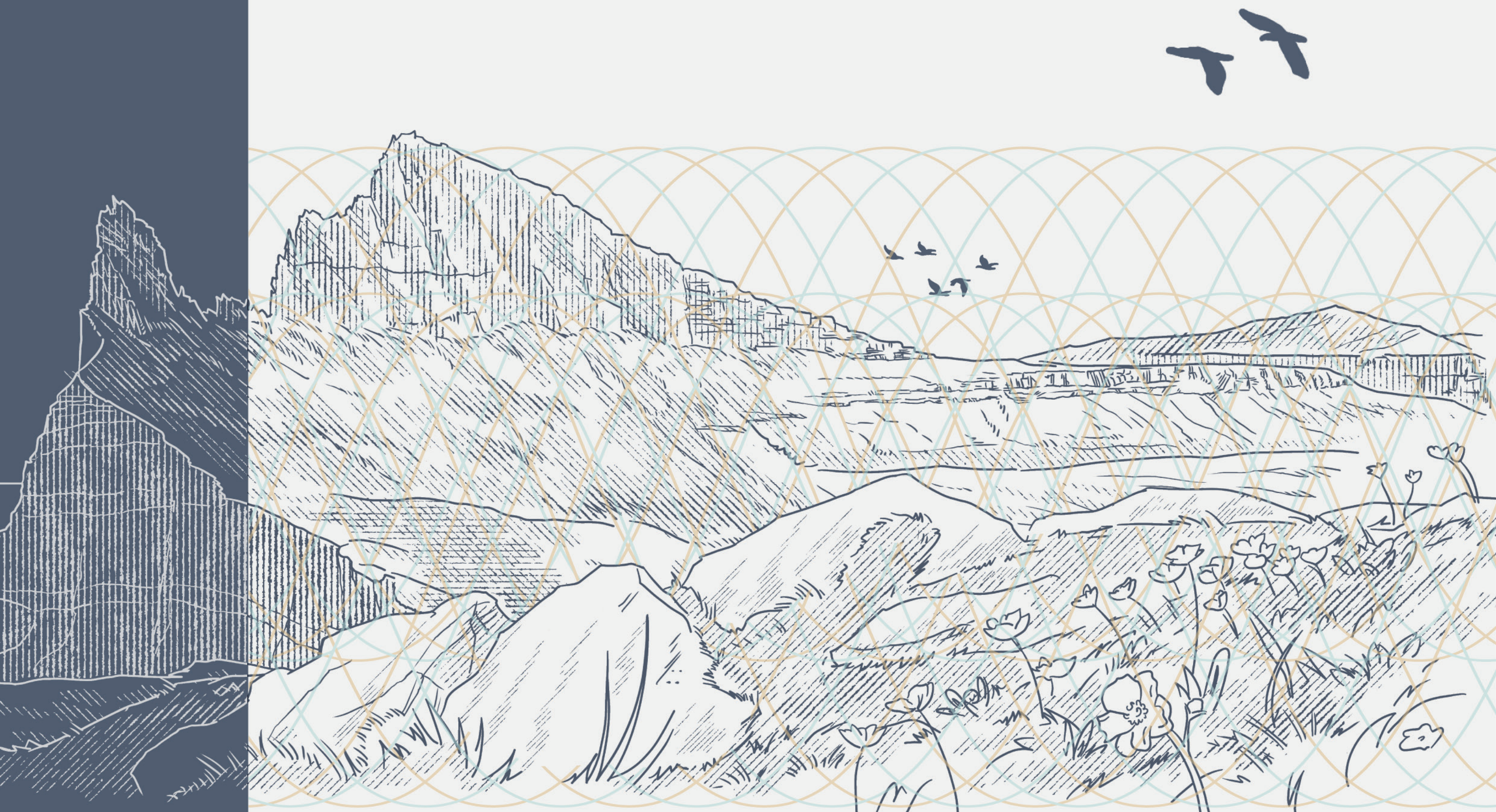
WORKING PAPER

A Hedonic Housing Model for Macroprudential Policy



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A Hedonic Housing Model for Macroprudential Policy*

Önundur Páll Ragnarsson†

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Abstract

I examine a granular dataset on residential real estate transactions, both sales and rental, in Iceland's main urban area, provide descriptive statistics for both markets and develop a hedonic model of the sales market multi-dwelling segment. Main findings are: (1) An average quality difference of 8.8% between sold and rented apartments suggests bias in a non-quality adjusted price-to-rent ratio over the period 2011-2022. Asymmetric quality developments over time in the sales and rental markets also suggest time-varying quality-bias. (2) Accumulated bias in a CPI-deflated non-quality adjusted index for the greater Reykjavík area multi-dwelling sales market, from 2007 to 2024, compared to a quality-adjusted index, is 3.7%. (3) The estimated time-varying new house premium can provide insight into housing sales market supply and demand conditions and aid the identification of housing bubbles. (4) A hedonic price-to-building cost ratio shows different short-run dynamics than a non-quality adjusted ratio.

Keywords: Hedonic model, index number, real estate, macroprudential policy.
JEL classification: J31, C43, E58.

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1 Introduction

Along with mortgage credit, real estate prices are considered a core indicator on cyclical systemic risk, see e.g. Jordà et al. (2015a & 2015b). Thus, information on house prices is essential for the justification of macroprudential regulation aimed at the mortgage credit market. In Iceland, the Central Bank is the designated authority for all such regulation and supervision. Furthermore, the Central Bank may need to concern itself with issues related to natural disasters, when pursuing its policy targets. Natural disasters include Iceland's pervasive volcanic and seismic activity, which can have drastic but highly localized effects on housing markets. This suggests that the Central Bank should take on a granular analysis of the residential real estate market. To that end, hedonic modeling is an advantageous approach.

Hedonic models are versatile and provide means to perform a multitude of analyses. This includes, but is not limited to, quality-adjusted sales and rent price indices, quality-adjusted and property-specific price-to-rent ratios, estimates of housing investment return and house price expectations, calibration of macroprudential instruments, and studies on the effects of macroeconomic shocks on housing demand and imbalances in housing markets. In addition, hedonic models enable spatial analysis, which can provide rationale for geographically differentiated macroprudential regulations and aid scenario design for macro-stress testing. This paper is about laying the groundwork for these subjects from the vantage point of central bank policy in Iceland.

We hope to achieve three things: First, to gain an understanding of the role played by quality and quality changes in real estate price formation and measurement. In this respect we take special interest in similarities and differences between the sales and rental markets. Differences would indicate bias in the non-quality adjusted price-to-rent ratio. Second, to make the framework for analysis robust to future quality differences and quality changes. Third, to reveal what useful information we can glean from a multi-purpose hedonic model, regarding supply and demand dynamics, construction sector profitability and more.

The paper proceeds as follows: Section 2 provides a review of theory and literature. Section 3 describes the dataset. Section 4 contains descriptive statistics from the dataset. Section 5 presents a hedonic model for the capital city area sales market multi-dwelling segment. Section 6 presents results. Section 7 concludes.

2 Theory and literature review

2.1 The basics of hedonic modeling

A hedonic model is a reduced form regression equation which models the price of a product as a function of the product's characteristics. In other words, the priced product is viewed as a bundle of products and services, whose separate prices are not directly observed in the market. Hedonic methods were pioneered by Waugh (1928), who considers determinants of the selling prices of vegetables in the Boston market in 1927, followed by Court (1939) and Griliches (1961) who both consider the pricing of automobiles. The methodology and theoretical basis are elaborated and generalized by Lancaster (1966) and Rosen (1974). Since then, hedonic models have become the household name within real estate economics and are widely used. For the basic understanding of hedonic modeling, I build directly on Hill (2013), the OECD et al. (2013) Handbook on Residential Property Prices Indices, particularly de Haan & Diewert (2013) therein, and on Diewert, Heravi & Silver (2009).

In the context of residential housing, a hedonic model treats a dwelling as a bundle of components such as bedrooms, bathrooms, storage rooms, square meters of floor space, balconies, garages, gardens, and various other amenities and services. Services include e.g. panoramic views, low-maintenance needs, proximity to schools, shops, public transportation, green spaces, and city centers, a tranquil, secure and crime-free neighborhood, and prestige in the case of stately and conspicuously located homes. These components and services we jointly refer to as characteristics. This is by no means an exhaustive list of characteristics, as housing is, as noted by Hill (2013), an extreme case of a differentiated product. Every house is unique when all characteristics, including location, are considered. Whereas property developers, construction contractors and investors view real estate in terms of replacement cost or ability to generate revenue and capital gains, the basic insight of hedonic models is to view real estate as a consumption good.

Hedonic models enable the pricing of various characteristics at the margin, even though they are not priced in the market. These methods are therefore sometimes referred to as non-market methods, as they can be used to price a specific bundle which has not been traded in the market during the sample period. A common form of hedonic models is the log-linear equation:

$$\ln(p_n^t) = \beta_0^t + \sum_{k=1}^{K} \beta_k^t z_{nk}^t + \epsilon_n^t \tag{1}$$

where p_n^t is the sale or rent price of property n in period t, β_0^t is an intercept term for period

t, the β_k^t are the K marginal characteristic prices estimated in period t, and z_{nk}^t are the $k \in \{1, \dots, K\}$ characteristics of property n in period t. Typically, some characteristics are quantitative (e.g. floor area in square meters) while others are categorical and represented with dummy variables (e.g. location by geographical area). Finally, ϵ_n^t is an error term.[1]

The first thing to notice is that equation (1) separates market prices into the quality-adjusted sample mean component β_0^t and the quality adjustment component $\sum_{k=1}^{K} \beta_k^t z_{nk}^t$. Which component is of greater interest depends on the objective. When the objective is to construct a quality-adjusted price index, β_0^t can be our main focus. The simplest way to extract an index number from equation (1) is to view $exp(\beta_0^t)$ as the index number for period t. Quality adjusted price movements over time can then be drawn up with $exp(\beta_0^t)$ for $t \in \{1, \dots, T\}$. In that case, a relatively high degree of collinearity between the regressors z_{nk}^t can be tolerated, as their respective parameters are not to be independently interpreted. More regressors can be included to achieve high goodness-of-fit and extensive quality adjustment. If, on the other hand, the objective is to interpret each estimated marginal characteristic price or study household preferences in detail, care should be taken to avoid multicollinearity and to obtain stable estimates of the β_k^t.

Equations such as (1) form a subclass of hedonic models referred to as "hedonic imputation" models and are often used to construct Laspeyres and Paasche-type price indices. Those indices track the price of a given property or basket of properties over time. As noted by Hill (2013), the Laspeyres and Paasche approaches typically require the presence of all the items in the basket in every time period in the sample. As that is typically not the case with real estate transaction data, the fitted value for property n in time t, $\hat{p}_n^t$, referred to as the imputed price, is used instead of the selling price.

The second thing to notice about equation (1) is that the estimated marginal characteristic prices, β_k^t, are allowed to vary between time periods. In practice this means that a separate regression is run for each period, t. As de Haan & Diewert (2013) note, quoting Pakes (2003): "This is in line with the idea that housing market conditions determine the marginal contributions of the characteristics: when demand and supply conditions change, there is no a priori reason to expect that those contributions are constant." Estimating the β_k^t for every month is not always feasible, however, due to small sample size. For our intents and purposes, we aim for estimates which can be updated monthly, which provide an uninterrupted time series representation over our sample period and which provide the most dynamic quality adjustments possible, given the data. As we describe in Section 3,

[1] The equation need not be log-linear. The choice of functional form depends on the regressors available, and whether they are likely to enter prices additively or multiplicatively.

the monthly sample size is quite limited in Iceland's small real estate market. In addition, sample size in the sales market is under the influence of short-to-medium term cycles, with the minimum quarterly number of contracts around one tenth that of the maximum number. Estimating a separate equation of sufficient complexity is therefore feasible for some but not all periods in our sample. Another class of hedonic models offers a workaround solution to this problem:

$$\ln(p_n) = \beta_0 + \sum_{\tau=2}^{T} \delta^\tau D_n^\tau + \sum_{k=1}^{K} \beta_k z_{nk} + \epsilon_n \tag{2}$$

In equation (2), the characteristic parameters are assumed to be fixed over time and are written as β_k. To account for difference in the average quality-adjusted price level between periods, the parameters δ^τ are added to the model and multiplied by the corresponding time-dummy variables, D_n^τ. These models are referred to as "time-dummy hedonic" models. They preserve degrees of freedom and yield narrower confidence bands for estimated parameters, compared to hedonic imputation models.[2]

Deriving a price index from (2) is also straightforward, with $\exp(\hat{\beta}_0), \exp(\hat{\delta}^2), \ldots, \exp(\hat{\delta}^T)$. However, Hill (2013) recounts that under the assumption of normally distributed errors, Goldberger (1968) has shown that $\exp(\hat{\delta}^\tau)$ is a biased estimator, since exponentiating $\hat{\delta}^\tau$ introduces bias. This, of course, applies to all dummy variable coefficients in a semi-log equation, not only the time-dummy coefficients. To remedy this, Kennedy (1981) suggested $\exp\left[\hat{\delta}^\tau + \frac{1}{2}\hat{V}(\hat{\delta}^\tau)\right]$ as an estimator, where $\hat{V}(\hat{\delta}^\tau)$ is an estimator of the variance of $\hat{\delta}^\tau$. According to Syed, Hill & Melser (2008) the bias in $\exp(\hat{\delta}^\tau)$ is very small in a sample for Sidney, Australia in 2001-2006, indicating that it can in most cases be safely ignored. De Haan & Diewert (2013) also mention that unless the sample size is extraordinarily small, the bias can usually be neglected in practice. The results of an examination of this bias for the Icelandic case, using the approach of Kennedy (1981), are presented in section 6.1.

Equation (2) is a pooled regression, not a panel. First, repeat sales are rather few in our dataset, partially because of its limited time dimension and perhaps also because of the high home-ownership rate in Iceland. For-profit real estate firms tend to actively manage their portfolios, unlike individuals who often seek the stability of a permanent home. Each property identifier in our dataset for the multi-dwelling sales market appears 1.8 times on average and 1.5 times on average in the detached and semi-detached segment. This indicates that a panel setup with monthly frequency would suffer from a sparsely populated regressor matrix. Second, much useful information would be discarded by excluding the thousands of

[2] For example, if $T = 50$ and $K = 5$, the number of coefficient estimates is reduced from 300 in equation (1) to 55 in equation (2).

observations related to properties which only appear once. Hill (2013) notes that repeat-sales indices are a special case of hedonic indices, where property identifier dummies replace the housing characteristic variables.

Although more parsimonious, the time-dummy approach suffers from two drawbacks. First, it violates the non-revisability criterion. As new data arrives and the model estimate is updated, all the time-dummy parameter estimates change. So, a price index derived from the model is revised retroactively when updated. This can cause confusion among index users, who may be unfamiliar with the method. Second, there is increased risk of incorrect model specification. If the data generating process really contains time-varying marginal characteristics prices, their estimates according to the time-dummy hedonic approach will be biased. De Haan & Diewert (2013) point out that it is reasonable to assume that if marginal characteristics prices are indeed time-variant, they only change gradually, at least over the short term. As the timespan of our dataset reaches into the medium term (i.e. over a longer period than most business cycles) with 11 years of rental market data and 17 years of sales data, it is useful to ponder what could cause time-varying marginal characteristic prices. In the case of greater Reykjavík from 2011 to 2023, we can think of four potential factors. The first two probably contribute only to gradual changes, but the latter two could potentially cause abrupt shifts.

First, the development of household income and housing affordability could have such an effect, by enabling households to reach higher (or constrain them to lower) indifference curves along their concave utility functions, where different marginal rates of substitution between characteristics apply. It so happens that our sample period for the sales market contains a credit-fueled expansion, a housing market crisis and deep recession, the longest continuous economic growth phase of the republic's history and the Covid-19 related price movement. It can therefore be said to cover a period of house price instability. Nominal disposable income per person of working age, nationwide, grew 126% from Q1 2011 to Q3 2023. Meanwhile, according to the Icelandic Housing and Construction Authority (i. Húsnæðis- og mannvirkjastofnun, HMS) the countrywide median per square meter nominal price rose 195% for apartments in multi-dwelling buildings. See HMS (2025). For the median household then it seems that housing has grown less affordable overall, over the sample period.

