-period. We select a 5% random sample of transactions for computational reasons, and merge all transactions onto all other transactions occurring within that same year. For each transaction, we then have information about the price and characteristics of a large number of other transactions that occur at the same time. Specifically, we calculate the share of other transactions that the buyer could afford based on their actual purchase and the purchase price of all other properties they could have bought. We define the properties that would have been available for purchase as properties with a transaction price lower than what the buyers paid for their actual choice. Using the actual price that the buyers paid has the advantage that we can be sure that buyers have the means to pay at least this much, but it neglects that some buyers may have additional funds to pay even more. As a robustness check, we use register data to calculate the maximum amount each household could pay. However, since this measure is somewhat noisy and depends on several assumptions, we focus on the purchase price as an indicator of purchasing power. All results are unchanged if we use the maximum purchase price instead.

The choice set in housing differs from other financial assets, which typically impose few restrictions on the *amount* of an asset a buyer must purchase. For stocks, for example, households could invest in any stock they believe will outperform, regardless of their income. Richer buyers will naturally invest more than poorer ones, but they could acquire the same asset. Any differences in returns are then more plausibly linked to differences in skill or information. If housing were purely about investments, the household could purchase a small amount of housing in an area where they believe that house prices will increase and achieve high returns. As we show in Section 2, however, most Danes combine housing investments with housing consumption. Causa, Woloszko and Leite (2020) find similar results for 20 OECD countries (see Figure 17), showing that housing for investment properties is mostly held by the top 10% of the wealth distribution.

Because of consumption needs and because buyers combine housing consumption with investments, a buyer will have to invest an amount in housing that corresponds to their consumption needs, naturally dictated by, for e.g., household size, income, and age. Previous studies show that housing demand is income-inelastic (see Gaubert and Robert-Nicoud, 2025, and citations within), suggesting that consumption needs may be more binding at lower income levels. For instance, a household with two parents and two young children will require a larger property than a single retiree with no children living at home. Since housing is the largest component of household consumption, housing demand may also determine housing choice (Combes, Duranton and Gobillon, 2019). We investigate how housing consumption shapes location choices by examining how having to choose a similar-sized property limits the choice set.

The results are presented in Table 7, where we regress income rank on the share of properties that the buyers could afford. The constant in the regression is the share of transactions that the lowest income percentile can afford, and the coefficient on Income rank measures the increase in the choice set for a one percentile increase in rank. We also provide results using binned scatterplots in Figure 11. The figure shows that the relationship between income rank and the choice set is approximately linear. We explore several different samples, examining how the choice set is limited by selecting properties of the same type or size among all transactions and among transactions in high-return areas, defined as municipalities in the top quintile of average returns. In Appendix Table A3, we show very similar results if we use the maximum purchase price based on total available borrowing instead.

A few results from Table 7 are worth highlighting. First, the coefficient on income rank is similar across all specifications. Second, housing consumption has a limited impact on the choice set among all transactions in columns 1-4. While lower-income buyers have a smaller choice set than higher-income buyers, the constant is only slightly reduced when we select transactions with a similar size or the same property type. Third, and most importantly, the share of properties that buyers can afford is considerably lower in high-return areas, reflecting the higher average purchase prices in these areas. Fourth, the choice set is further reduced if buyers want to purchase a similarly sized property in high-return areas. The key implication is that both housing consumption and the purchase price limit the ability of lower-income households to buy housing in high-return areas.

7.1 Financial constraints and location choice

What limits lower-income buyers from purchasing housing in high-return areas? One potential explanation is financial constraints. To investigate how financial constraints shape the choice set, we calculate the maximum amount a household could invest in housing and use this measure to define their choice set at the time of purchase. In Denmark, the most salient financial constraint is the loan-to-value limit for mortgage debt at 80% of the property value. In addition, mortgage banks evaluate borrowers on their ability to repay based on the monthly payment-to-income ratios. We calculate the maximum purchase price for each buyer as the sum of their financial wealth plus their maximum borrowing, subject to two constraints. First, the maximum loan-to-value (LTV) ratio in Denmark is 95%, with the bottom 80% consisting of low-interest mortgage debt and the top 15% consisting of higher-interest bank debt. Second, households must afford mortgage payments and are therefore subject to a payment-to-income (PTI) constraint. Since there is no regulatory PTI limit, we set the maximum payment-to-income as 30% of disposable income, a choice that is admittedly somewhat arbitrary. While the LTV ratio is regulated by law, the actual PTI limit is determined by mortgage banks and the households' own preferences. Our results are not changed if we use a different limit. Since borrowing is limited by the lower of the two constraints (Bäckman and Khorunzhina, 2020), we set maximum household borrowing according to the lower of the LTV and PTI limit.

Figure 12 shows that lower-income buyers use *less* leverage, although the difference is small above the 50th percentile of the income distribution. While it may be tempting to conclude from these facts that lower-income buyers are not, in fact, restricted from buying in more expensive areas, some caution is advised. While lower-income buyers use less than the maximum leverage, the purchase price of properties in high-return areas is an equilibrium object that can change in response to increased demand. If the supply of owner-occupied housing in expensive areas were elastic, as in for e.g. Kaplan, Mitman and Violante (2020), then lower-income buyers would be able to buy housing if they could meet the required purchase price. However, if there is competition between buyers and supply is limited, it is not clear that lower-income buyers would be able to out-compete higher-income buyers for the limited number of objects available in high-return areas. 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. Figure 13 shows that the maximum purchase price is increasing in income rank, suggesting that high-income buyers could outbid low-income buyers if needed. Higher demand for lower-income households may just lead to higher prices paid by higher-income buyers, and lower-income buyers may not wish to compete in markets where they expect that they would not be able to buy after a competitive bidding process.

To illustrate this idea, we show that low-income buyers in the bottom half of the income distribution have represented a relatively stable share of buyers in high-return municipalities over time, even as there have been several policies that affected their ability to afford housing. More importantly, the share of low-income buyers is seemingly unaffected by major macroprudential shocks, most notably 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 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 municipality i in year t:

$$ShareLowIncome_{it} = \alpha_i + \gamma_t + \sum_{k=1998}^{2019} \beta_k (HighReturn_i \times \mathbf{1}_{t=k}) + \epsilon_{it} \tag{6}$$

where $ShareLowIncome_{it}$ is the share of buyers in the bottom half of the income distribution, and $HighReturn_j$ is a dummy equal to one if the municipality was in the upper quintile of average house price growth between 1996 and 2019. Figure 14 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 share of low-income buyers is also not affected by any of the borrower-based macroprudential policies introduced after the financial crisis period of 2008. These include stress-tests of borrowers' ability to repay introduced in 2013, a minimum 5% downpayment requirement introduced in 2015, higher LTV requirements in the high-house price growth areas in Copenhagen and Aarhus, and DTI restrictions in 2018.

7.2 Social ties

Another hypothesis that explains why individuals do not move to attractive areas is that they have local ties to a location, perhaps in the form of family or social networks, that raise the cost of moving to other locations. Social networks are typically spatially concentrated, with most friends and family living in close proximity (Koenen and Johnston, 2025). The spatial concentration of friends is also apparent in Denmark: individuals are much more likely to be connected to other individuals within their region than to individuals in other regions.[15] These social ties are economically important; for example, they lower migration rates in response to local economic shocks (see Munshi, 2003, for a recent literature review).

We document the geographical distance between households and their parents, and examine differences across the income distribution. For simplicity, we examine whether the child lives in the same municipality or region as at least one of their parents. We find that the share living in the same municipality as their parents has an inverse U-shape across the income distribution.

[15] We collect data from the Social Connectedness Index (SCI) from Meta, a measure of how socially connected different geographies are. The data comes as an index that measures the relative probability that two individuals across two locations are friends with each other on Facebook. Data is available for NUTS-3 regions in Europe, but we only select Danish regions. To assess the prevalence of social ties between regions, we calculate the ratio between the within-region connectivity and the outside-connectivity. For example, the SCI index value for the within-region connectivity for Copenhagen City-Copenhagen City is 847169. The outside-region connectivity for Copenhagen City- Copenhagen Surroundings is 379869, which gives a relative value compared to the within-region SCI of 379869/847169 = 0.44. Across all regions, the average relative connectivity is 9.5%, showing that social ties in Denmark are highly spatially concentrated.

The share peaks for individuals around the 40th percentile and declines to around 20 percent for the highest income percentiles. There is a similar pattern for regions, a larger geographical unit.

8 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 returns, 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. Housing returns are not related to risk, and differences in returns at the municipality level are mostly driven by income 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 wealth inequality.

Ultimately, this paper documents differences in realized returns and not differences in expected returns. An important question is whether the patterns in housing returns 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 housing returns, and there is limited evidence that returns 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, housing returns, 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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9 Figures

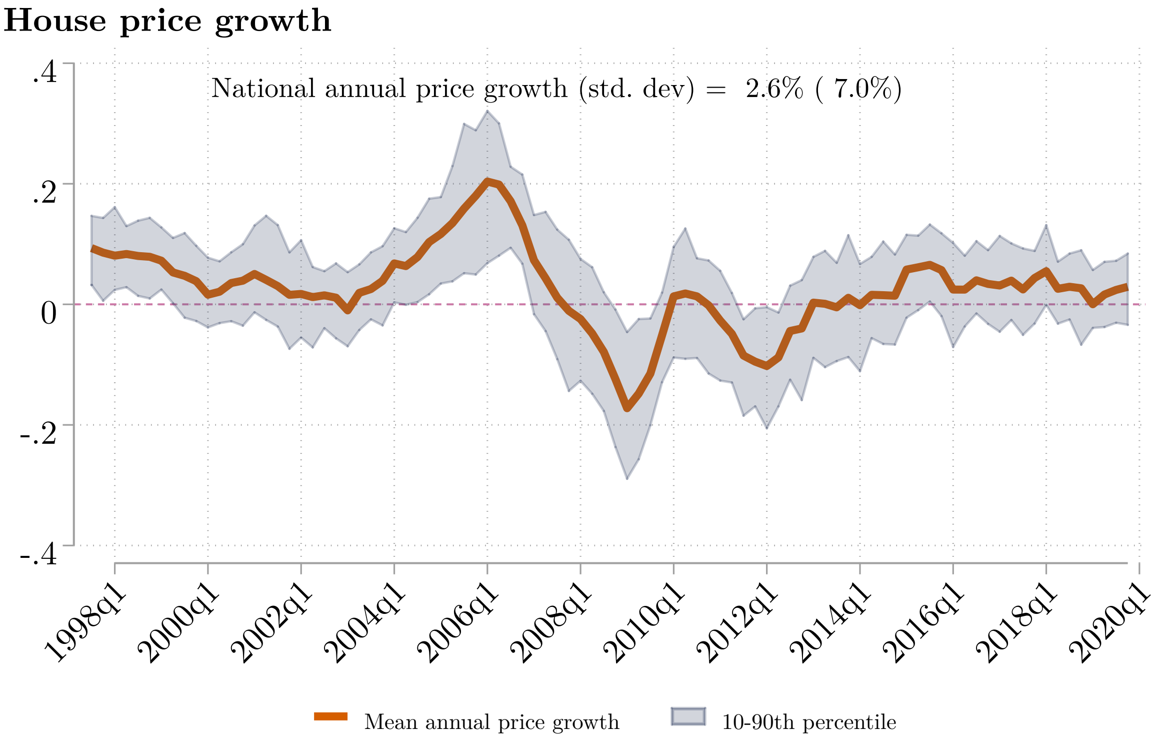
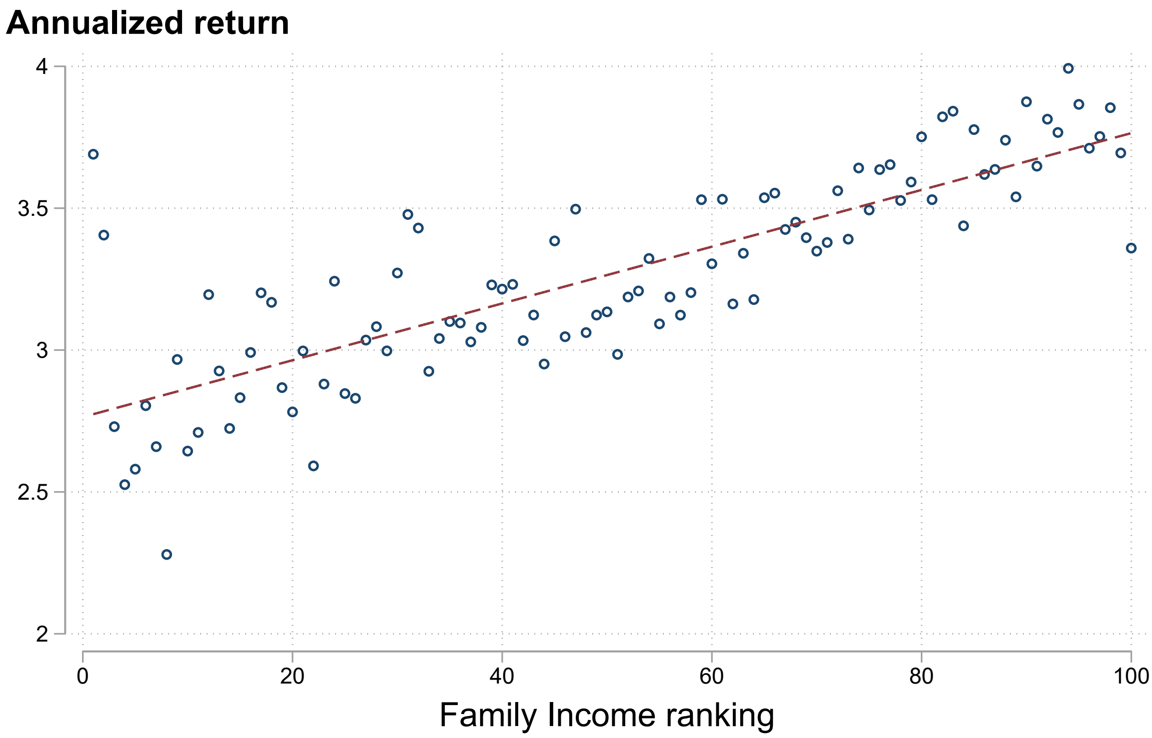
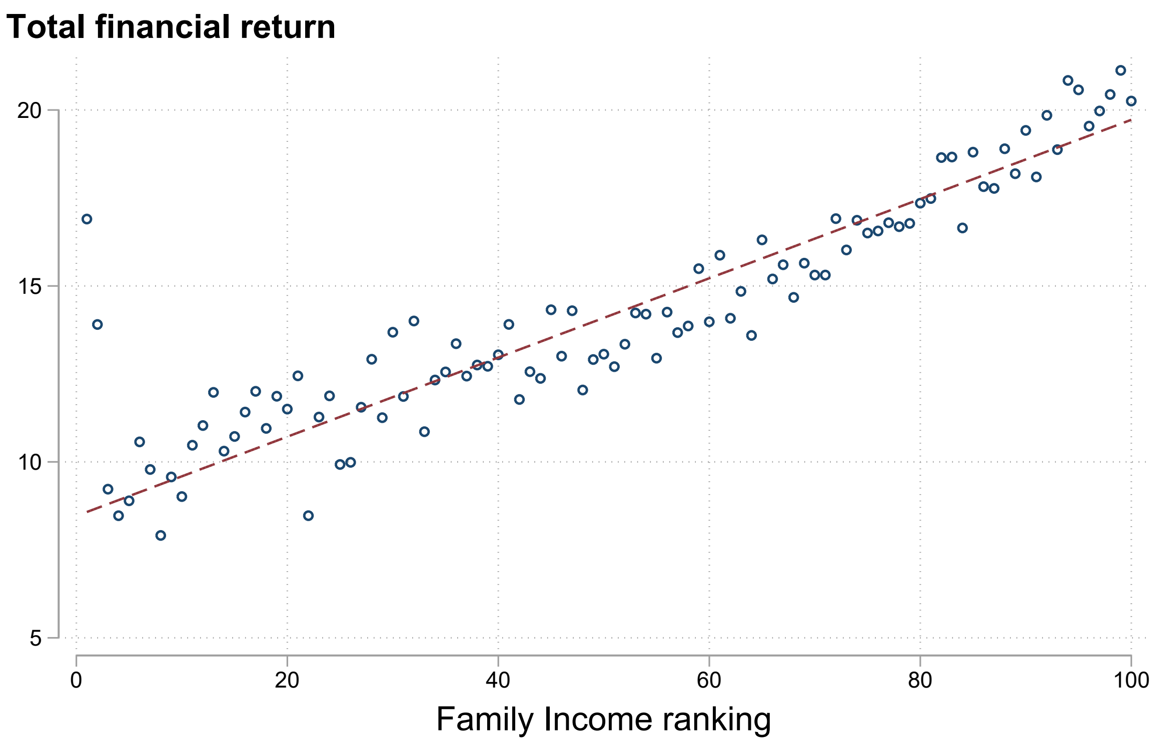


Figure 1: House price growth over time

Notes: The figure plots the average year-over-year growth rate in inflation-adjusted property prices at the municipality 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 at the municipality level from FinansDenmark. 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. The annual national price growth and standard deviation is calculated as the average of the Denmark square meter price growth from 1996 to 2019.



(a) Annualized returns



(b) Total return

Figure 2: Return by income ranking

Notes: This figure plots different return measures against income ranking. Income rankings are adjusted for age and are described in Section 3. Panel a) plots income rank against the annualized log return, and panel b) plots income rank against the total return, calculated as the difference in real price growth between the purchase price and the sales price.