Second, demographic changes over the sample period might affect the median household's preferences. For example, housing preferences change over a person's lifetime. The preferences of a childless student are different from those of a middle aged breadwinner whose preferences are different still from those of a widowed senior citizen. According to Statistics Iceland (2024a), some modest changes to family status occurred between 2011 and 2021. The share of single person households increased by roughly 4 percentages from 20.4% to 24.5%, while the share of childless people in marriage or registered partnership increased from 13.5% to 14.9%. Furthermore, according to Statistics Iceland (2024b), the population's average age increased from 36.6 years in 2011 to 38.6 years in 2023. Although these changes are indicative of an important ongoing trend, it is our guess that the sample period would likely need to be longer for this to meaningfully affect marginal characteristics prices.

Third, the COVID-19 pandemic may have shifted preferences, perhaps temporarily, in the direction of larger properties with more rooms and less attachment to other properties. This could be due to social distancing regulations, the need for work-at-home spaces and the COVID-baby boom. According to Statistics Iceland (2024c), the number of newborns grew by 8.1% between years in 2021, the third highest year-on-year growth since 1951.

Fourth and last, since early 2021 the perceived threat of natural disaster in parts of the greater Reykjavík area and its vicinity may have increased somewhat. Prior to 2021, seismic and volcanic activity was a distant worry for the area, as it had not seen an eruption for nearly 800 years. Since then, eleven eruptions have taken place in the Reykjanes peninsula, ca. 15-25 kilometers removed from the southern edge of greater Reykjavík. Close to 4,000 people outside greater Reykjavík have been forced to leave their homes and infrastructure such as powerplants, powerlines, roads and hot water pipes are at risk. As this environmental factor can be accounted for by location, household's risk aversion may have led to changes in parameters related to location.

These four considerations suggest that changes in estimated marginal characteristics prices over time should be accounted for. As described in section 5 we opt for a rolling-window time-dummy hedonic model with a window sufficiently long to estimate the model, but sufficiently short to allow the β_k^t to vary in a meaningful way. Equation (2) is then estimated repeatedly over the total sample period, shifting the window one month forward in time for each iteration. A slightly modified equation (2) is thus:

$$\ln(p_n^h) = \beta_0^h + \sum_{\tau=2}^{T} \delta^{\tau h} D_n^{\tau h} + \sum_{k=1}^{K} \beta_k^h z_{nk}^h + \epsilon_n^h \tag{3}$$

where $h = \{1, 2, \ldots, H\}$ indicates the rolling sample window and the regression iteration. I.e. p_n^h is transaction price n within window h.[3] Rolling-window time-dummy hedonic models

[3]To clarify, the sample size in window h is N_h, not $T \times N$. The sample size in period t within window h

were first proposed by Shimizu et al. (2010) who refer to them as "overlapping-period" hedonic models. Display of the time profile of estimated $\hat{\beta}_k^h$'s in section 6 follows their precedent.

For rolling-window time-dummy hedonic models, the simplest way to construct a price index for the entire sample period is to obtain quality-adjusted price level differences between the last and second-to-last periods in every window, and then chain linking them. For window h, this difference is expressed as $\exp(\hat{\delta}^{Th})/\exp(\hat{\delta}^{T-1,h})$. One potential drawback of such an index is that if any rolling-window sample is small, imprecise parameter estimates can lead to a shift in the index for all subsequent periods. Here it is useful that equation (3) enables some robustness checks. For example, $\exp(\hat{\delta}^{Th})/\exp(\hat{\delta}^{T-1,h})$ and $\exp(\hat{\delta}^{T-1,h+1})/\exp(\hat{\delta}^{T-2,h+1})$ are two estimates of the same quality adjusted price level change between the same two periods. Period T in window h is the same period as $T-1$ in window $h+1$. These estimates can be compared to get an idea of the robustness of time dummy parameter estimates to the underlying sample. For example, this can help detect unwarranted shifts in price indices. Such a robustness check is reported on in section 6.

But there are other ways of constructing price indices from a hedonic model. The prices of specific properties can be imputed in both a base period (e.g. the period when they were observed) and a reference period (e.g. the immediately succeeding or immediately preceding period), and the average price differential taken as the index change between the two periods. In the context of equation (3), the main difference between that approach and using only the exponentiated time dummy coefficients is the following: For each chain-linked price differential, the time-dummy coefficient approach uses the same estimated marginal characteristics prices, $\hat{\beta}_k^h$, to adjust for quality between periods $T-1$ and T in window h. In contrast, the imputation approach uses both $\hat{\beta}_k^h$ and $\hat{\beta}_k^{h-1}$ to adjust the price of a given property between periods T in window $h-1$ and T in window h.

Multiple variants of the latter type arise from comparisons between different combinations of observed and imputed prices, the choice of characteristics z_{nk}^h for imputation and method of averaging. Hill (2013) presents a survey and taxonomy of hedonic methods and price indices. From the array of indices he derives, we choose to present geometric double-imputation indices of the Laspeyres, Paasche and Törnqvist type, in section 6. This choice is due, first, to the "natural affinity", described by Hill (2013), of geometric indices with the semi-log form of equation (3). Second, double-imputation indices are recommended over single-imputation indices by most sources, including Hill (2013) and Diewert, Heravi & Silver

is defined as N_{th}. That notation is used for the definitions of price indices in equations (4) to (6).

(2009), for their limitation of omitted-variable bias. Using our notation and Hill's definitions, the aforementioned indices are:

$$P_{T(h-1),Th}^{GeometricPaasche} = \prod_{n=1}^{N_{T,h}} \left[\hat{p}_n^{T,h}(z_n^{T,h})/\hat{p}_n^{T,h-1}(z_n^{T,h})\right]^{1/N_{T,h}} \tag{4}$$

where:

- $z_n^{T,h}$ is a vector of K characteristics for property n, observed in period T of window h.
- $\hat{p}_n^{T,h}(\cdot)$ is the imputed price of property n in the period when it was observed. It is a function of the property's characteristics $z_n^{T,h}$ and the estimated coefficients from regression h.
- $\hat{p}_n^{T,h-1}(\cdot)$ is the imputed price of property n in period T of window $h-1$, i.e. the period before the period when it was observed. It is a function of the same characteristics $z_n^{T,h}$ and the estimated coefficients from regression $h-1$.
- $N_{T,h}$ is the total number of properties observed in period T of window h.

In other words, with this index, all properties observed in period t are priced in both period t and period s, where $s = t-1$, and a geometric average is taken of all those price differentials. Conversely, the geometric double-imputation Laspeyres index is defined as:

$$P_{T(h-1),Th}^{GeometricLaspeyres} = \prod_{n=1}^{N_{T,h-1}} \left[\hat{p}_n^{T,h}(z_n^{T,h-1})/\hat{p}_n^{T,h-1}(z_n^{T,h-1})\right]^{1/N_{T,h-1}} \tag{5}$$

With this index, all properties observed in period s are priced in both period s and period t, and a geometric average is taken of all those price differentials. As the Paasche index tends to underestimate price increases and the Laspeyres index tends to overestimate them (in the usual scenario where average characteristic quantities grow over time), averaging them is considered best practice. Thus, lastly, the double-imputation Törnqvist index is defined as:

$$P_{T(h-1),Th}^{Törnqvist} = \sqrt{P_{T(h-1),Th}^{GeometricPaasche} \times P_{T(h-1),Th}^{GeometricLaspeyres}} \tag{6}$$

As Hill (2013) shows, changes in the Törnqvist index can be broken down into contributions of individual variables. This can help policy makers realize to what extent house price changes are driven by changing quality and to what extent by changes in the quality-adjusted house price level. Sometimes, policy makers are faced with anecdotal evidence of particularly high-quality properties being sold in a given period, without realizing to what extent that applies to the market as a whole. In section 6, such a breakdown of month-on-month changes in a Törnqvist index for the greater Reykjavík area multi-dwelling sales market is displayed.

It is debatable at what point the rolling window is too long, masking relevant changes in parameters. Although not covered fully in this paper, one main aim with this project is to detect signs of market overvaluation in a robust and timely manner. Jordà, Schularick and Taylor (2015b) report the average duration of residential real estate price bubbles in the post-WWII developed world as 3.2 years (ca. 38 months) from the year when prices reach one standard deviation above trend until they fall back below that mark. Using their definition and a non-quality adjusted CPI-deflated HMS price index for the Reykjavík capital city area, the pre-banking crisis price bubble lasted from January 2005 until September 2008, for a total of 45 months. This indicates that the rolling-window should be long enough to estimate the model and substantially shorter than, say, three years. In section 6 we describe how the choice of window-length can be guided by validation excercises.

The estimated coefficients from equation (3), estimated on sales market data, enable us to quantify the average quality difference, i.e. the difference in the magnitude of the quality-adjustment component $\sum_{k=1}^{K} \beta_k^h z_{nk}^h$, between properties in the rental market data and the sales market data. This provides an indication of the bias in non-quality adjusted price-to-rent ratios. The percent difference in average quality, between the two markets, in period t of window h, is:

$$\hat{Q}_T^h = \left[exp \left[\sum_{k=1}^{K} \hat{\beta}_k^h (\bar{z}_k^{Th,sale} - \bar{z}_k^{Th,rent}) \right] - 1 \right] \times 100 \tag{7}$$

where the $\bar{z}_k^{Th}$ are the averages for characteristic k in the sales and rental markets respectively, in the last period of window h. In section 6 we report this difference for greater Reykjavík in the period 2011 to 2022.

2.2 Model specification issues

Endogeneity and simultaneity are known problems in hedonic regressions, and they affect our sample choice. For example, proximity to economic goods or bads not properly accounted for in the model can act as a confounder. Both house prices and property characteristics may be a function of such proximity, in which case the estimated relationship of characteristics and prices is spurious. In the case of the Reykjavík area, this is reflected in the tendency to locate detached and semi-detached housing near economic goods such as green areas, or in their midst, such as southward facing hillsides. Likewise, there is a tendency to locate multi-dwelling housing near economic bads, such as traffic-heavy streets. Some areas are even encircled by such streets with multi-dwelling housing lined along the periphery and detached houses nestled in the middle. In such settings, imperfect location modelling omits the price effects of proximity to goods and bads and overemphasizes the price difference between dwelling types.

But this is only a tendency, not a universal rule, in the Reykjavík area. The model specification helps, as each marginal characteristic price is estimated for the whole region, including areas where this tendency exists, and areas where it does not. Location is accounted for relatively thoroughly in the model, with 17 geographical assessment areas and variables for grouped sub-assessment areas to capture highly localized price effects, both negative and positive. Their marginal prices are allowed to change gradually over time.

Even so, we limit our sample to multi-dwelling buildings, partly to avoid this endogeneity problem but also because some characteristics are not equally applicable to both market segments, detached and multi-dwelling, as price determinants. Including both segments would complicate model design or force it down to a common denominator. Given our sample choice, we don't see endogeneity or simultaneity as a big problem. However, risk-taking by home buyers may sometimes be concentrated in the detached market segment. By restricting our sample this way we run the risk of missing certain risk developments. This is best dealt with by a separate model for detached housing.

As the dataset contains GPS-coordinates for every property, a possible avenue for further research is to use a spatio-temporal weights matrix to model spatial dependence, instead of accounting for location with area dummies. Hill (2013) provides an introduction to spatial dependence methods and considers them a superior method to area dummy variables.

2.3 Applications for macroprudential policy purposes

Hedonic models are used to adjust average house prices for the quantity and price of housing characteristics. This can be done solely for the properties most recently traded, for the entire stock of properties or for any other part of that stock. Which is most pertinent depends on the focus of attention. The first option may be best suited when gauging residential housing market demand and supply dynamics. The second may apply when studying the aggregate wealth effects on households from house price changes. Why, for example, should a rational homeowner experience a positive wealth effect from rising average house prices, if their rise is driven by demand for locations and living arrangements which the owner's home does not provide? The third option of adjusting for the average characteristics of some subsection of the housing stock, other than that most recently traded, may apply when comparing house prices to fundamental variables.

One such fundamental variable is household's disposable income (or wages as a proxy for disposable income). The intuition is that house prices out of line with disposable income will eventually strain households' debt servicing capacity, bringing prices back in line with income. The realignment of house prices with household income can wreak havoc on household finances, private consumption, banks' financial health and the economy at large (see e.g. Mian & Sufi (2014)). Comparing the development of an aggregate house price index to the development of aggregate disposable income may be a reasonable indicator of house price sustainability overall. But it can also mask heterogeneity between geographical areas and demographic groups. Hedonic models may enable the analyst to match the available disaggregation of disposable income statistics with appropriate house price indices.

Another fundamental is rent prices. The intuition there dates back to Poterba (1984). At housing market equilibrium, households are indifferent between owning and renting a given apartment, since the monthly rent price should equate to the monthly user cost of owning it. Thus, the equilibrium condition is satisfied when the quality adjusted price-to-rent ratio equates to one over the user cost of owning:

$$R_t = u_t * P_t \implies \frac{P_t}{R_t} = \frac{1}{u_t} \tag{8}$$

Using the price-to-rent ratio to gauge housing market equilibrium in this way inherently assumes that the sold and rented dwellings being compared are identical, or at least of comparable quality. This, however, is typically not the case for the average sold property and the average rented property. In sections 4 and 6 this is shown for the Icelandic real estate market. Owner-occupied dwellings are often of higher quality than rented dwellings, which results in biased comparisons. Quality-adjusted price-to-rent ratios can be obtained using hedonic methods, by imputing prices for rented dwellings and/or imputing rents for sold dwellings. Hill and Syed (2016) do this for Sidney, Australia, and Chen et. al. (2022) for Shanghai, China. On average, according to their results, adjusting for quality results in an 18% lower price-to-rent ratio for Sidney and a 14% lower one for Shanghai. In other words, non-quality adjusted price-to-rent ratios tend to exaggerate housing market tension.[4]

[4]In June 2024, Statistics Iceland adopted the method of rental equivalence for evaluating the imputed rent for owner occupied housing in the consumer price index for Iceland. From 1992 up until that time it had applied a user cost approach, which was a direct function of a house price index, among other things. The

Also, the aforementioned equilibrium condition can be used to estimate market participant's expectations of future house price increases, an important factor in the user cost of owning. If the equilibrium condition cannot hold without assuming exuberant price expectations in the market, that is an indication of a bubble.

Using U.S. data, Gilbukh et al. (2023) use the aforementioned equilibrium condition, and imputed price-to-rent ratios to derive a policy rule for loan-to-value caps as a borrower-based macroprudential tool. Lo et al. (2023) examine the relationship between the price-to-rent ratio and various macroeconomic and financial indicators using UK data. They find relationships with money supply, the foreign exchange market and the stock market. Cronin & McQuinn (2016) use the price-to-rent ratio and the fundamentals contained in the user cost measure to examine the binding effects of maximum loan-to-value rules in Ireland.

The third fundamental is building cost. High house prices in comparison to building cost present a profit opportunity for the building sector, leading to increased housing investment and, with some lag, housing supply. See e.g. Elíasson & Pétursson (2009). Subsequently, increased supply (if not a negative demand shock) should lead to renewed convergence in prices and building cost. Statistics Iceland provides a monthly building cost index, which measures the cost of constructing a multi-dwelling building with particular characteristics. That cost measure, however, doesn't include land prices, value-added tax, infrastructure levies, design cost or the cost of capital. In this context, hedonic models could enable the estimation of both a land price index and a tailor-made price index for new apartments of roughly equal quality as the reference building of the building cost index.[5] In section 6 we show such a re-estimated price-to-building cost ratio for the greater Reykjavík area, using a hedonic price index.