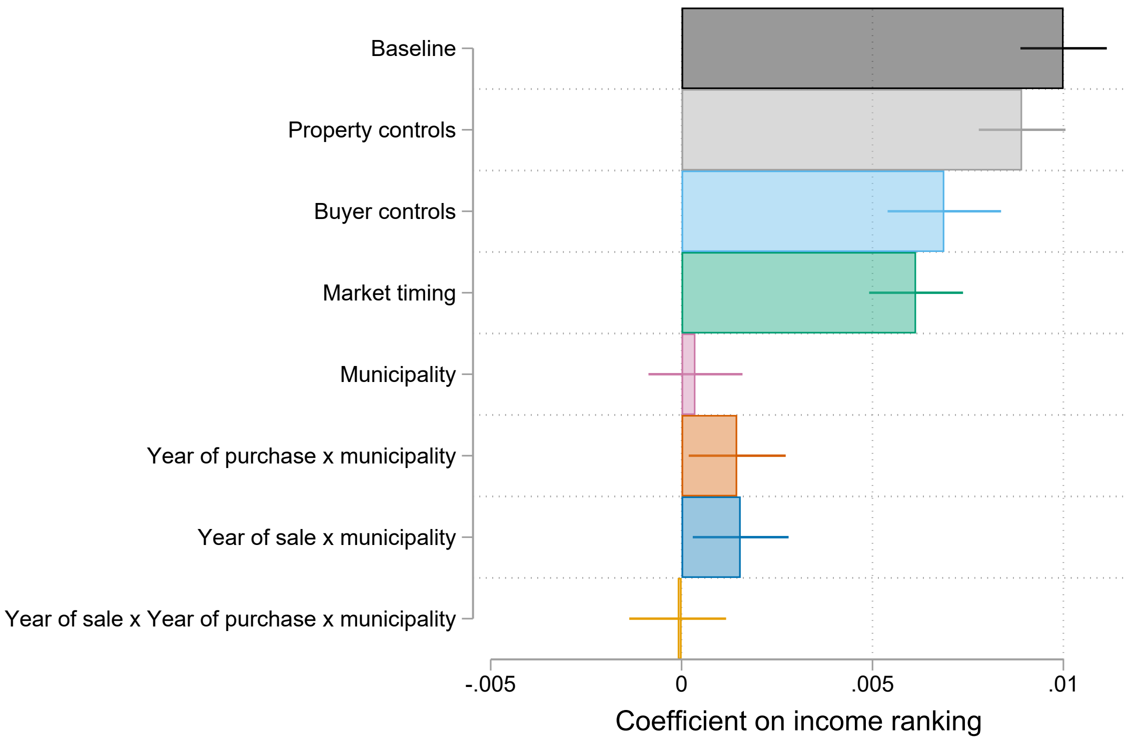


Figure 3: Housing returns and Income rank for repeat sales

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 returns. The *baseline estimate* includes no control variables and corresponds to the slope of the line in Figure 2(a). We then progressively add 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. For buyer pairs, we calculate the maximum age and education level. *Market timing* adds fixed effects for year of purchase. *Municipality* adds fixed effects for municipality. *Year of purchase x municipality* adds fixed effects for year-of-purchase and municipality. *Year of sale x municipality* adds fixed effects for year-of-sale and municipality. *Year of purchase x year of sale x municipality* adds fixed effects for year-of-sale, year-of-purchase and municipality.

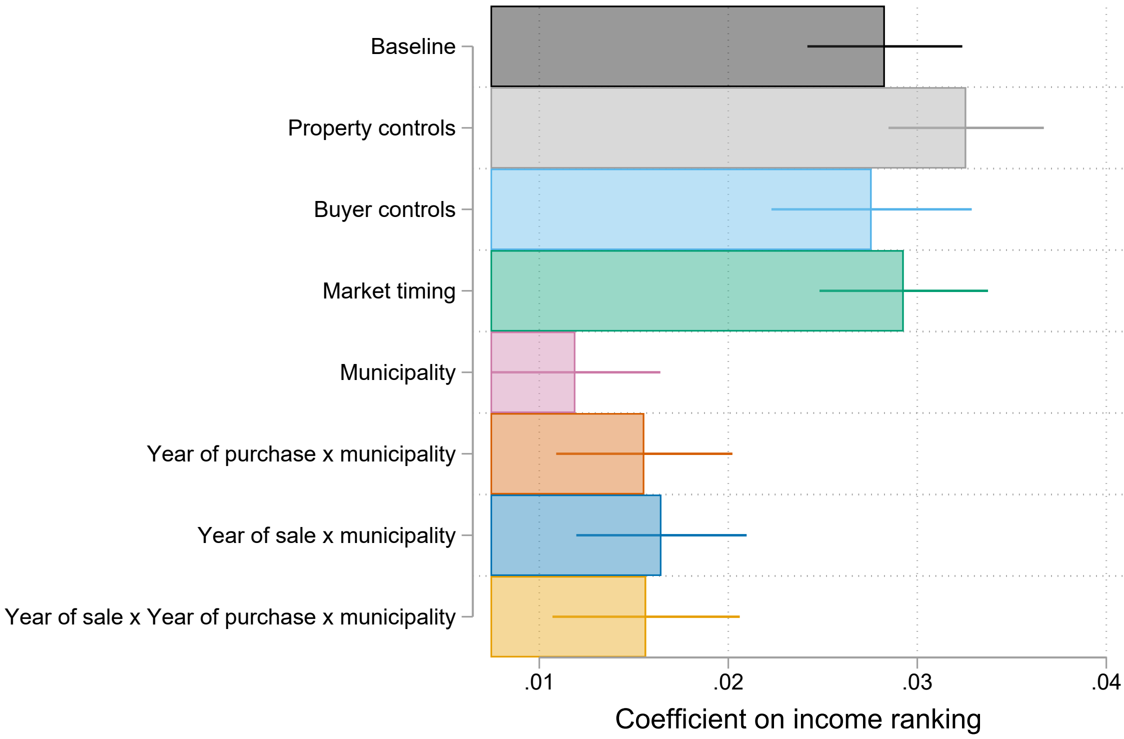


Figure 4: Levered housing returns and income rank

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 2(a). We then progressively add 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. For buyer pairs, we calculate the maximum age and education level. *Market timing* adds fixed effects for year of purchase. *Municipality* adds fixed effects for municipality. *Year of purchase x municipality* adds fixed effects for year-of-purchase and municipality. *Year of sale x municipality* adds fixed effects for year-of-sale and municipality. *Year of purchase x year of sale x municipality* adds fixed effects for year-of-sale, year-of-purchase and municipality.

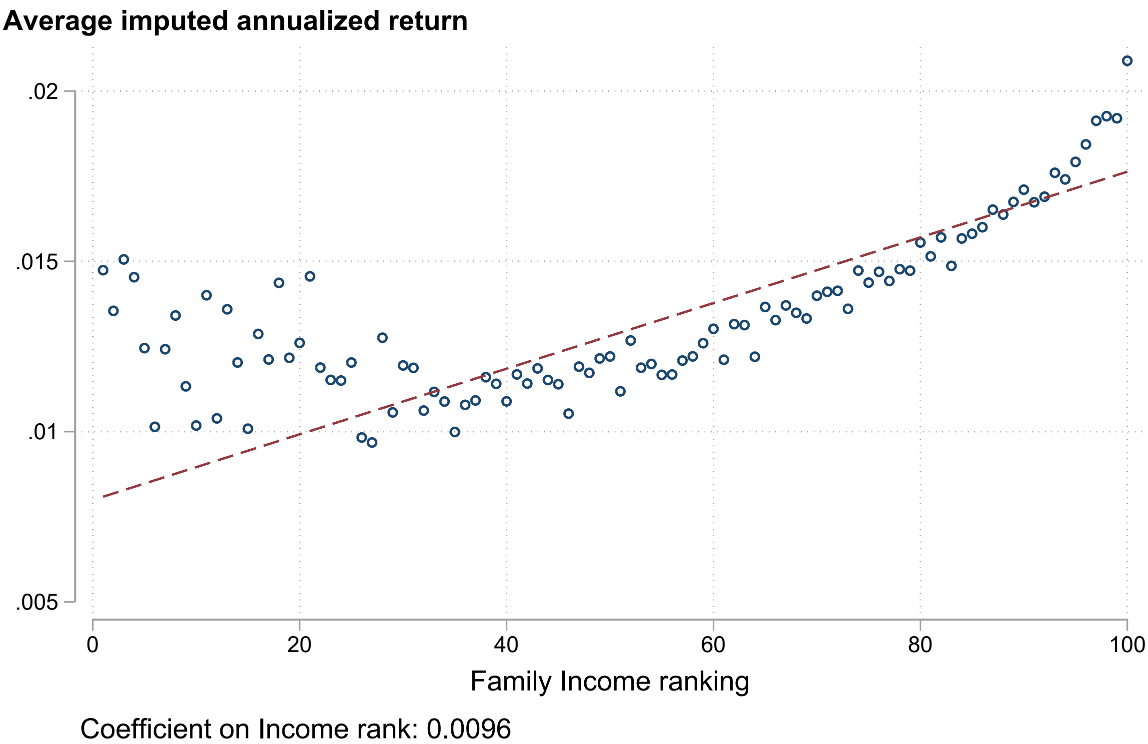
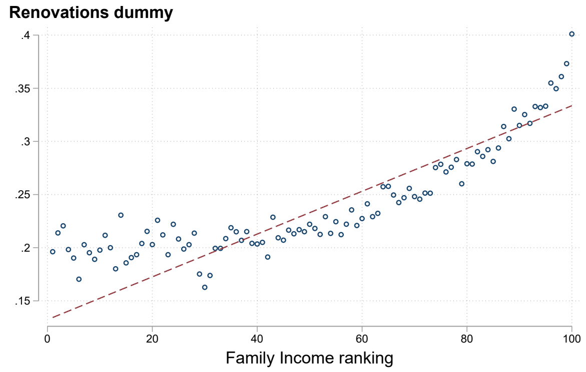
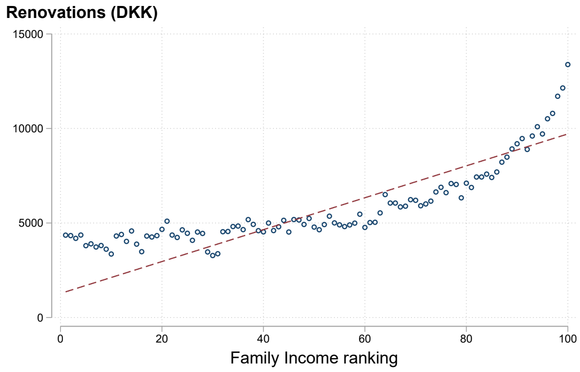


Figure 5: Imputed housing returns and income rank for single transactions

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 2019Q4. The sample does not include repeat-sales transactions.



(a) Renovation Usage and Income Rank



(b) Renovation Amount and Income Rank

Figure 6: 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.