The list of potential applications of hedonic models for macroprudential policy purposes goes on. The new building premium, i.e. the estimated coefficient for a new building dummy variable, can be interpreted as largely resulting from Akerlof's (1970) *Lemons Problem*, i.e. the risk of hidden defects. In the case of new construction that risk should be either limited or, when the property purchase is covered for several years by comprehensive contractor

methodology is described in Statistics Iceland (2024b). Since exuberant expectations of house price increases tend to feed into house prices but not rent prices, this raises the question whether the consumer price index will, going forward, be less correlated with housing market excesses and cyclical systemic risk build-up than before. If so, the systematic response of monetary policy to house price developments might become weaker, potentially highlighting the role of macroprudential policy in dealing with such developments. This would underline the Financial Stability Committee's need for a robust analytical framework for the housing market.

[5]The Central Bank of Iceland possesses a national credit registry containing loan-level information with extensive coverage of credit to the non-financial private sector since 2021. A possible avenue for future research is to use information from the registry to estimate the building sectors‘ cost of capital.

liability, virtually nonexistent. Therefore, new builds should carry a price premium over older housing. This coefficient can be an interesting measure of supply and demand conditions in the market. For example, a low premium can indicate that inventories are high and supply-side competition intense (a bubble symptom), that consumers do not differentiate between dwellings based on quality (a bubble symptom), that the building sector is undercutting prevailing market prices (a sign of distress) or any combination of these factors.

If the market goes through "bubble" and "panic" phases, price discrimination by buyers of real estate may become less focused on property characteristics, as captured by the model, and more on other considerations. Such considerations may include expectations of future price changes. In other words, buy before everything gets even dearer or get out before prices fall even more. Other considerations might be building rights and the density allowance of existing planning and zoning regulations and the buyer's ability to remodel properties using easy credit. The cheaper credit is perceived to be, the less property characteristics matter, as they can be upgraded cheaply. This sort of irrationally exuberant behaviour might be reflected in coefficients such as the new building premium.

Hedonic methods might also be used to study price-to-short term rent ratios and whether there is, at any given time, a strong pulling force from longer-term rent contracts into short-term (i.e. tourism related) rent contracts. Deboosere et al. (2019) study a hedonic model of web-scraped Airbnb transaction data for New York City and find that Airbnb hosts, particularly those with properties in accessible residential neighbourhoods, earn a significant premium by converting long-term housing into short-term rentals.

2.4 Why not use official property valuations?

The HMS applies similar methods for property valuation, has achieved extensive coverage of the country's housing stock, high goodness-of-fit and extensive quality adjustments. Then, why not just use those official valuations? The answer is that those models are not directly applicable to macroprudential policy purposes.

First, HMS valuations provide the basis for the levying of public dues like property charges and inheritance tax. Thus, they are designed to have the greatest possible coverage of the nationwide housing stock. For macro-prudential policy, valuation of important parts of the housing stock may very well suffice, while leaving other parts outside the models' scope. This may allow for different model specification.[6] The HMS may require very gradual

[6]When hedonic models cannot provide a good fit, the HMS applies other methods of valuation. In the 2024 valuation, published in October 2023, 98.9% of residential real estate was valued using hedonic methods.

changes in estimated parameters, to avoid volatile and unpredictable tax incidence for taxable persons. Thus, for the annual valuation process, a rather long sample window may be preferred. For our purposes, a dataset covering a long period is also necessary, since house price developments are marked by medium term cycles with important implications for macroeconomic analysis (see e.g. Einarsson et al. (2016) for the Icelandic case). Nonetheless, allowing for more dynamic changes in the β_k^t may be preferred, if that aids the timely identification of policy-relevant developments in the markets. Thus, a relatively short rolling window in a rolling-window time-dummy hedonic model may be appropriate.

Second, HMS valuations are updated annually, whereas ours are intended to provide monthly updates for policy making purposes. Surely, the latest annual HMS valuations could be updated on a monthly basis, based on a monthly house price index. That would be less conceptually appealing, though, as the model's out of sample properties may not be the same as within sample and these updates would not take account of structural changes in the market, i.e. changing marginal characteristics prices.

Third, and perhaps most important, we are equally interested in the sales and rental markets. Omitted variable bias inevitably affects models of both markets. Thus, when using the result from those models to impute property-specific price-to-rent ratios, it is preferrable that the models for both markets are very similar, if not identical. This means that their associated omitted variable bias should mostly cancel out in the price-to-rent ratio, leaving only that which stems from different effects of omitted variables in the two markets. For a more extensive treatment of missing observations and omitted variable bias in the price-to-rent setting, see Hill & Syed (2016). We turn next to the data.

3 Data

3.1 Sales contract data

The HMS dataset on residential real estate sales contracts in the greater Reykjavík area has a sample size of 100,955 observations after filtering. For each contract, the dataset contains information on prices, transaction dates, contract characteristics, property characteristics and various property registry information. The data is filtered on many criteria, i.e. housing type, tax category, municipality, assessment area, utilization descriptor, building stage, floor area, selling price, per-square meter selling price and building age. Despite the many criteria,

See HMS (2025). That exceeds the coverage we need to achieve.

filtering is kept at a bare mininum and is mostly focused on identifying faulty observations. A closer account of the data treatment process is provided in appendix A.

Out of the 100,955 observations, 78,420 relate to the multi-dwelling segment and 22,535 observations to the detached and semi-detached segment. The average quarterly sample is 1,074 observations for multi-dwelling, and 302 for detached and semi-detached houses. As shown in the left panels of figure 1, turnover in the sales market is marked by short to medium term cycles. For multi-dwelling buildings, the quarterly sample size varies between roughly 200 contracts in 2009 Q1 and roughly 2,000 contracts in 2021 Q1. For detached and semi-detached, it ranges between 62 in 2009 Q1 and 484 in 2016 Q4. The low-turnover periods are problematic, requiring a long rolling-window, while probably bringing faster-varying β_k^h compared to the preceding periods of higher turnover.

3.2 Rent contract data

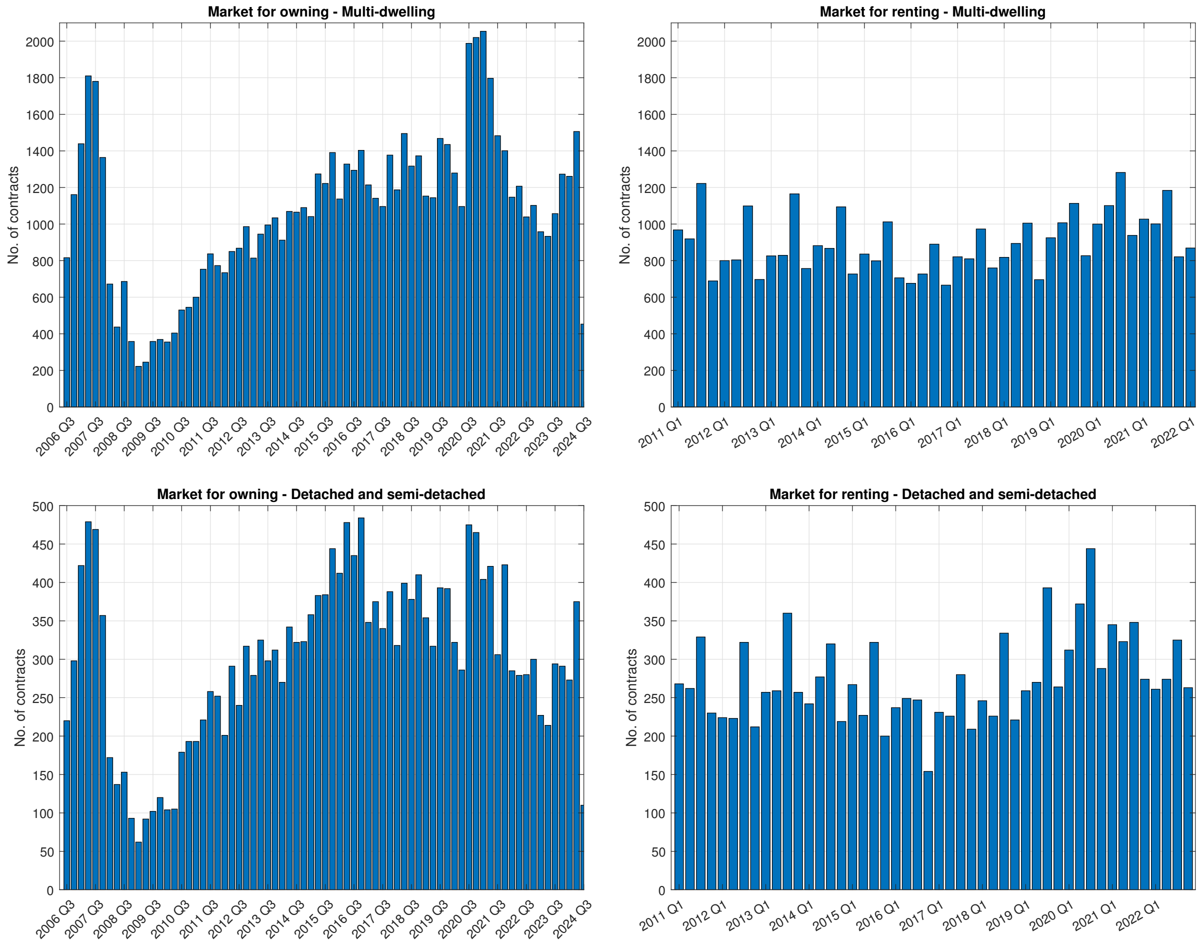
The HMS dataset on residential rent contracts has a sample size of 56,354 observations, after filtering, spanning the period from 1st January 2011 to 31st December 2022. A closer account of that filtering process is also provided in appendix A. The sample period is shorter on both ends than for the sales contracts, for two reasons.

First, Iceland has a long-standing owner-occupancy policy with respect to residential housing. This led to most Icelandic households owning the dwellings they lived in shortly before the financial crisis of 2008, making the rental market too shallow for statistical analysis. In 2007, when Iceland's total population was around 308,000, over 86% of the public owned the dwellings they lived in.[7] During and after the financial crisis greater numbers took to renting, due both to foreclosures and to prospective market entrants losing their savings during the crisis and having difficulty obtaining mortgage loans during the recession that followed. In 2011, the rental market had finally reached sufficient depth to allow analysis.

Second, the rent contract register is comprised of contracts which have been notarized by local magistrates. Until 2023, notarization was a prerequisite for receiving housing benefits from the government. This provided the incentive for the notarization of contracts. Not all rent contracts were notarized however, in particular those related to high-income renters not entitled to housing benefits. This causes sample-selection bias. Recent changes in the rental market's legal framework have changed this. Registration of a contract in HMS's new rent database is now mandatory for landlords, irrespective of notarization. In conjunction with these changes the older rent contract register was discontinued and a new one adopted.

[7] See Statistics Iceland (2024a).

Figure 1. Quarterly turnover by market and market segment



Note: Quarterly number of contracts in the greater Reykjavík city area sales and rental markets' multi-dwelling and detached segments, after filtering. 2011 Q1 – 2022 Q4 for the rental market, 2006 Q3 – 2024 Q3 for the sales market.

Therefore, as of the first months of 2023 the sample size in the older register, which our dataset is based on, tapers off. We therefore opt for a data cut-off point at the end of 2022. Possible future updates to the analysis presented here will have to be based on the new rent contract register.

After filtering, the rent contract sample is split between 43,194 for dwellings in multi-dwelling buildings and 13,150 for detached and semi-detached houses. The rent contract sample is thus a little over half the size of the sales contract sample. As it covers a shorter period, the difference in quarterly sample size is smaller. This is shown in the right panels of figure 1. Average quarterly sample size is 1,174 contracts, split between 900 contracts for dwellings in multi-dwelling buildings and 274 contracts for detached and semi-detached houses. Despite the smaller average sample size, rental market turnover is less cyclical than sales market turnover, which ameliorates small sample problems. On the other hand, seasonality is more pronounced in the rental market turnover, with the annual spike coming in Q3 of each year.

An important part of the dataset are variables obtained from the HMS's property valuation database. There, the primary source of information is not sales and rent contracts, but registry information such as property-specific size specification tables, maintained by municipal building inspectors. This part of the data builds only on the property valuation database as it stood in 2023, not on vintage data from the time when each contract was signed. This may be a troublesome issue for the detached and semi-detached market segment, as extensive remodeling with modified internal organization and extensions is more common there. Here, we assume that this is not a big problem for the multi-dwelling segment, as extensions are uncommon and there is less scope for internal reorganization.

To examine whether there is need for quality-adjustments, descriptive statistics on both the sales an rental market are presented in section 4.

4 The development of housing characteristics

Quality changes can relate to a single market over time. Therefore, we emphasize the time dimension by presenting all figures in this section in time series form at quarterly frequency. Quarterly frequency is chosen for ease of inspection and to emphasize the longer term changes rather than month-on-month volatility. That volatility also matters, though, as is shown in section 6.2. Difference in average quality between markets at any given time and diverging quality development in separate markets over time also matters. This applies particularly when we take interest in price-to-rent ratios. We emphasize this by describing the two markets jointly in each figure in this section.[8]

4.1 Categorical variables

Examples of categorical variables are main building material, location by municipality or assessment area, utilization descriptor, property categorization as new or used based on the ÍST 120:2012 standard for registration and classification of geographic information (see Iceland Standards (2012)). Overall, the categorical variables show somewhat differing shares of categories between the sales and rental markets. In general, the market shares don't

[8]Presenting all figures for the two markets in whole and their segments, detached and multi-dwelling, is unnecessary, since the aim of this section is simply to motivate quality adjustments.

show much variability over time within each market, however. That should not come as a surprise. In a free market, prices adjust to clear the market. Market shares of different categories should therefore develop slowly, in line with their shares in the housing stock. This also underlines that the other side of the same coin are the characteristics' marginal prices. Marginal prices of different categories may shift while the same categories' share in turnover remains stable.

The market share of different property types is shown in figure 2. At first glance the two markets are similarly segmented. Most importantly, apartments in multi-dwelling buildings account for around 75% of traded dwellings in both markets on average.[9] Upon closer inspection there are subtle differences. First, the share of contracts on dwellings categorized as unsanctioned by building authorities or in non-residential housing is more than twice as high in the rental market (2.6%) as in the sales market (1.2%). Most cases of unsanctioned dwellings in the detached and semi-detached market segment are spare units, often in basements or attics.[10]

Second, on average serviced apartments for the elderly and disabled account for 1.4% of contracts in the sales market while barely registering in the rental market. Since the rolling-window aimed for is short, reliably estimating the price effects of these categories is not feasible. In section 5 and 6, serviced, unsanctioned and non-residential property related contracts are therefore discarded.

Third, the detached and semi-detached market segment is differently composed in different markets. Somewhat surprisingly, detached houses account for a slightly larger share on average in the rental market (8.9%) than in the sales market (8.0%). That difference is at least partly offset by duplexes and terraced houses accounting for almost twice the share in the sales market compared to the rental market. Apartments in two-dwelling houses weigh more heavily in the rental market.[11] Segmentation by building type also seems stable over time. The most notable movement is where the combined share of detached and semi-detached dwellings, in the sales market, falls from 26.8% of the total number of traded dwellings in 2016 Q1 to 16.4% in 2021 Q1.[12] During the same period, their share in the

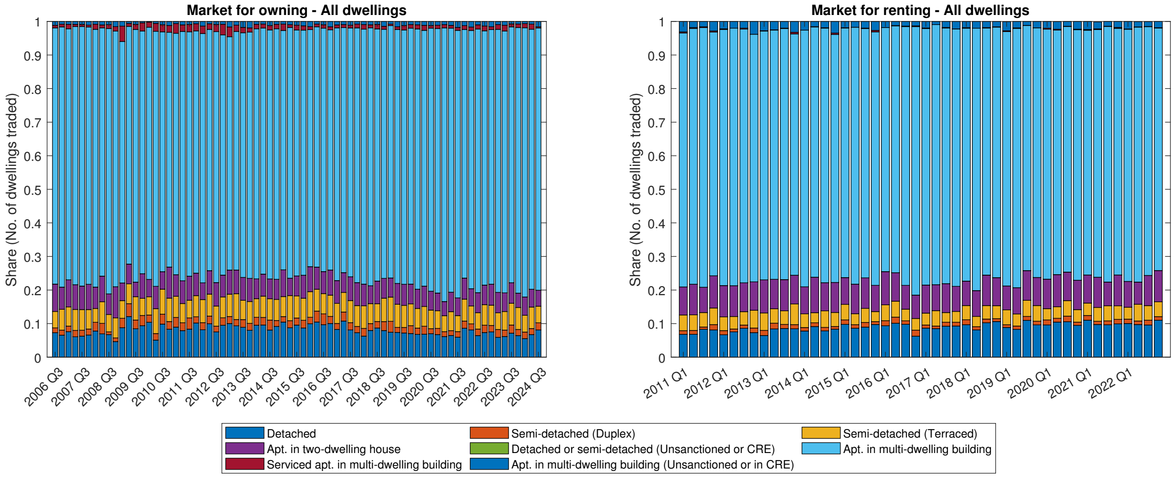
[9] All percentages here refer to shares of the total number of dwellings traded. When examined as shares of market turnover in Icelandic krónur, the segmentation of the two markets is less alike. In that case, apartments in multi-dwelling buildings account for 77% of turnover in the rental market, but only 65.2% in the sales market.

[10] Dwellings of this type are referred to by names such as interior units, granny-flats or in-law flats.

[11] In Icelandic krónur turnover detached, duplex and terraced houses weigh more heavily in the sales market than the rental market. Within the detached and semi-detached market segment, apartments in two-dwelling buildings account for twice the share in the rental market (38%) as in the sales market (19%) in krónur terms.

[12] Discontinued non-quality adjusted price indices published by the HMS take account of this movement

Figure 2. Property type share in quarterly turnover



Note: Property types' share of the number of dwellings traded within each quarter in the greater Reykjavík market. Recoded property type variables according to procedure described in appendix A. 2011 Q1 - 2022 Q4 for the rental market. 2006 Q3 - 2024 Q3 for the sales market.

rental market stays relatively stable.

The utilization descriptor offers more insights into the different types of dwellings being traded. The shares of different categories, by market and market segment, are displayed in figure 3. Within the multi-dwelling segment, basements account for 5.4% of sold dwellings on average, compared to 8.7% of rented apartments. Attics also account for a larger share of the rental market, at 2.7% compared to 2.0% of the sales market.[13] The bulk of the multi-dwelling market segment is represented by apartments "on floor", i.e. neither in an attic nor a basement. These represent 92.3% of the sales market and 87.4% of the rental market, on average.

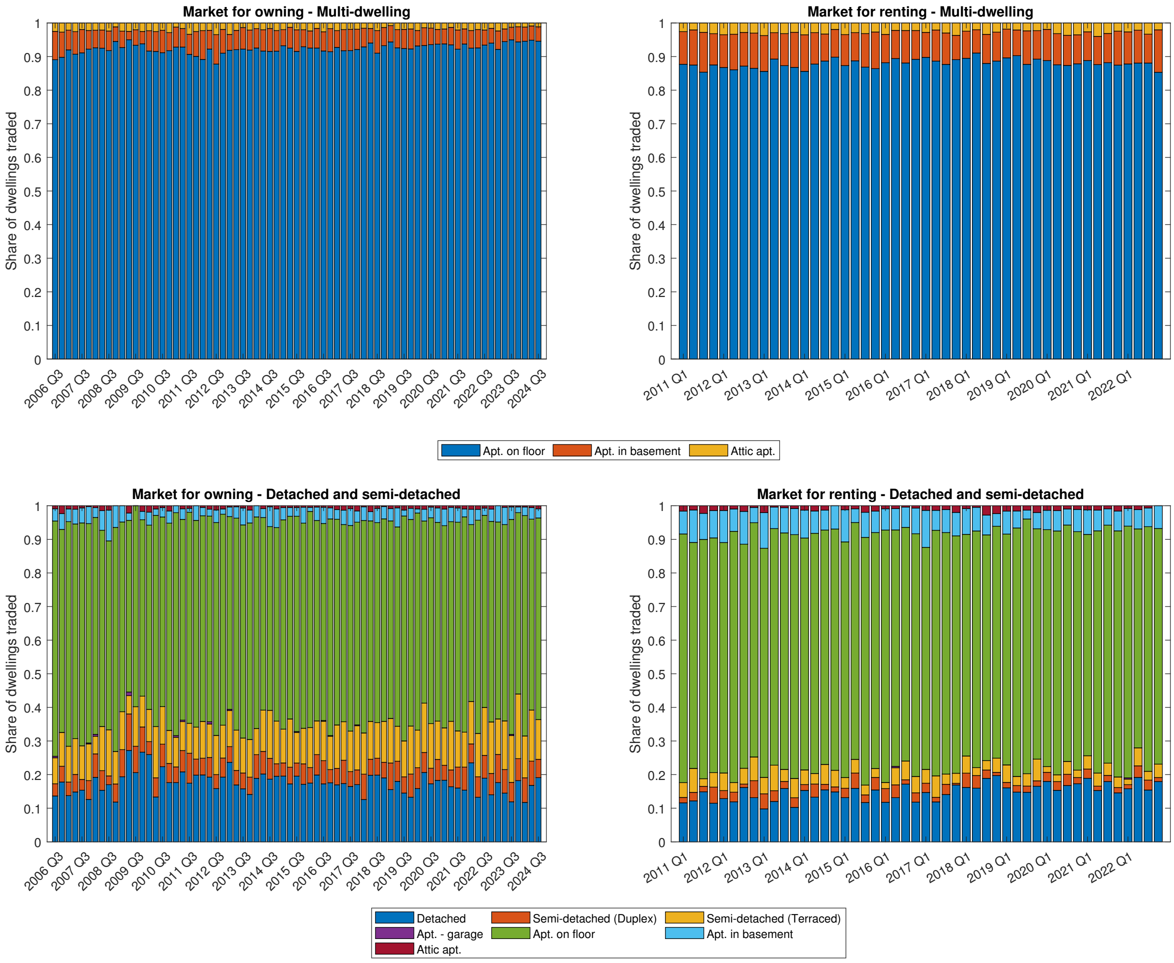
In the detached and semi-detached segment, duplexes and terraced houses account for a much larger part of the sales market than the rental market. In both markets, "apartments on floor" within that segment, probably mostly apartments in two-dwelling houses, account for a majority of contracts. As in the multi-dwelling segment, basement apartments make up a larger part of the detached rental market than the detached sales market. These are spare units in detached and semi-detached houses.

The market share of different municipalities is shown in figure 4. Town councils can affect real estate prices in many ways, most notably through setting property tax rates and

by stratification, where strata are weighted based on ISK turnover.

[13]The price effect of attics is not clear, ex ante. Registered floor space only refers to ceiling height of 180 cm or more. Thus, attics actually have more floor space than the floor space variable would indicate. This indicates a positive price effect. On the other hand, attics' internal organization tends to be problematic, indicating a negative effect.

Figure 3. Quarterly share of utilization descriptions



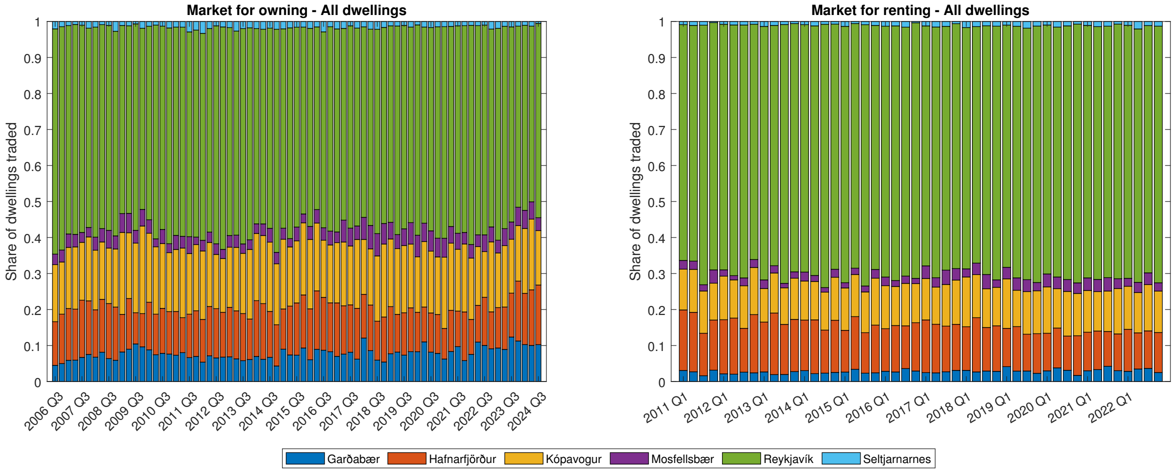
Note: Quarterly number of utilization descriptions of traded properties in the greater Reykjavík city area sales and rental markets' multi-dwelling and detached segments, after filtering. 2011 Q1 – 2022 Q4 for the rental market, 2006 Q3 – 2024 Q3 for the sales market.

municipal income tax rates.[14,15] The effects of other municipal policies also come into play, such as the quality of school districts and extracurricular activities on offer. On average, roughly 57% of dwellings sold in the capital city area within each quarter are in Reykjavík city, compared to almost 69% of rented dwellings. Reykjavík city was home to 57% of the region's total population and, thus, has a proportional share in the sales market, but a disproportionately large share in the rental market. The city's share of both markets has remained relatively stable over time. Four suburban municipalities (Garðabær, Kópavogur,

[14] As of 2023, municipalities could decide on an income tax percentage for individuals between 12.44% and 14.74%. In that year, Reykjavík and Mosfellsbær had the highest allowable percentage. Garðabær had the lowest percentage in the capital city area, at 13.92%. Other had percentages in between those numbers.

[15] In general, the property tax rate for residential housing can reach 0.5% of HMS's valuation. In 2023 the municipalities in the capital city area had rates ranging from 0.166% to 0.246%.

Figure 4. Quarterly turnover by municipality

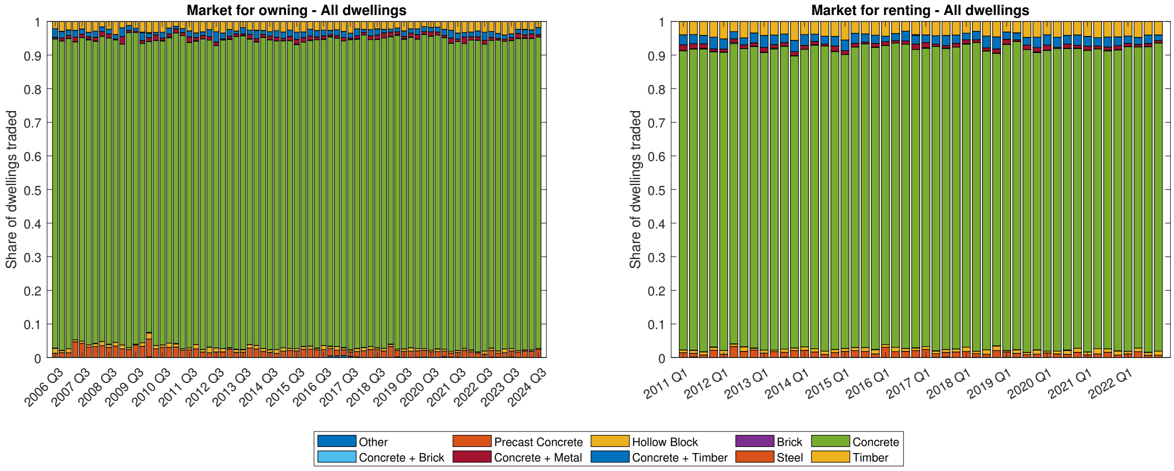


Note: Municipalities' share of the number of dwellings traded within each quarter in the greater Reykjavík market. 2011 Q1 - 2022 Q4 for the rental market. 2006 Q3 - 2024 Q3 for the sales market.

Mosfellsbær and Seltjarnarnes) representing 31% of the region's 2023 population, have a proportional share in the sales market but a disproportionately small 18.5% of the rental market, on average over the sample period. Their combined share in the rental market grows slightly from 2011 to 2022. Hafnarfjörður is the only municipality equally and proportionally represented in both markets.

Location is more precisely represented by assessment areas, which usually don't cross municipal boundaries and are designed to capture common environmental and social factors not captured by other variables. With 77 assessment areas in the sample, the development of their individual share in turnover over time cannot be displayed conveniently here. In general, the quarterly market share of assessment areas fluctuates substantially, but longer-term trends are less noticeable. A few peripheral areas have slowly gained market share as they have been developed, but as Reykjavík city's policy in recent years has been that of densification, there has also been growth in more centrally located areas. Grouping the 77 areas into 29 blocks of contiguous areas (to avoid quarterly shares of 0%), the maximum quarterly market share of a block is around three (two) times as large, as the minimum quarterly share in the sales (rental) market. This difference is exaggerated for market segments. Looking at these blocks of contiguous assessment areas, their combined market share can change quite a bit between consecutive quarters. For example, in the rental market the thirteen most centrally located assessment areas had a combined share of 17.4% during 2012 Q2 and 27.3%

Figure 5. Quarterly turnover by main building material



Note: Share of no. of dwellings traded within each quarter in the greater Reykjavík market, by building material of frame and/or supporting walls. 2011 Q1 - 2022 Q4 for the rental market. 2006 Q3 - 2024 Q3 for the sales market.

during Q3 of the same year.[16] Longer duration movements are also visible. For example, counting from center to periphery, areas that represented 41% of rent contracts during 2017 Q4 accounted for 53% of contracts during 2020 Q3 after a nearly continuous increase. In the sales market, the sixteen most peripheral assessment areas went from representing 17.7% of sales contracts during 2006 Q3, up to 31.4% two quarters later.[17] These fluctuations in market shares indicate quality changes that may affect quality-adjusted price indices and price-to-rent ratios, if their related price effects differ.

When it comes to building materials, concrete buildings dominate the Icelandic housing stock and thus the dwellings traded in the marketplace, as is displayed in figure 5. The share of different building materials in the quarterly sample varies little over time. Buildings with concrete or precast concrete as the main building material account for 93.9% of sold properties, on average. The corresponding number for rented properties is a slightly lower 91.3%. In particular, timber as the main building material accounts for 3.9% of rented dwellings compared to 2.6% of sold dwellings.[18]

[16] These are assessment areas 11, 20, 25, 26, 27, 31, 70, 71, 72, 74, 75, 94 and 403. See Appendix B.

[17] These areas encompass Mosfellsbær, Hafnarfjörður, the Álftanes peninsula in Garðabær and the outermost neighborhoods of Reykjavík and Kópavogur.

[18] This variable may be increasingly affected by changes in construction techniques. First, it doesn't take account of whether concrete houses are internally or externally insulated, which can affect energy efficiency, maintenance cost and the likelihood of mildew infestation. Concrete houses are increasingly externally insulated in later years. Second, techniques for using timber as the main building material have changed in recent years. Prefabricated cross-laminated timber elements (CLT) are increasingly used as the main building material. This is even done in a mix with concrete. CLT qualities are more similar to concrete

The share of new buildings is reported in the lower left panel of figure 6. New buildings are defined as those where the year of the transaction minus the registered year of construction is 2 or less. They are represented by a dummy variable in the model. The share of new buildings in the sales market increases rapidly up until 2008 Q1 when it plummets and the share of new buildings in the sample decreases from 18% to a mere 2.4% in 2011 Q2. The share increases again and remains relatively steady from 2013 Q2 to 2019 Q4, ranging from 8% to 14% in the sales market. In the rental market the share of new buildings also remains steady from 2011 Q1 to 2016 Q2, ranging from 0.7% to 5.5%. It then increases and catches up with the sales market reaching 12% share in 2017 Q4. In 2019 the two markets move rapidly in opposite directions in this regard. In the sales market the share of new buildings skyrockets and reaches almost 26% in 2021 Q1. It then remains high but volatile throughout 2023 Q4. The opposite occurs in the rental market in 2019 Q1 when new buildings fade out of the sample until 2022. Here, the aforementioned sample selection bias may be at work. As housing became increasingly costly, few to no renters entitled to housing benefits may have signed rent contracts for newly built properties. This indicates a potentially serious bias in the non-quality adjusted price-to-rent ratio.