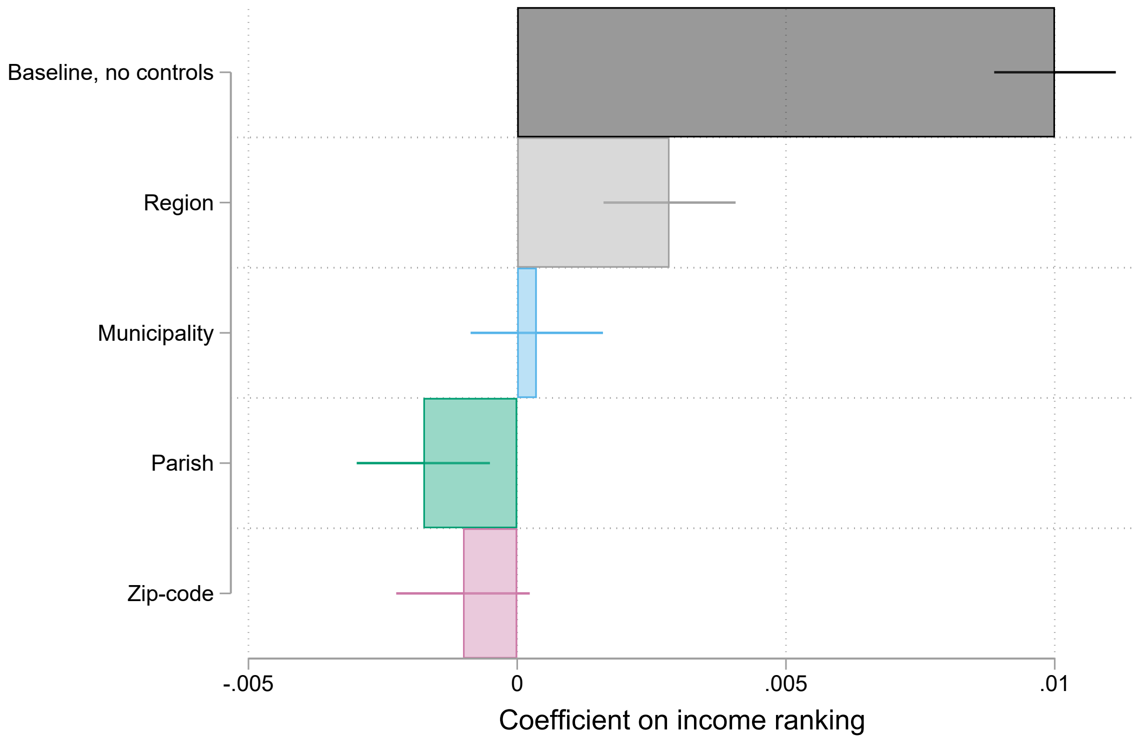


Figure 7: Level of geographical aggregation

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 first four coefficients show results for fixed effects for region, municipality, parish and ZIP-codes. The last four coefficients provide results for interactions of the geographical level and the time of purchase.

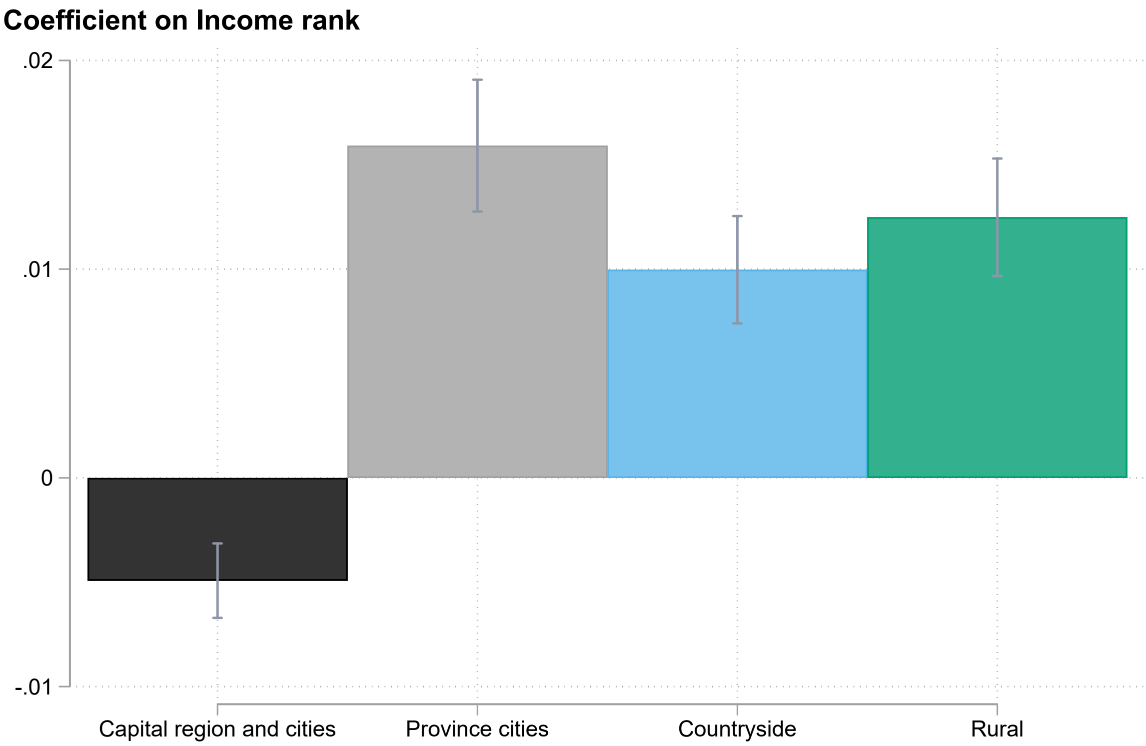


Figure 8: Coefficient on income rank by area

Notes: The figure plots the coefficient on Income Rank on the x-axis from estimating Equation (3) for various levels of geographical aggregation with no controls or fixed effects. The aggregations are provided by Denmark Statistics. We run separate regressions for each area. The bars plot the coefficient on income rank from four different regressions.

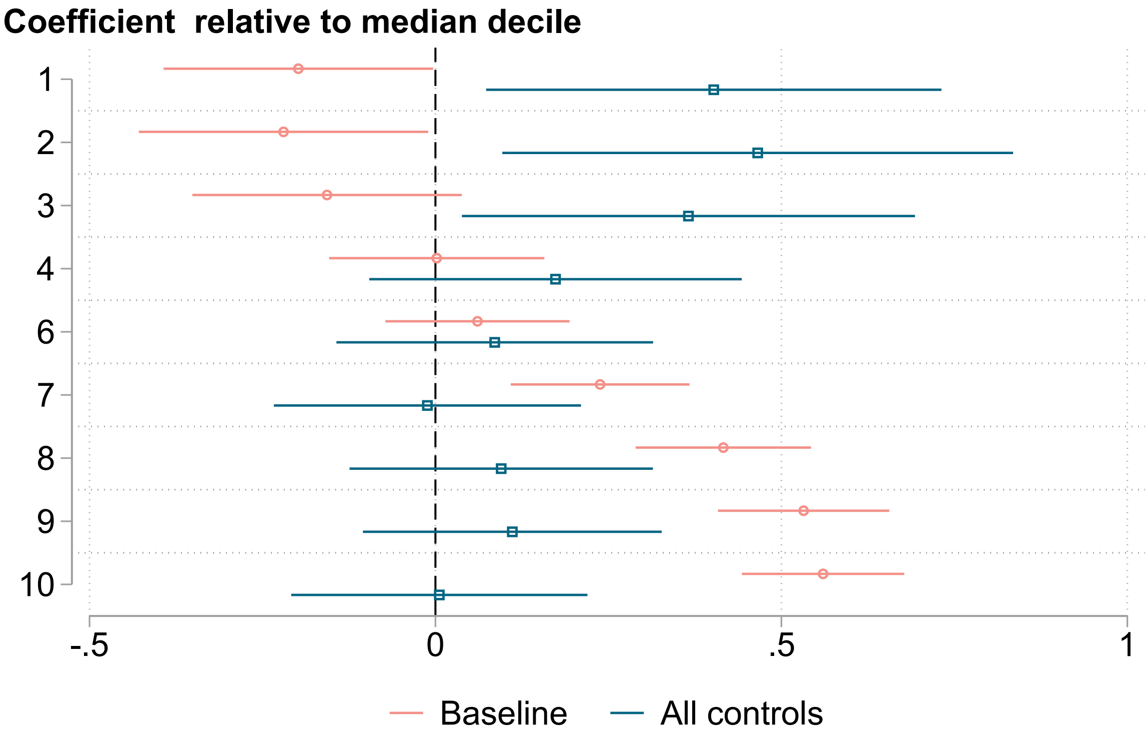


Figure 9: Non-linear effects, relative to median decile

Notes: The figure plots the coefficient for deciles of Income Rank, with and without control variables. The outcome variable is the annualized log returns. We divide the sample into deciles based on income rank. Decile 5 is the excluded category. The specifications with controls, marked with blue, include controls for property characteristics, buyer characteristics, and municipality, time-between sales, purchase year and sales year fixed effects. The specification and controls correspond to the *Municipality* row in Figure 3.