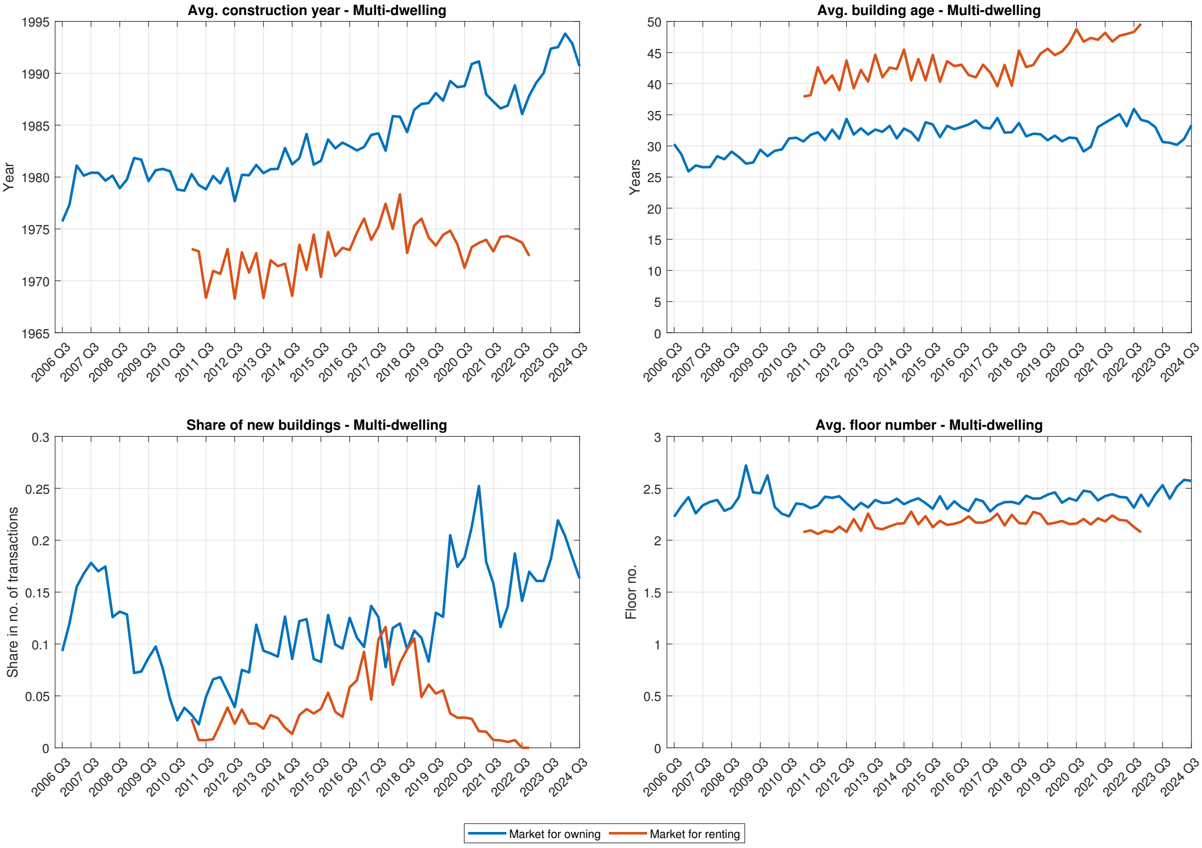
4.2 Quantitative variables

Some quantitative variables show a substantially different level of average characteristics between the two markets. Additionally, as shown in figures 6. to 9., some show substantial variability over time and sometimes in opposing directions in the two markets. Here, only statistics for the multi-dwelling segment of the two markets are displayed. The story is similar in many respects for the detached and semi-detached segment.

From 2011 to 2022, dwellings in the rental market were on average 11 years older than in the sales market. In 2011, the average rental apartment was built in the early 1970's and the average sold apartment in 1980. More than a decade later, the average rental was still built in the early 1970's, whereas the average sold apartment was built in the late 1980's. Average dwelling age remained relatively stable in the sales market over the whole 17-year sample period. In the rental market, average building age grew from 38 years to almost 50 years in the much shorter sample period. This is shown in the upper panels of figure 6. This asymmetric development is most visible from 2018 Q2 to 2022 Q4 when average building age grew by 25% in the rental market, while not changing much in the sales market. This

than older style wooden frames. These considerations should, however, be captured to some extent by the construction year and age variables described below.

Figure 6. Building age, new buildings and floor number



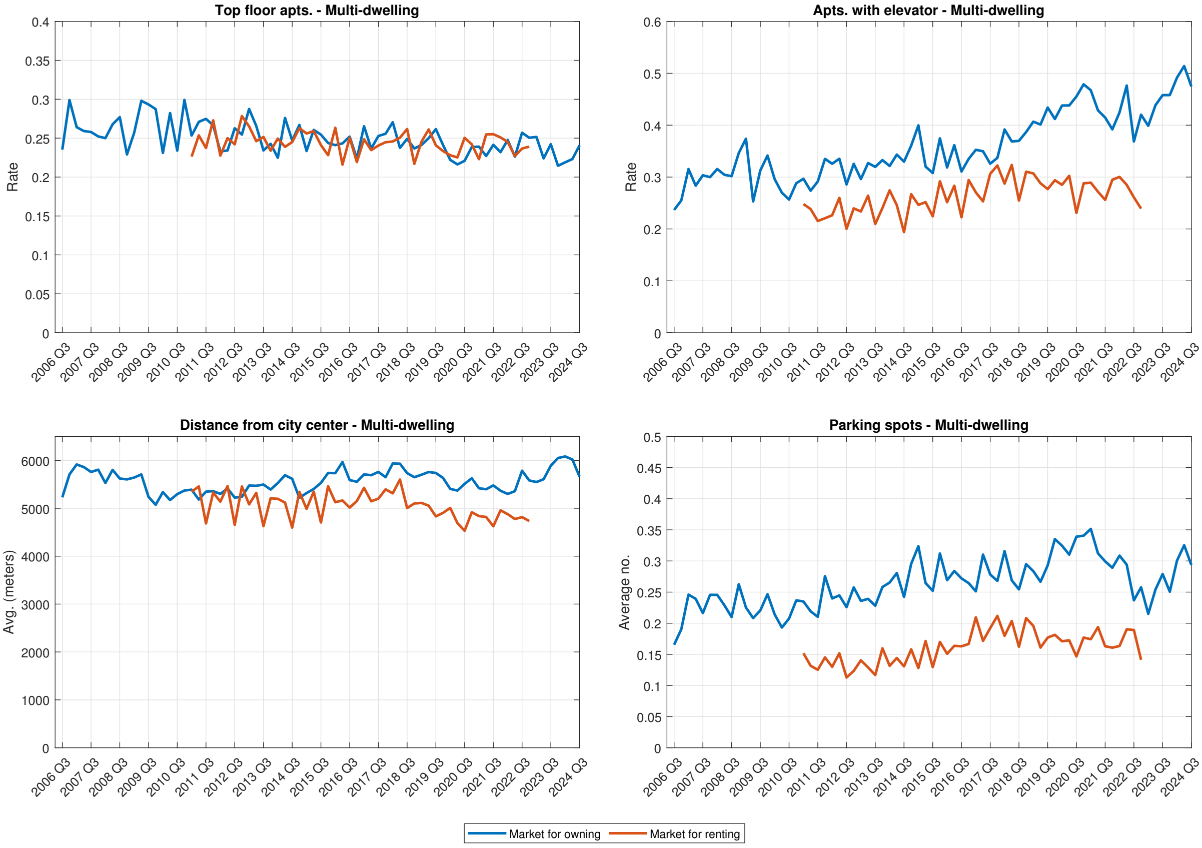
Note: Quarterly average of construction year, building age, share of new buildings and floor number, by market, for the multi-dwelling segment. Greater Reykjavík market. 2011 Q1 - 2022 Q4 for the rental market. 2006 Q3 - 2024 Q3 for the sales market.

indicates quality-bias in comparisons between the two markets.

As seen in the lower right panel of figure 6, the average floor number of a rented apartment is around 0.2 floors below the average sold apartment. This is reflected in the higher prevalence of basements in the rental market, as described above. This also indicates a quality difference, in favor of sold properties, as higher floors can be expected to fetch a higher price.

The rate of top floor apartments is relatively consistent ranging between 21% and 31% in the sales market and 22% and 28% in the rental market with a median rate of 25% in both markets. This is shown in the upper left panel of figure 7. A slight downward trend indicates that the rate of top floor apartments is in general lower in the latter half of the period. A plausible reason is that the average number of floors in apartment buildings has increased with the city's policy of densification, lowering the ratio of top floor apartments in the housing stock. Here, attics are not included.

Figure 7. Top floors, elevators, central location and parking



Note: Quarterly average of the rate of top floor apartments, the rate of elevators in the building, average distance from the city center and the number of dedicated parking spots, by market, for the multi-dwelling segment. Greater Reykjavík market. 2011 Q1 - 2022 Q4 for the rental market. 2006 Q3 - 2024 Q3 for the sales market.

In the sales market, the share of apartments with elevator access gradually rises during the sample period, with the lowest value of 23% being in 2006 Q3 and the highest, 49%, in 2024 Q1. This is displayed in the upper right panel of figure 7.[19] In the period from 2011 Q1 to 2018 Q2 this share rises in the rental market, while being on average five percentage points lower than in the sales market. From the latter half of 2018 through 2022 this rate declines in the rental market while shooting up in the sales market. Again, this suggests biased comparisons between the two markets, in the absence of quality-adjustments. Some degree of seasonality is visible in this variable for the rental market, with the average share of elevator-houses dropping in the third quarter of each year. This may be caused by students entering the market to secure rental housing for the coming school year.[20]

[19] Here, the elevator variable has been recoded as a dummy, i.e. if the number of elevators in the building is 1 or more, the variable takes the value 1, but 0 otherwise.

[20] This seasonality is seen despite a large proportion of student related rent contracts being filtered out

As the dataset contains GPS-coordinates for every property, we can calculate new variables based on distances. The average distance from Reykjavík's city center is relatively stable in the sales market, fluctuating between five and six kilometers.[21] This is displayed in the lower left panel of figure 7. On average, apartments in the rental market are about half a kilometer closer to the city center than those in the sales market. This may suggest that renters are on average younger and prefer central locations or proximity to junior colleges and universities, which are rather centrally located, on the whole. When it comes to the average distance from the geographical center of the capital city area (not displayed graphically) there is virtually no difference between the rental or sales market.[22]

On average, apartments in the sales market have 0.28 dedicated parking spots (usually in a parking garage) whereas apartments in the rental market have 0.16 spots on average. This is a 74% difference. This number trends upwards in both markets from 2011 Q1 to 2018 Q4. In 2019 and thereafter, however, it decreases in the rental market, while continuing to rise in the sales market, reaching a peak in 2021 Q1 at 0.36 spots per dwelling, before dropping to 0.22 in 2023 Q1. This development, and the rate of elevator houses in the sample can be seen to coincide with changes in the rate of new buildings described above. Once more, a difference is observed in the average level of characteristics, as well as diverging developments in the two markets over time.

The dataset contains two different sources of information. First, information registered in the sales contract and second, information registered in the HMS property and property valuation registries. With respect to floor space we opt for the property valuation registry information as it offers disaggregation into apartment living space, storage rooms and garages, with the added variable of balcony floor space. Together, these variables yield somewhat better regression results than the contract information. They are displayed in figure 8. First, apartments sold are larger on average than those rented. Average apartment floor space is stable around 90 square meters compared to around 80 in rentals.[23]

Second, storage rooms are roughly equal in floor space between the two markets. Thus it seems that storage space is a larger portion of total floor space in rentals than in owner-

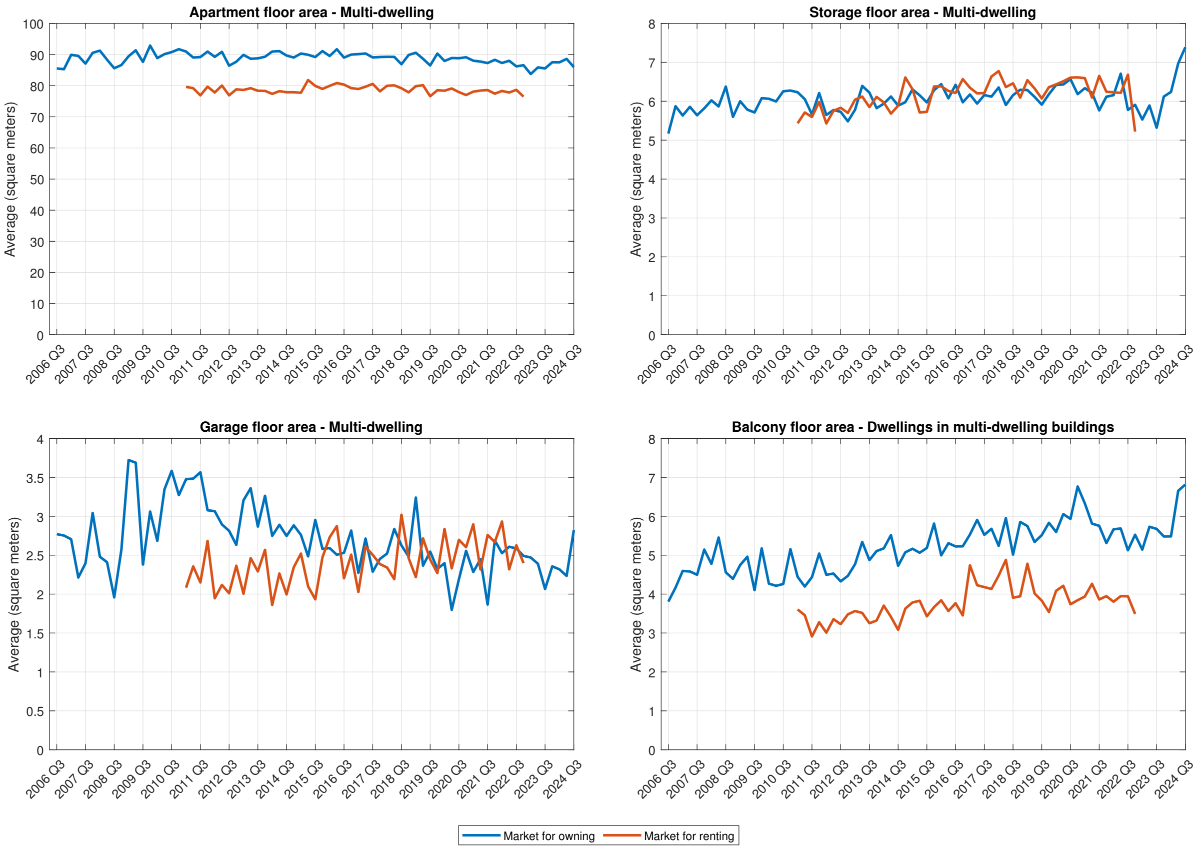
of the sample, since Student Housing, the real estate firm of Iceland Student Services, is not categorized as profit driven and cannot be said to charge market prices.

[21]This refers to the as-the-crow-flies distance, calculated using the haversine formula.

[22]The city center is defined as the intersection of the streets Lækjargata, Bankastræti and Austurstræti, in downtown Reykjavík. The geographical center is defined as having the median longitude coordinate and the median latitude coordinate in the sales contract register.

[23]By living space we mean living rooms, bedrooms, kitchens, bathrooms, halls and hallways. In other words, anything not storage or garage. There may be some discrepancy in how washer rooms are registered in this regard, as some of them are communal, in apartment blocks' basements, whereas others are combined with storage facilities or bathrooms within the apartment.

Figure 8. Floor space variables



Note: Quarterly average of floor space variables, in square meters by market, for the multi-dwelling segment. Greater Reykjavík market. 2011 Q1 - 2022 Q4 for the rental market. 2006 Q3 - 2024 Q3 for the sales market.

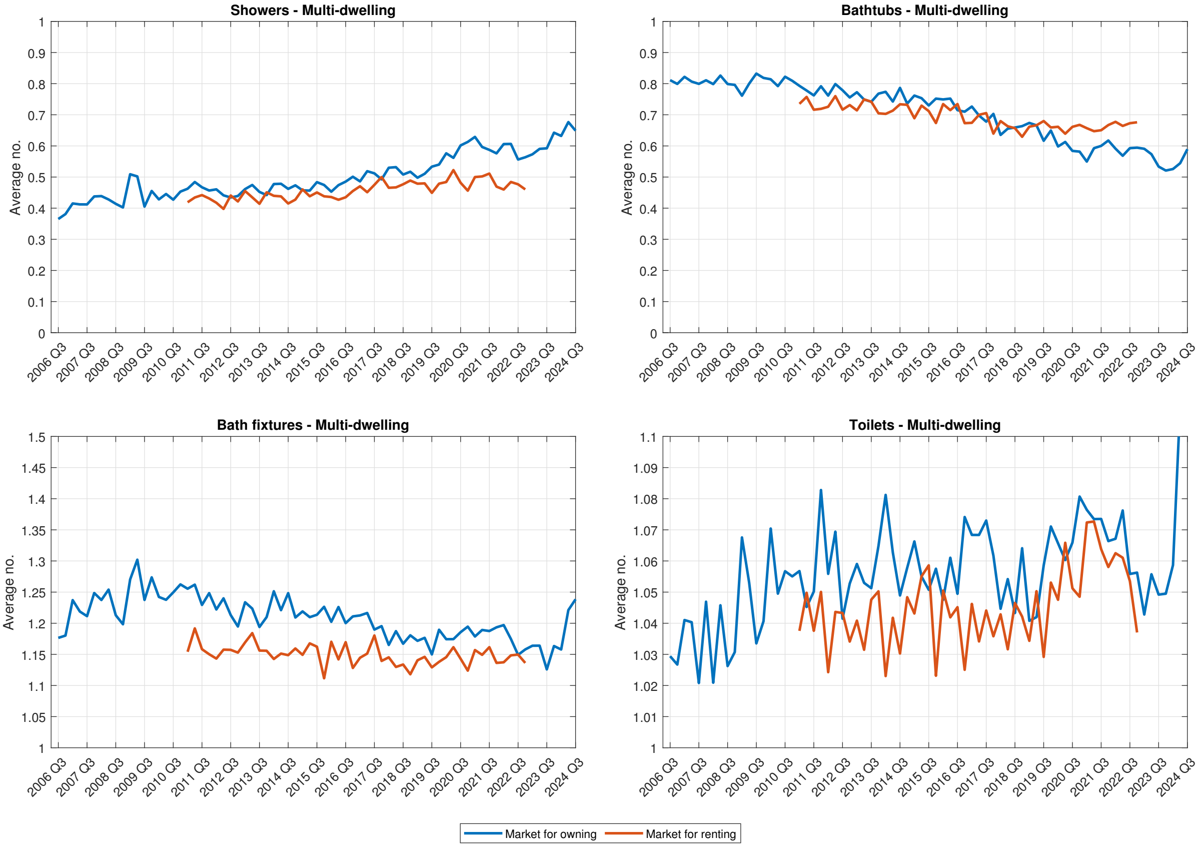
occupied flats. This can indicate, for example, better internal organization in the latter group or simply that storage rooms in owner-occupied flats (which are newer) have more ceiling height and therefore more cubic meters than the floor area variable would indicate.

Third, most apartments in multi-dwelling buildings don't have private garages. Therefore the average garage floor area is only around 2.5 square meters. Somewhat surprisingly, it is higher in the rental market for the last three years of rental market data. This might indicate a larger portion of rented apartments being in housing officially registered as garages, or a correlation with older apartments.

Lastly, balconies are larger in sold flats. Trending upwards over time, the average balcony floor space is around 4 sq.m. in 2006, but reaches almost 7 sq.m. in 2024. The average balcony of a rental apartment is around 1.5 sq.m. smaller. Perhaps, this difference is mostly accounted for by the higher prevalence of basements in the rental market.

Throughout the rental market sample period, the average number of showers in rentals is

Figure 9. Bath fixtures and WCs



Note: Quarterly average of the number of bath fixtures and WCs, by market, for the multi-dwelling segment. Greater Reykjavík market. 2011 Q1 - 2022 Q4 for the rental market. 2006 Q3 - 2024 Q3 for the sales market.

around 11% lower than in sold flats. This average grows steadily and in sync up until 2019 Q1 when it stagnates for rentals, but keeps growing at an accelerated pace in sold apartments. The opposite happens with regard to bathtubs. Their average number in rentals falls from 2011 to 2018, but then stagnates. Meanwhile, bathtubs fall out of fashion in owner-occupied flats, as their average number falls some 34% from 2006 to 2024. This is in line with the growing share of newly built sold flats, where walk-in showers are common in later years. Using these variables separately in a hedonic regression can prove problematic, as owners somtimes remodel bathrooms by switching out one bath fixture for another, without any change in registration (plus, the dataset only contains one 2023 snapshot of these variables). Using the combined number of bath fixtures can prove more effective. It is shown in the lower left panel of figure 9. Rental apartments have on average almost 5% fewer bath fixtures over the sample period, but without the downward trend in the sales arket. The number of fixtures ends up similar in the latter half of 2022.

A number of other variables tell a similar story. These are variables measuring the number of different rooms, the number of WC's, the outdoor and indoor aesthetics parameters and house and lot inspection parameters (see section 5), assigned by HMS appraisers. Mostly, these indicate a difference in average characteristics in favor of sold apartments.

Taken together, this chorus of evidence mostly sings the same refrain: There is a sizable difference in average property characteristics between the rental market and the sales market, for the period from 2011 to 2022. And there is a sizable change in average characteristics within each market, over time. But comparing difference in balcony size to the difference in the number of bath fixtures is a confusing task, without knowing their respective prices. And so is comparing the value of an extra bathroom at different points in time, without knowing its imputed price at each time. To quantify these sorts of quality differences, we need the marginal prices of these characteristics. They tell us what value consumers assign to them at each time. For that and other tasks involving price imputation and quality adjustment, a model is needed.

5 A hedonic model

The rolling-window time-dummy hedonic model for the capital city area multi-dwelling sales market is of the form given in equation (3), with an 18 month rolling-window. Given the dataset, this hedonic regression can be run on 200 rolling sample windows, $h = \{1, 2, \ldots, 200\}$ where the sample period for the first window reaches from 1st July 2006 through 31st December 2007 and the sample period for the last window reaches from 1st February 2023 through 31st July 2024. The model is estimated with ordinary least squares. The dependent variable is the natural logarithm of the price registered in the contract, at constant July 2006 prices deflated using the Statistics Iceland consumer price index.[24]

Regressors are the same for all rolling windows. That is to say, the number and selection of regressors is the same in all windows, and each is defined the same way in every window. This enables the interpretation of changes in coefficient estimates over time as changes in marginal characteristic prices, and not as stemming from changes in model specification. Equation (3) for window h can be rewritten as

$$\bar{y}^h = \bar{\mathbf{1}}\beta_0^h + \boldsymbol{D}^h\bar{\delta}^h + \boldsymbol{Z}^h\bar{\beta}^h + \bar{\epsilon}^h \tag{9}$$

[24] Other versions such as deflating with the CPI excluding housing costs, using current prices, and not taking the logarithm have been tested, and have not improved model performance.

where:

- $\bar{y}^h = \ln(\bar{p}^h)$ is an $N_h \times 1$ vector of CPI-deflated log-prices
- $\bar{\mathbf{1}}$ is an $N_h \times 1$ vector of ones
- β_0^h is the scalar intercept parameter
- $\boldsymbol{D}^h$ is an $N_h \times 17$ matrix of time dummy regressors.
- $\bar{\delta}^h$ is a 17×1 vector of time dummy parameters
- $\boldsymbol{Z}^h$ is an $N_h \times 45$ matrix of characteristic regressors
- $\bar{\beta}^h$ is a 45×1 vector of characteristic parameters
- $\bar{\epsilon}^h$ is an $N_h \times 1$ vector of error terms

and where N_h, the sample size, is unique for each window.[25] The dummy variable for the first period and the corresponding parameter δ^{1h} are omitted, so $t = 1$ serves as the base period. This is done to avoid perfect collinearity among the time dummy regressors. In practice, the characteristic regressor matrix $\boldsymbol{Z}^h$ is a concatenation of a few smaller regressor matrices and vectors:

- $AREA^h$ is an $N_h \times 16$ matrix of grouped assessment area dummies. The base area, located in central Reykjavík is omitted to prevent multicollinearity, just like the base time period dummy. The assessment areas are based on those defined by the HMS in its database for property valuation. Because of the short span of the rolling-window, estimating a coefficient for each and every one of the HMS assessment areas is not feasible for all windows. Geographically contiguous areas are therefore grouped until a coefficient for each group can be estimated in every rolling-window without serious overfitting. Coefficients significantly different from zero are not expected in all instances. The granularity is kept low enough so confidence intervals are not exceedingly wide and coefficient signs are the expected ones, in those cases where there are sign expectations at all. For example a highly peripheral area should not carry a positive

[25] The maximum N_h is 10,422 observations in the window ending 31st December 2021, with 160 observations per estimated parameter. The minimum N_h is 1,758 observations in the window ending 30th April 2010, with 27 observations per estimated parameter. Estimating this equation for 200 windows means we make 12,600 parameter estimates in total. But we also use large parts of the sample up to 18 times, meaning that the sum of all rolling sample sizes is 1,236,861 and on average there are 98 observations per parameter.

price effect over central Reykjavík. This brings the number of separate assessment areas down from 77 in the HMS data, to 17 in the model. This can be regarded as a high level of geographic granularity for a macroprudential policy study. In multi-city studies such as Gilbukh et al. (2023), a city is sometimes represented by a single assessment area variable.[26] A description of the grouping is provided in appendix B.

- $SUBAREA^h$ is an $N_h \times 2$ matrix of grouped sub-assessment area dummies. Here, areas are grouped on the expected price effects of the different sub-areas, as they are generally not geographically contiguous. For simplicity, there are two regressors; one represents subareas with positive expected price effects stemming from close proximity to economic goods such as green areas, ocean fronts and lake fronts and from unusually high structural quality not fully captured by other variables. The second regressor represents subareas with a negative expected price effect because of close proximity to economic bads, mostly traffic-heavy streets. A description of the grouping is provided in appendix C.
- $BUILDINGSIZE^h$ is an $N_h \times 3$ matrix of building size dummies, based on the number of dwellings in the building. The intuition is that smaller multi-dwelling buildings are correlated with greener immediate surroundings and more private, if not fully private, gardens, entrances and garages. The first regressor takes the value 1 for dwellings in buildings with three to four dwellings. The second does so for buildings with five to seven dwellings, and the third for buildings with more than twenty dwellings. The interval 8 to 20 dwellings serves as the base building size. A positive price effect is expected from the smaller categories and a negative effect from the largest one.
- NEW^h an $N_h \times 1$ dummy variable for newly built dwellings. New buildings are defined as those where the year of the contract date minus the registered construction year is 2 or smaller. A positive price effect is expected for new buildings, referred to as the new building premium. Nonetheless, the new building premium need not be positive for all rolling-windows, as a negative premium might arise in bubble or crisis scenarios where price differentiation is lacking or the building sector is distressed.
- AGE^h, an $N_h \times 3$ matrix of dummy and quantitative building age variables. The expected marginal price effect of an added year is negative and diminishing in age

[26] Observations from the Álftanes area within Garðabær municipality are discarded as it cannot be estimated separately and is rather far removed from the rest of the Garðabær urban area. Furthermore, Álftanes was a separate municipality, merged with Garðabær at the beginning of 2013 due to financial difficulties in the aftermath of the recession of 2008-2010.

(in absolute terms). Buildings typically follow a lifecycle where they are relatively maintenance-free in their early years, benefiting from the latest construction standards and minimal wear. As they age, the maintenance need grows. Around 50 years of age many buildings are fully depreciated in economic terms. Beyond this threshold, age could be less of a price determinant than past maintenance, renovations and upgrades. To account for the diminishing marginal price effect, we spline the age variable linearly with a knot between 49 and 50 years. I.e. the variable is split up along the intervals 4 to 49 years and 50 years or older. Thus, as new buildings are defined as two years old or younger, three years is the base age. As Gordon & Winkler (2019) point out, a "newness premium" may be associated with new buildings. Defining the age variable this way means that the estimated new building premium may contain such a newness premium in addition to the lemons problem-related premium mentioned earlier.

Multicollinearity needs to be dealt with explicitly when it comes to splines. Splitting the variable into buckets in levels, without any transformation, creates negative correlation between the resulting regressors. To circumvent this, these variables are represented as deviations from the within-bucket sample mean (excluding the zeros which represent observations in other buckets), and accompanied by bucket dummy variables which serve as intercept terms for each age bucket. The dummy for the first bucket is omitted. Thus, AGE^h has 3 columns, where columns 1 and 3 are quantitative and column 2 is a dummy. This yields regressors that are nearly orthogonal.[27]

- $APTFLOOR^h$, an $N_h \times 5$ matrix of quantitative (columns 1, 3 and 5) and dummy (columns 2 and 4) apartment floor area variables. The expected marginal price effect is positive and diminishing in floor area. The variable is splined along the following intervals: $<$ 70 sq.m., 70 to (but not including) 130 sq.m. and $\geq$ 130 sq.m.
- $STORFLOOR^h$, an $N_h \times 3$ matrix of quantitative (columns 1 and 3) and dummy (column 2) storage floor area variables. The expected marginal price effect is positive and diminishing in size. The variable is splined along the following intervals: $<$ 15 sq.m. and $\geq$ 15 sq.m.
- $GARFLOOR^h$, an $N_h \times 3$ matrix of quantitative (columns 1 and 3) and dummy (column 2) garage floor area variables. The expected marginal price effect is positive

[27] If k is the column index of the 50+ age bucket within $\boldsymbol{Z}^h$, if that column has a sample mean of 65 years, and if $k-1$ is the column index of the respective dummy variable, the estimated log-real price effect of age on an apartment in a 70 year old building is $\hat{\beta}^h_{k-1} + (70-65) * \hat{\beta}^h_k$ where both expected signs are negative.

and diminishing in size. The variable is splined along the following intervals: < 25 sq.m. and ≥ 25 sq.m.

- $BALCFLOOR^h$, an $N_h \times 1$ quantitative balcony floor area variable. The expected marginal price effect is positive.

- $FLOORNO^h$, an $N_h \times 4$ matrix of quantitative and dummy regressors. First, a dummy variable for basement dwellings is based on the utilization descriptor. There a large negative price effect is expected. Floor numbers 2 and higher are represented with two variables, interacted with the elevator dummy variable described in section 4. A positive marginal price effect of higher floor numbers is expected in buildings with an elevator, but not necessarily in those without elevators.[28] Lastly, a dummy variable for top floor apartments is included. It takes the value 1 if the registered floor number is equal to the registered number of floors in the building and the property is not an attic, but 0 otherwise. A positive sign is expected for this variable.

- $AESTHETICS^h$, an $N_h \times 1$ quantitative variable indicating a score assigned to the dwelling by HMS appraisers for aesthetics inside the dwelling. Aesthetics in this case means ornamentation, interior design or notable artistry and craftsmanship in finishes. The dataset also includes an outside aesthetics variable, which does not provide significant price effect estimates and is perhaps more suited for detached housing.