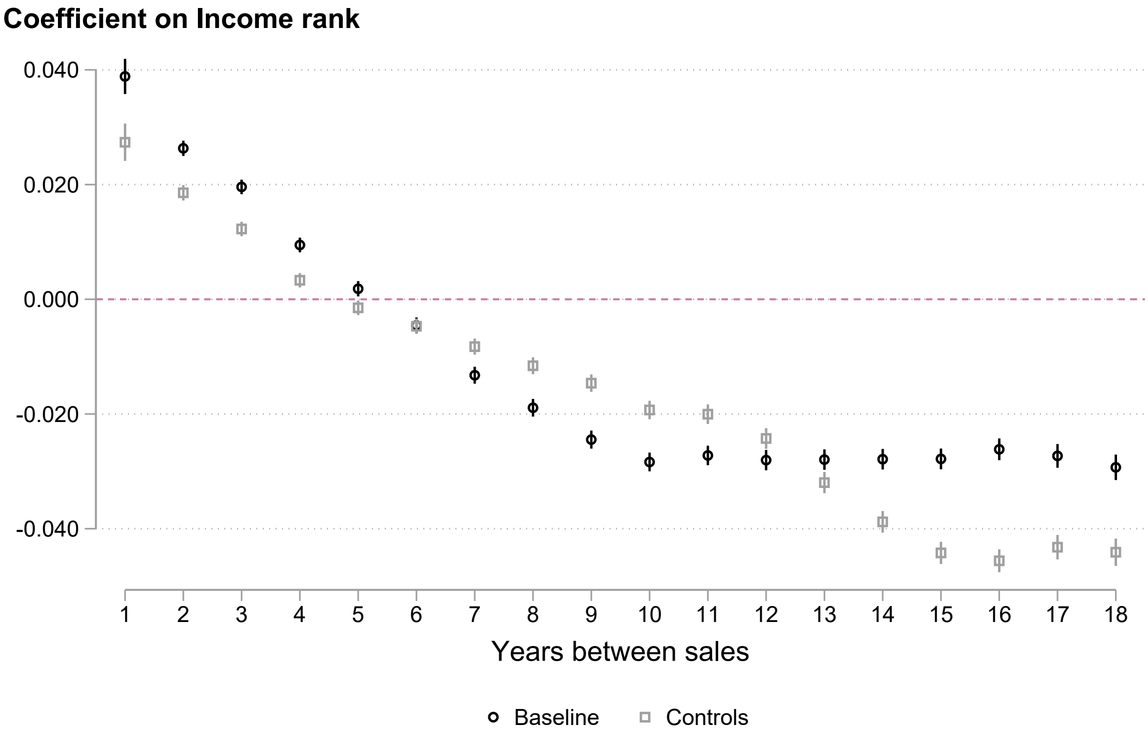


Figure 10: Coefficient on income rank by holding period

Notes: The figure plots how much borrowers can maximally afford based on their assets and income. We calculate maximum ability to pay, taking into account both a loan-to-value (LTV) cap and a payment-to-income (PTI) cap. We calculate the maximum ability to borrow according to a LTV cap as $assets/0.2$, where assets are total assets observed in the year prior to purchase. We calculate the mortgage payments as the annuity payment on a 30-year fixed-rate mortgage, where we take the long mortgage rate from FinansDanmark. We account for a 30% tax deduction on mortgage payments and add 70 basis points in fees. We set the PTI limit to 30% of monthly income. The maximum ability to pay is then calculated as the minimum of the LTV and PTI borrowing plus assets. The figure then plots the average of the log maximum purchase price for each buyer over the income distribution.

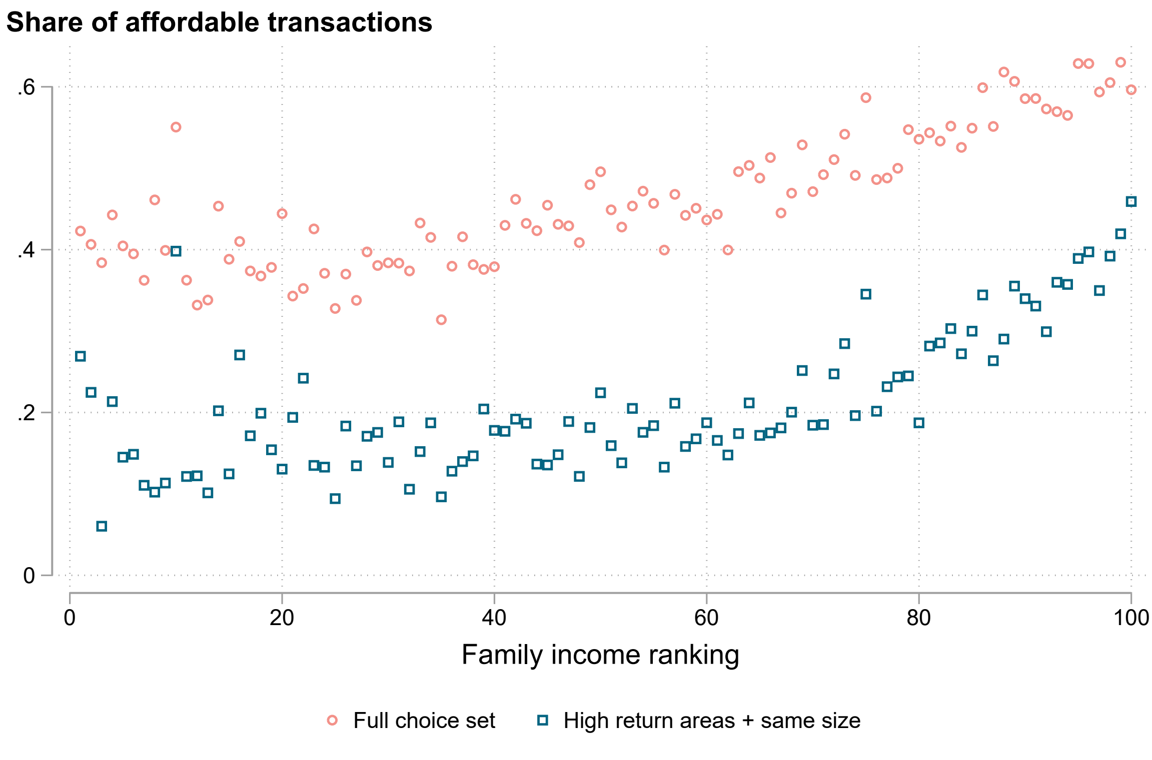


Figure 11: Choice Set by income ranking

Notes: The figure plots the choice set by (binned) income rank.

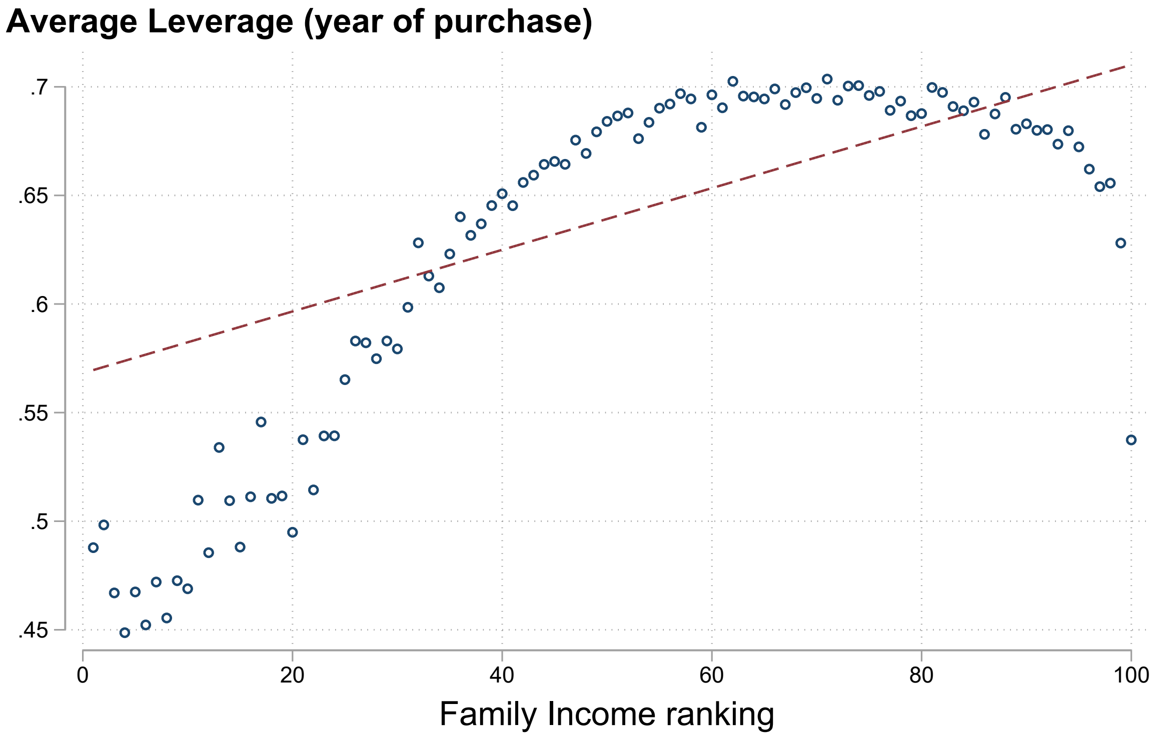


Figure 12: Leverage by income ranking

Notes: The figure plots average leverage by income rank. Leverage is calculated as mortgage debt in the year after purchase divided by the transaction price. We limit the sample to mortgages with a leverage ratio below 1 to reduce the influence of outliers.