- $INSPECTION^h$, an $N_h \times 1$ quantitative variable indicating a score assigned to the building by HMS appraisers for its external condition. The variable has a baseline value of 1, with deviations rather uncommon and very small. To prevent a large estimated coefficient from attributing a too-large share in quality to this variable, 1 is subtracted from all observations. This changes the baseline value to 0 without affecting the estimated coefficient.[29]

- $BATHROOM^h$, an $N_h \times 1$ quantitative variable indicating the combined number of bath fixtures, i.e. bathtubs and showers, and WC's in the dwelling.

- $PARKING^h$, an $N_h \times 1$ quantitative variable indicating the number of private parking spots for the dwelling, not in a private garage but usually in a car park facility.

[28] In Iceland the ground floor is the 1st floor. Therefore we subtract 1 from floor numbers 2 and higher, to indicate the number of floors by which they are elevated from the ground floor.

[29] The dataset also includes a lot inspection score, which does not provide significant price effect estimates, and is perhaps more suited for detached housing.

This model is not designed to perform exceptionally well for a certain point in time or certain rolling-window. Rather, it is designed to perform sufficiently well for all rolling-windows, so regressors are chosen to improve average regression statistics over all 200 windows, rather than for any one window. Furthermore, the model is designed to provide interpretable marginal characteristics prices. It therefore does not achieve the extent of quality-adjustment possible with the dataset, if less consideration were given to multicollinearity and if the only objective were to produce price indices. Results are reported in section 6.

6 Results

The model performs largely in line with expectations, is relatively stable and coherent and indicates time-varying marginal characteristics prices. Main regression results and diagnostics are presented in section 6.1, the marginal characteristics prices in section 6.2, and variance decompositions in section 6.3. Hedonic house price indices are presented in section 6.4.

6.1 Main results and diagnostics

Average, maximum and minimum regression diagnostics for the 200 regressions are shown in table 1. Goodness-of-fit is rather high with an average of 0.87, varying between 0.80 and 0.89 over time. The root mean squared error, in other words the mean log-real price prediction error, is 0.11 log-points or around 11.8% on average over all regressions. It is smallest around 0.1 (10.0%) and largest around 0.14 (15.6%).

	Average	Max	Window no.	Min	Window no.
Ordinary R-squared	0.87	0.89	82	0.80	30
Adjusted R-squared	0.87	0.89	82	0.80	30
F-statistic	686.04	1165.59	161	113.70	29
F-stat p-value	0.00	0.00	1	0.00	1
Mean squared error	0.01	0.02	31	0.01	155
Root mean squared error	0.11	0.14	31	0.10	155
Degrees of freedom	6121.31	10359.00	169	1695.00	29

Table 1: Regression statistics. Both min and max p-values for the F-test are reported in the first window because the p-value is zero to machine precision for all windows.

The main metrics are displayed for all regressions in figure 10. Model performance varies somewhat across time. The main diagnostics deteriorate the most in the years 2009 to 2011, in the aftermath of the financial crisis. This coincides with a large drop in sample size. It is doubtful, however, that sample size is the only or even the main reason. A more likely explanation is structural changes in the market, within the 18 month rolling window. Throughout the year 2021 during the pandemic (another period of potential structural changes), falling goodness-of-fit coincides with growing sample size. This suggests that fast-changing supply and demand conditions adversely affect the model's performance and that such changes were most profound in the post-crisis years of 2009 and 2010.

The assumptions underlying the use of OLS as the best linear unbiased estimator seem satisfied for the most part. Visual inspection of data and error terms suggests that the linearity assumption, after taking logs, is satisfied. Higher order regressors designed to catch potential non-linearity effects in general have not yielded much better outcomes and are for that reason not included in the model, for the sake of simplicity. The bias in dummy coefficient estimates discussed in section 2 has been measured according to the method suggested by Kennedy (1981) and found to be negligible.[30]

There is limited multicollinearity among regressors in any rolling-window. A Belsley et al. (1980) condition number is calculated for $\boldsymbol{Z}^h$ for all regressions. The highest value recorded is 11.6, comfortably below the benchmark value of 20, indicating that overall multicollinearity is not a problem. The high level of orthogonality is to a large extent by construction. Out of the 62 predictors, 17 are time dummies. Those are orthogonal to one another, and so are the 16 geographical assessment area dummy regressors. Correlation between other characteristic regressors is also limited. Appendix D contains a pairwise correlation matrix for all the predictors, averaged over such matrices for all 200 regressions. Inspection of pairwise correlation matrices for individual regressions reveals that such correlation coefficients seldom exceed 0.5 and never exceed 0.62 in absolute terms.[31] Variance inflation factors (VIFs) for all regressors in all windows are below the conservative benchmark value of 5. The highest VIF recorded is 4.2.[32] Error terms are normally distributed. A Jarque-Bera (1980) test cannot reject the null hypothesis of normality in any regression. Visual inspection of temporally ordered error terms reveals little indication of autocorrelation. A Breusch-Pagan (1979) test for error term heteroskedasticity reveals little indication of it in any of the 200 regressions.

[30]The bias was examined for all estimates of all 46 dummy coefficients. It does grow rapidly as sample size falls in the years 2008-2011 but still peaks at negligible levels. For example, the bias in the new building coefficient is greatest at a mere 0.01 percent of the exponentiated coefficient.

[31]The strongest pairwise correlation occurs between building size and floor number variables, as high floor numbers only occur in large buildings.

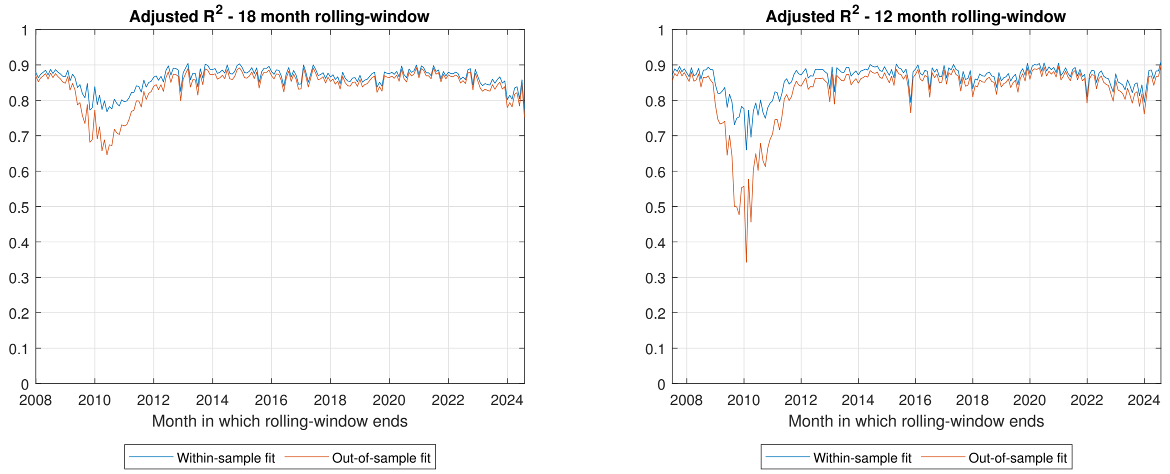
[32]Greene (1991, pp. 279) lists the symptoms of multicollinearity as wide swings in parameter estimates from small changes in data, very high coefficient standard errors and low significance levels in spite of high joint significance, wrong coefficient signs and implausible coefficient magnitude. None of these issues are present to any worrying degree.

Figure 10. Main regression diagnostics for all regressions

Note: Regression diagnostics for a rolling-window time-dummy hedonic model of the greater Reykjavík area sales market multi-dwelling segment, with an 18 month rolling window. First window ends in December 2007. Last window ends in July 2024.

For a model with many explanatory variables, overfitting is a worry. In particular when it comes to locational dummy variables, and splined variables. It is important to avoid overfitting, as the model is intended for the imputation of prices for properties outside the sample, which appear in the rent contract register. A model validation excercise is performed by splitting each rolling-window sample into a restricted set and a test set. The restricted set comprises 90% of the full dataset, and the test set is the remaining 10%. The test set is chosen as every 10th observation, after ordering the dataset on two levels; first by area dummies and then by contract date. The test set is thus stratified, including a proportional number of observations from each geographical area, and relatively evenly distributed over the sample period for each rolling-window. Prices are then imputed for the test set using coefficients

Figure 11. Test set goodness-of-fit in a validation exercise



Note: Goodness-of-fit for a test set comprised of every 10th observation in the sample for each rolling-window. Sample is ordered on two levels before the test set is chosen; first by area dummies and then by contract date. Test set thus includes a proportional number of observations from each area and across time, within each rolling-window. Left panel shows results when using an 18 month window. Right panel shows result using a 12 month window.

from the model estimated on the full dataset on the one hand, and on the restricted set on the other. Different within-sample and out-of-sample goodness-of-fit for the test set would indicate that the model does not generalize well to observations outside the sample.

The results of this excercise are shown in figure 11, using both an 18 month rolling-window and a 12 month rolling-window. For most 18 month windows, overfitting is not a problem. The exception is the post-financial crisis period of rolling-windows ending in April 2009 to July 2011, when turnover in the market decreases markedly. For this period, the out-of-sample fit suffers somewhat from overfitting, indicating that either locational granularity and splining should be reduced, or the window length increased. Changing the definition of the characteristics regressor matrix $\boldsymbol{Z}^h$ from window to window is not an appealing option, as this would complicate the interpretation of coefficient changes over time. But lengthening the window is not without problems either. Bubbles and crises probably bring structural changes to the real estate market, increasing the need for time-varying coefficients. Even so, lengthening the window to 24 months indicates tolerable goodness-of-fit both within and out-of-sample for this low-turnover period.

For a 12 month window, overfitting is not a problem when turnover is relatively high. For the highest-turnover periods such as the years 2006 to 2007 and 2020 to 2022, results indicate that a window as short as 3 to 6 months may suffice. Going forward, varying the window length seems appealing, bringing dynamic estimates when they are most needed.

From the standpoint of systemic risk analysis, poor out-of-sample performance for the low-turnover period of 2009 to 2011 is not a big problem. The problematic period is the aftermath of a systemic financial crisis, when systemic risk has been realized, and thus reduced, and it is pointless to apply macroprudential tools to contain it. The aim is to detect signs of exuberance, excessive risk taking and overvaluation of real estate in the run up to a potential crisis. Such developments tend to coincide with high turnover, not low. For short windows ending before October 2008, when the crisis erupted, overfitting is not a problem. Excercises of this sort can help guide the choice of varying window length.

6.2 Marginal characteristics prices

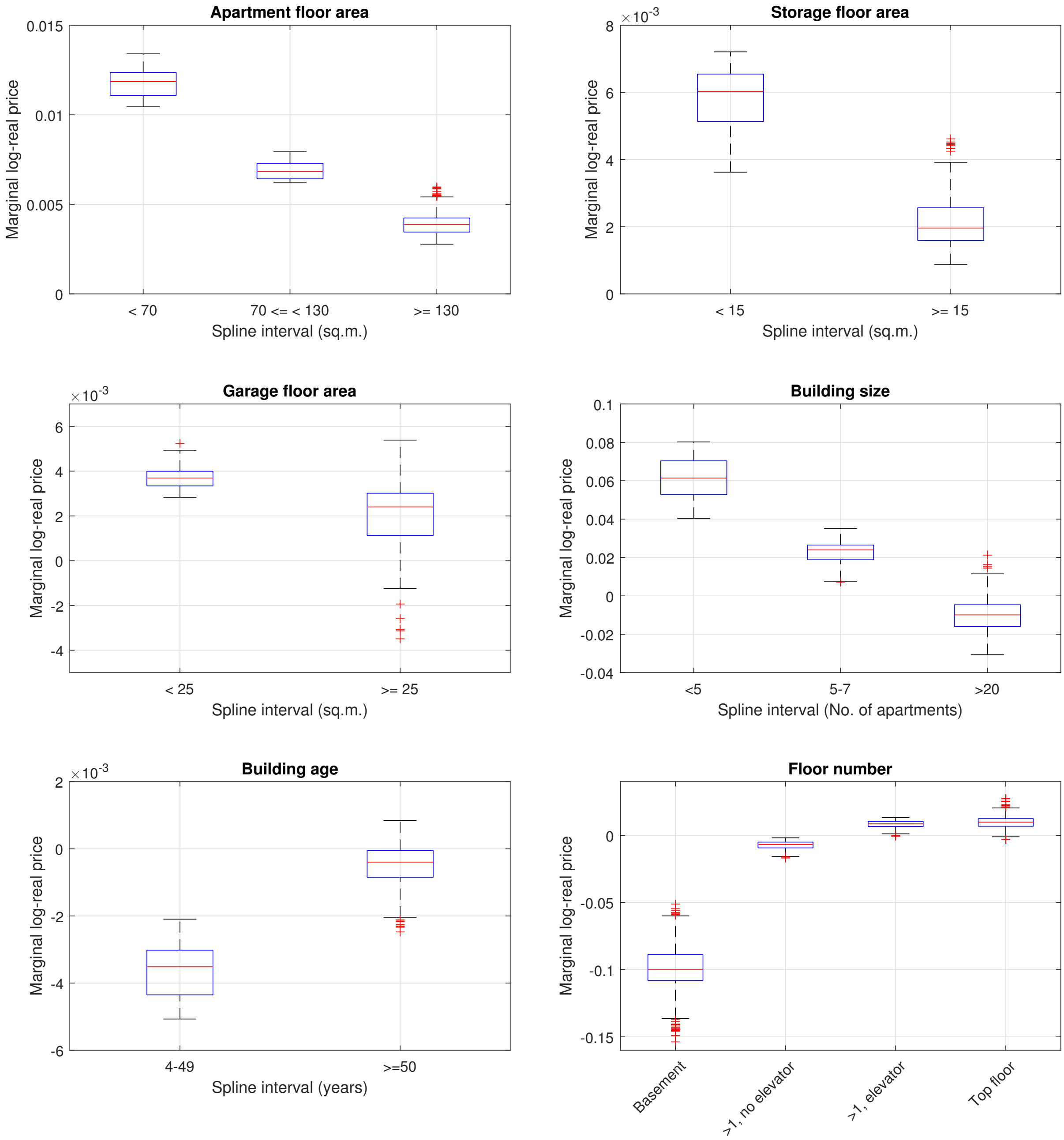
The assumptions underlying OLS seemingly being satisfied, the estimated marginal characteristics prices can be interpreted independently.[33] Figure 20 in appendix E displays assessment area coefficients, i.e. the log-real price effect of location within a given assessment area group, compared to the base area of central Reykjavík. The estimated coefficient for each assessment area group, averaged over 200 regressions, is shown in appendix B. As expected, log-real prices vary substantially by location. The base area has the highest average price. The lowest average area coefficient is -0.3011 (-26%) under the base area. In individual regressions, coefficients as high as 0.009 (0.9%) and as low as -0.403 (-33.1%) are seen. This indicates that accounting for location when comparing house prices to rent prices can remove serious bias. Negative price effects of location grow along the center-periphery axis, indicating that as sold and rented apartments have different average location relative to central Reykjavík, there is systematic bias in non-quality adjusted comparisons.[34]

The two sub-assessment area coefficients are displayed in the top row of figure 21 in appendix E. The first has an average estimated coefficient of 0.1243 (13.2%) and varies substantially over time, sometimes under the influence of a varying share of new dwellings, as dwellings in large new building sites are sold over a relatively short time period. A large movement in this coefficient from the year 2021 onward is marked by this, as a concentration of newly constructed luxury dwellings were entered into the market. The second subarea coefficient has an average estimate of -0.07 (-6.8%).

[33] Discussion of time dummy coefficients is left for section 6.4. As there are $45 \times 200 = 9,000$ non-time dummy estimates they are displayed in appendix E.