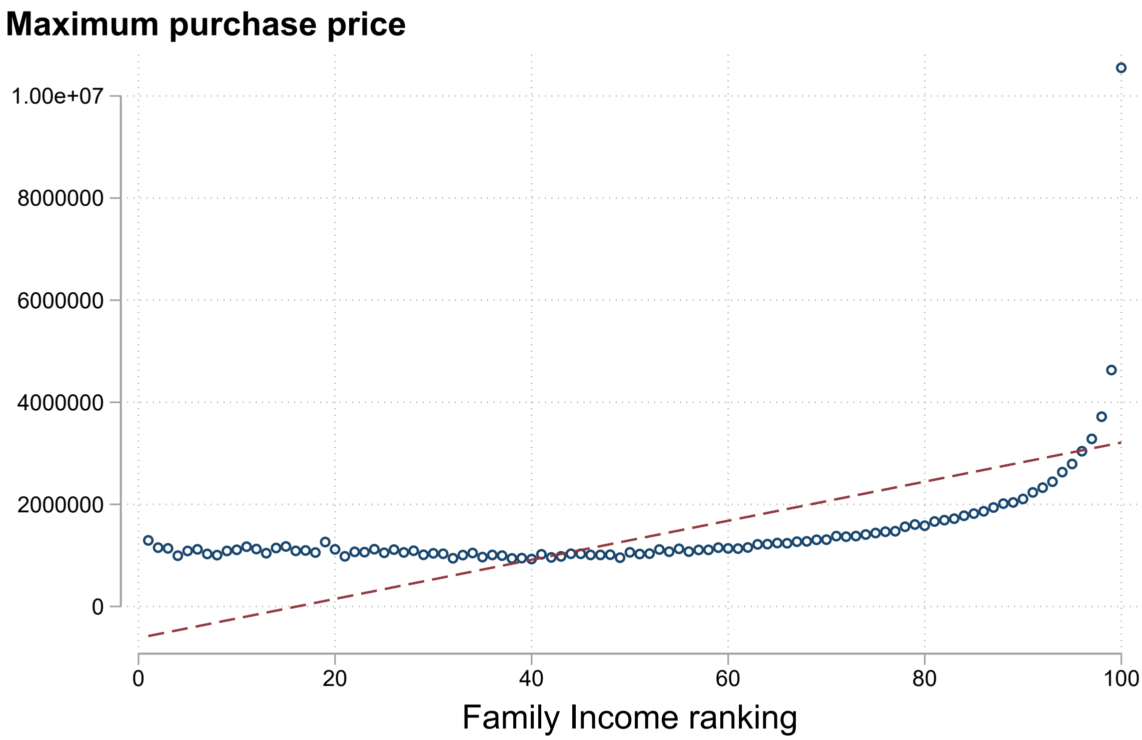


Figure 13: Share of low income buyers in high return municipalities

Notes: The figure plots the coefficients on β_k from the following regression $ShareLowIncome_{it} = \alpha_i + \gamma_t + \sum_{k=1998}^{2019} \beta_k (HighReturn_i \times \mathbf{1}_{t=k}) + \epsilon_{it}$. 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.

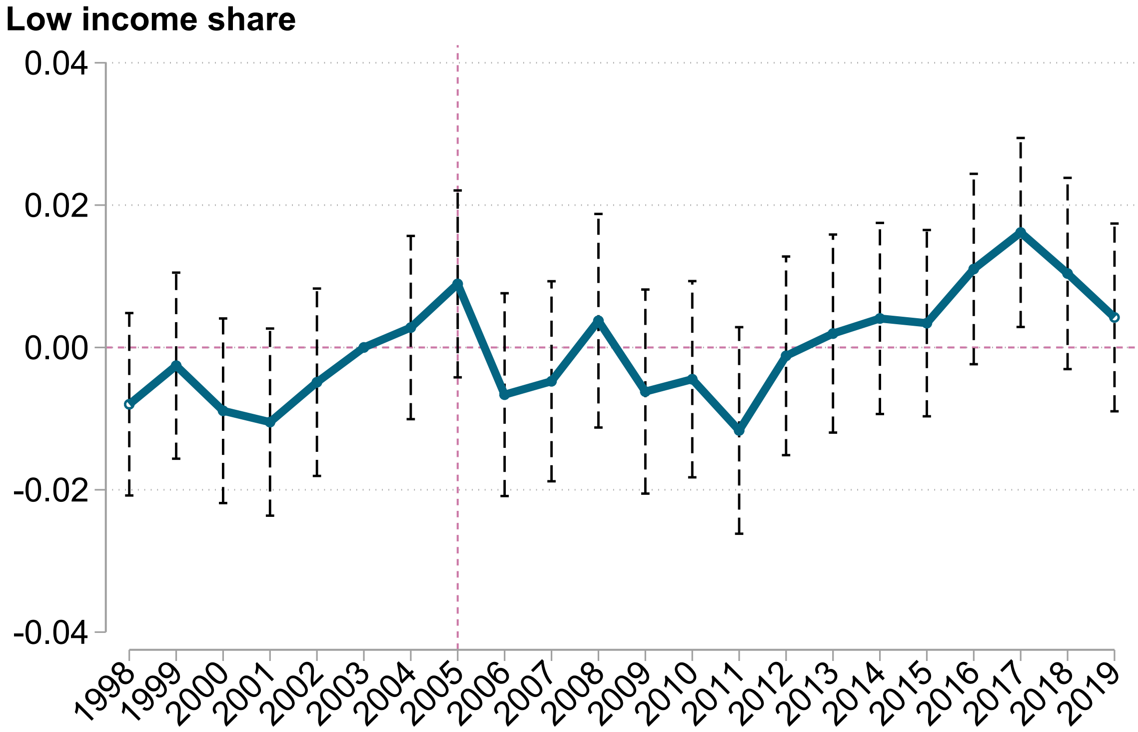


Figure 14: Share of low income buyers in high return municipalities

Notes: The figure plots the coefficients on β_k from the following regression $ShareLowIncome_{it} = \alpha_i + \gamma_t + \sum_{k=1998}^{2019} \beta_k (HighReturn_i \times \mathbf{1}_{t=k}) + \epsilon_{it}$. 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.

10 Tables

Table 1: Descriptive statistics

	(1) All	Income groups (2) Low income	(3) Middle income	(4) High income
Purchase price	1,155,178	948,537	1,005,061	1,289,641
	(700,416)	(572,641)	(523,661)	(785,719)
Sales price	1,378,723	1,088,957	1,174,354	1,563,434
	(898,180)	(705,719)	(663,019)	(1,010,118)
Purchase year	2003.993	2003.750	2003.788	2004.169
	(4.719)	(4.607)	(4.638)	(4.783)
Year between transactions	6.968	7.138	6.810	7.033
	(4.346)	(4.472)	(4.285)	(4.356)
Total capital gains	0.236	0.189	0.212	0.261
	(0.433)	(0.429)	(0.421)	(0.439)
Annualized real return	3.668	3.267	3.481	3.864
	(6.456)	(6.690)	(6.520)	(6.362)
Property characteristics				
Apartment indicator	0.328	0.342	0.256	0.370
	(0.469)	(0.474)	(0.436)	(0.483)
Floor number	1.928	1.947	1.661	2.092
	(1.668)	(1.705)	(1.447)	(1.765)
Rooms	3.829	3.584	3.890	3.839
	(1.429)	(1.315)	(1.343)	(1.496)
Square meter size	109.477	101.813	110.564	110.297
	(41.623)	(37.142)	(38.551)	(44.079)
Building age	54.382	56.031	53.328	54.719
	(36.126)	(36.764)	(35.022)	(36.659)
Geography				
Capital	0.302	0.242	0.212	0.370
	(0.459)	(0.429)	(0.409)	(0.483)
City	0.137	0.124	0.130	0.144
	(0.344)	(0.330)	(0.336)	(0.351)
Countryside	0.220	0.203	0.245	0.208
	(0.414)	(0.402)	(0.430)	(0.406)
Province	0.150	0.163	0.177	0.131
	(0.357)	(0.370)	(0.382)	(0.338)
Rural	0.190	0.267	0.236	0.147
	(0.393)	(0.442)	(0.425)	(0.354)
Buyer characteristics				
Total income, pre-purchase	323.341	121.513	219.002	428.202
	(438.873)	(33.636)	(28.359)	(569.569)
Net wealth, pre-purchase	387.993	451.617	180.128	505.659
	(2356.406)	(1180.781)	(832.039)	(3060.794)
Mortgage, pre-purchase	458.681	290.708	295.693	593.625
	(1053.617)	(990.260)	(631.120)	(1241.264)
Renovation indicator	0.269	0.202	0.226	0.310
	(0.444)	(0.401)	(0.418)	(0.462)
Renovation amount (DKK)	7011.998	4238.089	5221.879	8676.121
	(1.7e+04)	(1.2e+04)	(1.4e+04)	(1.9e+04)
Age	40.514	46.084	38.030	40.979
	(11.900)	(17.086)	(11.646)	(10.283)
Gender	0.465	0.519	0.524	0.418
	(0.356)	(0.372)	(0.322)	(0.367)
Number of buyers	1.498	1.458	1.597	1.443
	(0.500)	(0.498)	(0.491)	(0.497)
Education	14.640	13.128	14.200	15.212
	(2.601)	(3.182)	(2.411)	(2.410)
Family size	2.410	1.981	2.399	2.501
	(1.169)	(0.941)	(1.144)	(1.206)
Share of all transactions		0.108	0.344	0.549
Repeat sale share	0.301	0.312	0.276	0.262
N	180,238	19,381	61,931	98,926

Notes: This 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. For buyer characteristics, we use income and wealth data merged one year before the purchase (marked with "Pre-purchase". Renovation indicator is a variable equal to one if one of the buyers used a renovation tax break between 2011 and 2019. Education and age are caluclated as the maximum variable among the buyers.

Table 2: Returns and Income Ranking

	Baseline					Interaction Mun. with		
	(1) Baseline	(2) Property	(3) Buyers	(4) Timing	(5) Mun.	(6) P-year	(7) S-year	(8) S-year x P-year
Income rank	0.0100***	0.00892***	0.00688***	0.00614***	0.000364	0.00146**	0.00155**	-0.000102
	(17.33)	(15.40)	(9.08)	(9.79)	(0.58)	(2.25)	(2.42)	(-0.16)
Apartment indicator		0.112**	0.0964	-0.0662	-0.695***	-0.707***	-0.786***	-0.742***
		(2.22)	(1.55)	(-1.29)	(-13.61)	(-13.22)	(-14.94)	(-13.94)
Floor number		0.218***	0.209***	0.268***	0.0490***	0.0367***	0.0576***	0.0534***
		(17.08)	(13.69)	(21.27)	(3.82)	(2.78)	(4.40)	(4.21)
Rooms		0.160***	0.134***	0.134***	0.0802***	0.0664***	0.102***	0.0901***
		(8.46)	(5.96)	(6.93)	(4.18)	(3.35)	(5.25)	(4.47)
Size M2		-0.0145***	-0.0130***	-0.0112***	-0.00637***	-0.00749***	-0.00597***	-0.00675***
		(-22.73)	(-16.96)	(-16.84)	(-9.57)	(-10.93)	(-8.80)	(-9.62)
Building age		0.0113***	0.0113***	0.0113***	0.00947***	0.00995***	0.00918***	0.00968***
		(27.26)	(22.70)	(26.20)	(21.20)	(21.56)	(20.31)	(21.05)
Age			-0.0542***	-0.0329***	-0.0245***	-0.0284***	-0.0210***	-0.0252***
			(-38.22)	(-27.82)	(-20.62)	(-23.10)	(-17.37)	(-20.46)
Number of buyers			-0.689***	-0.371***	-0.687***	-0.677***	-0.861***	-0.660***
			(-16.50)	(-10.38)	(-19.11)	(-18.37)	(-23.53)	(-17.84)
Wealth rank			-0.00416***	0.00566***	0.000720	0.00319***	-0.00118**	0.00445***
			(-7.55)	(11.91)	(1.51)	(6.44)	(-2.45)	(9.02)
Gender			-0.0167	0.0278	-0.116***	-0.136***	-0.115***	-0.105**
			(-0.32)	(0.63)	(-2.64)	(-3.04)	(-2.61)	(-2.41)
Education			-0.0337***	0.0408***	-0.00634	-0.0118*	-0.00507	-0.000203
			(-4.75)	(6.80)	(-1.06)	(-1.90)	(-0.84)	(-0.03)
Family size			0.0350**	0.0596***	0.0748***	0.102***	0.0916***	0.0619***
			(2.15)	(4.25)	(5.40)	(7.17)	(6.50)	(4.35)
Cumulative difference	0.083	0.074	0.056	0.050	0.003	0.012	-0.001	
Adjusted R-squared	0.00164	0.0215	0.0378	0.326	0.348	0.323	0.344	0.510
Observations	185918	185836	120710	120710	120710	120657	120671	117585

Notes: This table presents the regression results that relate returns and income ranking. The outcome variable is the annualized log returns. The *baseline estimate* includes no control variables and corresponds to the slope of the line in Figure 2(a). We then progressively add 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. For buyer pairs, we calculate the maximum age and education level. *Market timing* adds fixed effects for year of purchase. *Municipality* adds fixed effects for municipality. *Year of purchase x municipality* adds fixed effects for year-of-purchase and municipality. *Year of sale x municipality* adds fixed effects for year-of-sale and municipality. *Year of purchase x year of sale x municipality* adds fixed effects for year-of-sale, year-of-purchase and municipality.

Table 3: Levered returns and income rank

	Baseline					Interaction Mun. with		
	(1) Baseline	(2) Property	(3) Buyers	(4) Timing	(5) Mun.	(6) P-year	(7) S-year	(8) S-year x P-year
Income rank	0.0283***	0.0326***	0.0276***	0.0293***	0.0119***	0.0156***	0.0165***	0.0157***
	(13.53)	(15.54)	(10.20)	(12.87)	(5.19)	(6.54)	(7.16)	(6.19)
Apartment indicator		1.009***	1.323***	0.574***	-0.981***	-0.995***	-1.153***	-1.094***
		(5.11)	(5.55)	(2.91)	(-4.94)	(-4.79)	(-5.76)	(-5.08)
Floor number		0.589***	0.608***	0.763***	0.192***	0.175***	0.221***	0.161***
		(11.01)	(9.59)	(14.42)	(3.45)	(3.06)	(4.03)	(2.81)
Rooms		0.266***	0.156*	0.186***	0.0760	0.0252	0.111	0.0578
		(3.84)	(1.92)	(2.70)	(1.10)	(0.36)	(1.61)	(0.77)
Size M2		-0.0451***	-0.0361***	-0.0295***	-0.0140***	-0.0165***	-0.0143***	-0.0166***
		(-19.55)	(-13.13)	(-12.42)	(-5.83)	(-6.65)	(-5.87)	(-6.21)
Building age		0.0357***	0.0326***	0.0294***	0.0227***	0.0249***	0.0236***	0.0255***
		(23.01)	(17.47)	(18.20)	(13.57)	(14.39)	(14.07)	(13.68)
Age			-0.207***	-0.120***	-0.102***	-0.115***	-0.100***	-0.105***
			(-42.01)	(-28.23)	(-23.95)	(-26.06)	(-23.40)	(-22.11)
Wealth rank			-0.0434***	-0.0113***	-0.0261***	-0.0209***	-0.0257***	-0.0156***
			(-21.07)	(-6.36)	(-14.48)	(-11.18)	(-14.32)	(-7.81)
Gender			-0.172	-0.112	-0.496***	-0.563***	-0.421***	-0.502***
			(-0.89)	(-0.69)	(-3.05)	(-3.40)	(-2.61)	(-2.90)
Education			-0.131***	0.146***	0.0232	0.00572	0.0344	0.0519**
			(-5.21)	(6.70)	(1.07)	(0.25)	(1.57)	(2.17)
Family size			-0.0469	0.0358	0.0111	0.117**	0.0730	0.0464
			(-0.75)	(0.66)	(0.21)	(2.10)	(1.35)	(0.79)
Year between transactions	No	No	No	Yes	Yes	Yes	Yes	Yes
Cumulative difference	0.251	0.293	0.244	0.261	0.099		0.140	
Adjusted R-squared	0.00125	0.0232	0.0485	0.329	0.344	0.325	0.366	0.506
Observations	139213	139148	88463	88463	88463	88398	88417	84515

Notes: This table presents the regression results that relate levered returns and income ranking. 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 2(a). We then progressively add 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. For buyer pairs, we calculate the maximum age and education level. *Market timing* adds fixed effects for year of purchase. *Municipality* adds fixed effects for municipality. *Year of purchase x municipality* adds fixed effects for year-of-purchase and municipality. *Year of sale x municipality* adds fixed effects for year-of-sale and municipality. *Year of purchase x year of sale x municipality* adds fixed effects for year-of-sale, year-of-purchase and municipality. 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 4: Housing return predictors

	Levels				Changes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Levels								
Population	-2.205***	-2.079***	-0.295	-0.251				
	(-5.48)	(-5.15)	(-1.11)	(-0.93)				
Working age population	-6.682*	-8.494**	-4.025	-6.448**				
	(-1.71)	(-2.26)	(-1.32)	(-2.19)				
Disposable income	-0.0970***	-0.103***	0.126***	0.0463				
	(-4.21)	(-4.42)	(4.65)	(1.60)				
Employed population	8.955**	10.65***	4.386	6.753**				
	(2.19)	(2.72)	(1.40)	(2.23)				
Employment rate	0.207***	0.206***	0.0251	-0.00411				
	(7.17)	(7.22)	(0.80)	(-0.13)				
Panel B: Changes								
Change in Population					-0.229***	-0.227***	-0.0136	-0.0363
					(-7.42)	(-7.30)	(-0.28)	(-0.71)
Change in Working age population					0.454***	0.455***	0.124**	0.131**
					(14.24)	(14.23)	(2.18)	(2.27)
Change in Disposable income					0.293***	0.293***	0.167***	0.154***
					(12.48)	(12.49)	(6.22)	(5.67)
Change in Employment rate					-0.118***	-0.117***	-0.0201	-0.0140
					(-4.07)	(-4.06)	(-0.63)	(-0.44)
Housing supply elasticity		0.153**	0.0539	-0.00704		0.0505	0.0432	-0.0360
		(2.39)	(1.28)	(-0.17)		(0.93)	(1.21)	(-0.95)
Year	No	No	Yes	Yes	No	No	Yes	Yes
Region FE	No	No	No	Yes	No	No	No	Yes
Adjusted R-squared	0.0892	0.0922	0.560	0.566	0.234	0.235	0.570	0.577
Observations	2140	2140	2140	2140	2140	2140	2140	2140

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.

Table 5: Summary statistics for housing risk across income distribution

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Return										
Average return	0.010	0.009	0.009	0.009	0.009	0.009	0.009	0.010	0.011	0.012
	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Sharpe ratio	0.027	0.025	0.025	0.024	0.025	0.026	0.027	0.029	0.032	0.037
	(0.035)	(0.034)	(0.034)	(0.033)	(0.033)	(0.034)	(0.036)	(0.037)	(0.039)	(0.043)
Panel B: Risk										
Return std. dev.	0.471	0.477	0.476	0.475	0.472	0.470	0.467	0.461	0.456	0.445
	(0.136)	(0.138)	(0.139)	(0.138)	(0.139)	(0.141)	(0.145)	(0.146)	(0.146)	(0.145)
Beta, regional index	0.783	0.782	0.779	0.780	0.770	0.767	0.762	0.754	0.753	0.759
	(0.386)	(0.392)	(0.393)	(0.395)	(0.398)	(0.402)	(0.405)	(0.405)	(0.402)	(0.397)
Beta, aggregate index	0.787	0.788	0.785	0.784	0.778	0.778	0.778	0.774	0.773	0.774
	(0.359)	(0.364)	(0.368)	(0.371)	(0.372)	(0.379)	(0.385)	(0.385)	(0.387)	(0.382)
Number of negative returns	9.657	9.670	9.673	9.666	9.676	9.661	9.638	9.625	9.609	9.591
	(1.733)	(1.759)	(1.754)	(1.766)	(1.784)	(1.796)	(1.797)	(1.795)	(1.804)	(1.782)
Return if negative	-0.215	-0.209	-0.209	-0.209	-0.208	-0.210	-0.216	-0.220	-0.228	-0.237
	(0.132)	(0.133)	(0.132)	(0.134)	(0.135)	(0.137)	(0.142)	(0.142)	(0.146)	(0.144)
Sales times	165.256	169.538	169.167	168.585	168.250	166.746	164.034	160.964	157.725	152.307
	(41.743)	(40.535)	(39.959)	(39.111)	(38.435)	(38.096)	(38.332)	(38.829)	(39.444)	(40.314)
Covariance return cons. growth	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
Covariance return income growth	0.002	0.003	0.003	0.003	0.003	0.002	0.002	0.002	0.002	0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	22636	19944	25187	47629	73047	93447	107643	120343	137500	186062
Panel C: Idiosyncratic risk (Repeat sales only)										
Idiosyncratic risk, annualized	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Idiosyncratic risk	-0.033	-0.026	-0.032	-0.025	-0.022	-0.014	-0.020	-0.001	0.003	0.006
	(0.543)	(0.543)	(0.555)	(0.537)	(0.545)	(0.549)	(0.569)	(0.551)	(0.560)	(0.552)
Observations	6332	4980	6154	11934	17258	21039	23887	26130	28850	38803

Notes: The table provides summary statistics on average housing risk across income deciles. We describe how we calculate housing risk measures in . We divide the sample of all single and repeat buyers into 10 deciles according to their income rank, and merge the municipality level measures to each buyer. We then calculate the average for each decile. Panel A describes differences in municipality-level returns and Sharpe ratios. Panel B describes risk measures, calculated on the municipality level. We collect sales times from FinansDanmark. Panel C describes idiosyncratic risk, which is calculated for each transaction according to the methodology in Giacoletti (2021).

Table 6: Regressions of housing risk on income rank

	(1) Mun return	(2) Sharpe	(3) Std.dev	(4) Beta region	(5) Beta Denmark	(6) Sum negative
Income rank	0.0000458*** (109.32)	0.000168*** (101.91)	-0.000431*** (-68.94)	-0.000485*** (-27.51)	-0.000387*** (-22.31)	-0.00130*** (-16.98)
Adjusted R-squared	0.0134	0.0118	0.00524	0.000844	0.000548	0.000323
Observations	874163	874163	874163	874163	874163	874163
	(1) Return negative	(2) Sales time	(3) Cov. Cons	(4) Cov. Inc	(5) Id. Risk	(6) Id. Risk, unscaled
Income rank	-0.000347*** (-58.52)	-0.223*** (-122.30)	-0.00000760*** (-23.65)	-0.00000308*** (-11.45)	0.00000638*** (5.80)	0.000496*** (9.76)
Adjusted R-squared	0.00373	0.0187	0.000661	0.000152	0.000177	0.000504
Observations	874163	833438	874163	874163	185367	185367

Notes: The table provides results when we regress income rank on measures of housing risk. We describe how we calculate housing risk measures in . We merge the municipality-level measures to each buyer according to their property location.

Table 7: Choice set and income rank

	All areas				High return areas		
	(1) All	(2) Same size	(3) Same rooms	(4) All	(5) Same size	(6) Same rooms	(7) c7
Household income rank (age adjusted)	0.00281***	0.00310***	0.00308***	0.00326***	0.00284***	0.00282***	0.00293***
	(348.58)	(146.12)	(172.58)	(301.11)	(208.45)	(81.49)	(149.06)
Constant	0.313***	0.295***	0.298***	0.286***	0.178***	0.0568***	0.104***
	(545.43)	(197.74)	(236.58)	(374.13)	(187.79)	(24.73)	(76.77)
Adjusted R-squared	0.0197	0.0235	0.0235	0.0258	0.0217	0.0272	0.0262
Observations	5974530	875839	1222994	3371226	1896839	241556	839767

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 5% 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-return areas. High return areas are defined as municipalities in the top quintile of the average returns.

INTERNET APPENDIX

FOR ONLINE PUBLICATION

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Online Appendix: Tables

Table A1: Descriptive statistics for single and repeat sales

	(1) All transactions	(2) Repeat transactions	(3) Single transactions
Household income rank (age adjusted)	69	67	69
	(24)	(25)	(24)
Repeat sale	0.27	1.00	0.00
	(0.45)	(0.00)	(0.00)
Purchase price	1,235,918	1,074,702	1,296,221
	(903,870)	(694,870)	(963,644)
Purchase year	2,008	2,004	2,009
	(7)	(5)	(7)
Apartment indicator	0.189	0.277	0.156
	(0.391)	(0.447)	(0.363)
Floor number	1.54	1.79	1.45
	(1.37)	(1.58)	(1.27)
Rooms	4.07	3.80	4.17
	(1.41)	(1.39)	(1.40)
Building M2	214.21	255.16	198.90
	(402.46)	(447.09)	(383.32)
Size M2	112.984	104.177	116.279
	(44.964)	(42.556)	(45.395)
Building age	53.378	51.734	53.993
	(35.893)	(35.495)	(36.021)
Capital	0.222	0.259	0.208
	(0.415)	(0.438)	(0.406)
City	0.112	0.122	0.108
	(0.315)	(0.327)	(0.310)
Countryside	0.207	0.202	0.209
	(0.405)	(0.402)	(0.406)
Province	0.186	0.172	0.191
	(0.389)	(0.378)	(0.393)
Rural	0.274	0.244	0.285
	(0.446)	(0.430)	(0.452)
Share of all transactions		0.272	0.728
N	871,453	237,233	634,220

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

Table A2: Interaction of supply and income shocks

	Income growth		Interest rates	
	(1)	(2)	(3)	(4)
Income growth x Constrained	-0.0360	-0.0228		
	(-0.77)	(-0.80)		
Interest rate x Constrained			0.00248	-0.00561
			(0.11)	(-0.27)
Supply constrained	-0.0136	-0.0217	-0.0592	0.0290
	(-0.33)	(-0.74)	(-0.90)	(0.49)
Change in Disposable income	0.294***	0.167***	0.251***	0.325***
	(8.73)	(5.27)	(10.44)	(12.71)
Interest rate			0.0641***	-0.0797***
			(4.10)	(-4.40)
Year	No	Yes	No	No
Region	No	Yes	No	Yes
_cons	Yes	No	No	No
Adjusted R-squared	0.0759	0.577	0.0961	0.247
Observations	2140	2140	2140	2140

Notes: The table estimates how demand shocks interact with supply shock

Table A3: Choice set and income rank

	All areas				High return areas		
	(1) All	(2) Same size	(3) Same rooms	(4) All	(5) Same size	(6) Same rooms	(7) c7
Household income rank (age adjusted)	0.00489***	0.00445***	0.00461***	0.00477***	0.00562***	0.00614***	0.00633***
	(629.65)	(213.50)	(264.71)	(451.64)	(410.38)	(164.55)	(318.79)
Constant	0.253***	0.267***	0.263***	0.254***	0.146***	0.0655***	0.0644***
	(441.12)	(176.31)	(207.21)	(329.18)	(146.20)	(24.61)	(44.31)
Adjusted R-squared	0.0611	0.0491	0.0535	0.0563	0.0788	0.0953	0.103
Observations	5974530	875839	1222994	3371226	1896839	241556	839767

Notes: The table provides results when we regress income rank on the choice set for each buyer. Choice set is defined using the maximum purchase price for each buyer, calculated as the maximum borrowing plus assets. Maximum borrowing is defined as the minimum of borrowing according to a payment-to-income constraints, where mortgage payments have to be less than 35% of income, and a loan-to-value constraint, based on a 20% downpayment. The choice set based on financial constraints denotes the share of transactions for each buyer that is below their maximum purchase price. The results are based on a 5% 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-return areas. High return areas are defined as municipalities in the top quintile of the average returns.

Appendix: Figures

Figure B1: Risk and return in Danish housing markets

Notes: The figure plots average housing returns against the standard deviation of housing returns on the municipality level. Municipality level housing returns are calculated as the average log difference in annual square meter prices. Data is collected from FinansDanmark.

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:

$$\ln E[R_{t+1}] - \ln R_f = \gamma \operatorname{Cov}\left[\ln\left(\frac{C_{t+1}}{C_t}\right), \ln R_{t+1} - \ln R_f\right], \tag{7}$$

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, 2020) and calculate the covariance between consumption growth and housing returns.[16]

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.

[16]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:

$$\text{LME}_i = \frac{P_{i,T}/R_{t,T}^{\text{Mun}} - P_{i,t}}{P_{i,t}}, \tag{8}$$

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:

$$\frac{\log(1 + \text{LME}_i)}{\sqrt{\tau_i}} = X_i'\beta + \alpha_{\text{Mun}(i)} + \alpha_{p(i)} + u_i, \tag{9}$$

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 (9), as in Amaral et al. (2021).

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., 2025; 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 et al., 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:

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

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:

$$\Delta P_{k,r,t} = \psi_k + \delta_k \Delta y_{k,r,t} + \gamma_k \Delta P_{r,t} + \Psi_k X_{k,r,t} + v_{k,r,t} \tag{11}$$

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.