[34] The area closest to the seismic and volcanic activity in the Reykjanes peninsula, which commenced with an earthquake swarm in February 2021, seems unaffected by those developments. See coefficient for the 15th area dummy in figure 20 in appendix E. One possible explanation is that an influx of displaced people has offset a negative risk-aversion effect.

Figure 12. Variability in selected coefficients over all regressions



Note: Variability in selected coefficient esimates over all 200 regressions, for a rolling-window time-dummy hedonic model of the greater Reykjavík area sales market multi-dwelling segment. The red line shows the median coefficient. The box shows the interquartile range of coefficient estimates. Red markers outside whiskers show outliers.

Looking next at the quality of the structures themselves, estimated coefficients seem to conform well to basic economic assumptions. This is displayed in figure 12. First, the estimated marginal price of floor area (apartment, storage and garage separately) is diminishing in size. This conforms to the assumption of a concave utility function for consumers. As displayed in the top-left panel of figure 12, the median coefficient for apartment floor space under 70 sq.m. is roughly 0.012 (1.2%), falls to 0.007 (0.7%) in the middle interval, and to 0.003 (0.4%) in the last interval. The same pattern is seen with regard to storage floor area and garage floor area. As displayed in figures 21. and 22. in appendix E, this ordering of magnitudes does not hold strictly for all regressions, but for most.

A similar pattern is seen for building size, measured in the number of dwellings in the building. There is a sizable positive price premium on dwellings in small multi-dwelling buildings, of 6.2%, over the base size category of 8-20 dwellings. For 5-7 dwelling houses there is also a premium, but a much smaller 2.2%. Lastly, there is a small negative premium on dwellings in large apartment buildings with over 20 dwellings. As seen in figure 21 in appendix E, this ordering of magnitudes holds for all 200 regressions.

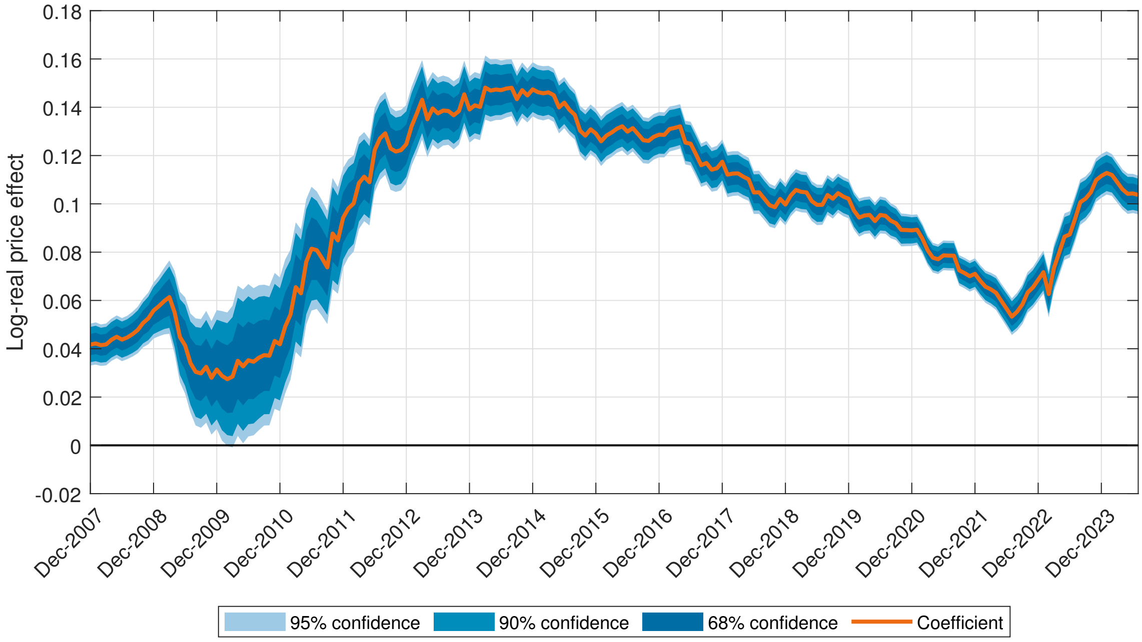
The variability of the estimated marginal price effect of building age is shown in the bottom-left panel of figure 12. It conforms to the assumption that building age is first and foremost a price determinant for younger buildings, but not for older ones. For the lower age interval of 4 to 49 years, each added year of building age has a median negative price effect of 0.4%. For the upper interval this effect is diminished to 0.04%.

Out of the floor number related variables, the basement coefficient is most important, indicating a median negative price effect of -9.5%. Above the ground floor, increasing floor numbers yield a positive median marginal price effect of 0.9% in buildings with an elevator, but a negative one of -0.7% in buildings without an elevator. In addition, top floor apartments (which are not attics) command a median price premium of 1.0% which is only statistically significant around half of the time. The floor number can make a difference for imputed prices. For example, an 8th floor top floor apartment with an elevator and a 15 sq.m. balcony carries a premium of almost 20% over an otherwise identical basement dwelling.

The price premium for new dwellings is displayed in figure 13. The median coefficient is 0.1009, which translates to a price premium of around 10.6% for new dwellings.[35] For rolling-windows ending in 2007 the premium is small, at around 4%. This period is generally considered part of a real estate bubble which popped in 2008, although the "hissing sound" started in the latter half of 2007. The low premium can be interpreted as reflecting price formation in a market in such a state, and is probably the result of both supply and demand-

[35]The level of the premium is somewhat sensitive to model specification. It's development over time however is quite robust to model specification and corresponds well with history as we know it. The premium relative to the historical median is therefore perhaps more interesting than the numerical value.

Figure 13. Estimated new building premium



Note: Estimated coefficient for new building dummy variable in all 200 regressions, in rolling-window time-dummy hedonic model for the greater Reykjavík area sales market multi-dwelling segment. Confidence intervals constructed using the Student's t-distribution with $N_h - 62$ degrees of freedom, where N_h is the sample size within each window.

side developments at the time. The supply of new dwellings was very high with almost 5,000 new dwellings finished, nationwide, in 2007. That number is 33% higher than the corresponding number for any year since.[36] In other words, supply-side competition was intense. On the demand side, consumers may not have differentiated sufficiently between properties based on quality, due to high future price expectations and easy credit.[37] After the onset of the financial crisis the premium falls and is barely significant at the 95% confidence level in the first half of 2010. A highly leveraged and liquidity constrained construction sector may have slashed prices to liquidate inventories in a firesale-type scenario.[38]

In the post-crisis years after 2010 the new building premium grows substantially, peaking at 16% in 2015. Perhaps this can be attributed to low housing investment and low building activity and a greatly diminished building sector, indicating low supply side competition and renewed quality discrimination by consumers, who are again credit constrained. As housing

[36] See Central Bank of Iceland (2024a), chart I-25

[37] The growing indebtedness of Icelandic households from 2004 to 2007 is well documented. See e.g. Special Investigation Commission (2010), figure 24, pp. 29.

[38] Bank credit to the construction sector grew by 377% between October 2003 and December 2008, and contracted by 70% from then on until January 2014, see Central Bank of Iceland (2024b). According to Central Bank of Iceland (2012), over 80% of domestic bank loans to the construction sector either had been restructured since 2008 or were still in arrears at the end of the 1st half of 2012.

investment grows and interest rates decline from 2015 to 2019 the premium declines as well, stabilizing close to the median coefficient throughout 2019. Next, the COVID-19 pandemic shock hits, with greatly lowered interest rates and heightened uncertainty. As consumer's credit access is eased and the building sector offloads inventories, the premium diminishes, reaching a short-lived low for the rolling-window ending in July 2022, at 5.5%. Thus, as real estate price increases are the most rapid (see section 6.4) and as bank mortgage rates are still low in historical comparison, the new building premium is moving back into "bubble territory". Probably, this process is then interrupted by increasing bank mortgage rates, induced by policy rate hikes and a tightened macroprudential policy stance by the Central Bank.[39] Consequently, the premium shoots up to 11.9% in January 2024. This may reflect the tight credit constraints due to high interest rates (a key policy rate of 9.25%), which forces consumers to price discriminate based on quality, in order to maximize their utility. At the same time, housing investment has remained rather high, and the supply of new housing rather steady.[40] All in all, this coefficient has promise as an indicator of market conditions.

The aesthetics coefficient consistently takes a positive sign and is significant at the 95% confidence level for most windows. The parameter is large as the variable has a very small variance, but decreases in magnitude with time. The house inspection coefficient is also large and significant for most windows, except for the recession years of 2009 to 2011.

The combined number of bath fixtures and WC's also positively and significantly affects prices. The coefficient, displayed in the bottom left panel of figure 22 in Appendix E, is in the range of 0.007 to 0.035 log-real price points. Thus the marginal price of a bathroom with one bath fixture and one toilet is in the rather wide range of 1.4% to 7.2%. Lastly, the marginal log-real price of a dedicated spot in a parking facility is significant in all regressionas and in the range of 3.8% to 7.7% fluctuating somewhat over time.

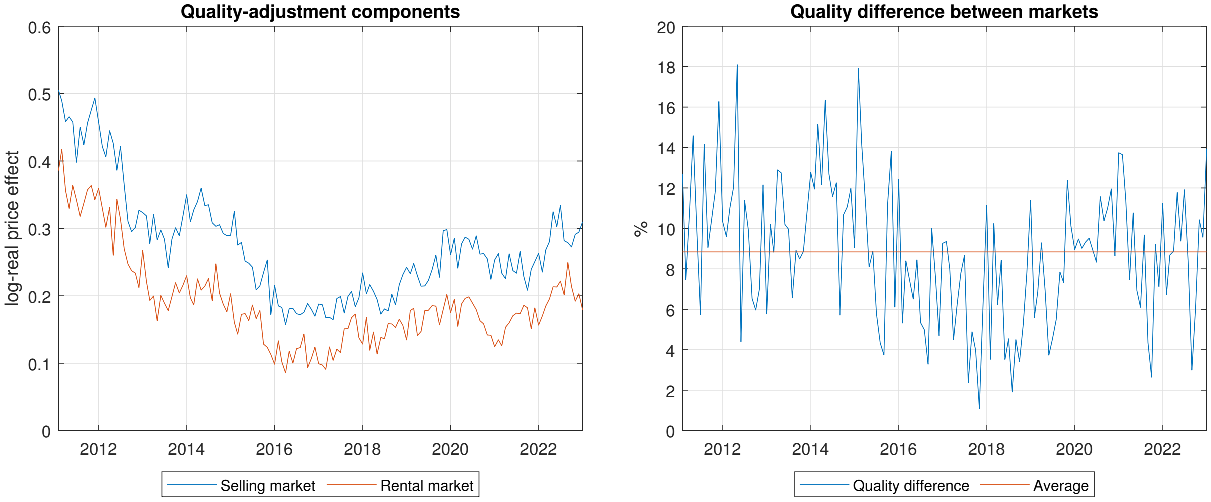
Having observed the average property characteristics in both the sales and rental market and estimated their marginal prices in the sales market, we can now quantify the average quality difference $\hat{Q}^h_T$ as defined in equation (7).[41] The average quality difference between the markets is displayed in the right panel of figure 14. Averaged over the period from

[39] The most consequential macroprudential tightening was the introduction of a minimum reference rate into the rules on maximum debt-service-to-income ratios, which was announced 15th June 2022. See Central Bank of Iceland (2022).

[40] A negative shock to the housing stock occurred when the town of Grindavík was evacuated due to the threat from a nearby volcano, in November 2023, pushing evacuees into the Reykjavík area housing market, contributing to demand growth there.

[41] Still missing, though, from the picture of bias in the price-to-rent ratio are the marginal characteristics rent prices. Furthermore, this difference, $\hat{Q}^h_T$, is partly due to actual difference in characteristics in the two markets, and partly due to sample selection bias, which is much greater in the rental market data.

Figure 14. Quality difference between the sales and rental markets



Note: Left panel shows the average quality adjustment component, for properties traded in the sales and rental markets within the month. Calculated based on marginal characteristic prices in the sales market, estimated using data within the 18 month window ending in the month in question. Right panel shows the percentage difference between the two markets within each month and its average over the period from January 2011 to December 2022.

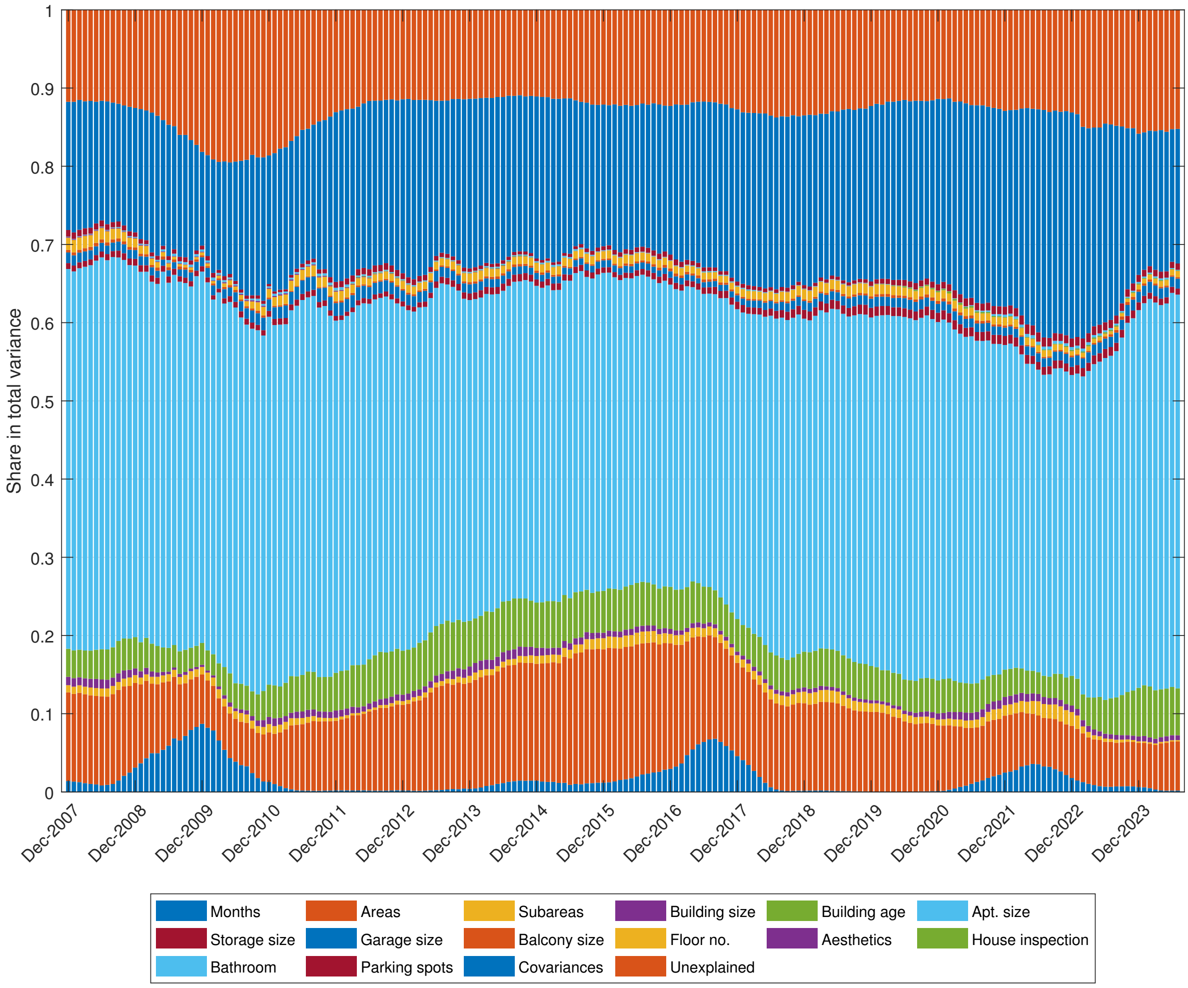
January 2011 to December 2022, this difference is 8.8% in favor of the selling market, varying substantially between 1.1% and 18.1% at monthly frequency. This indicates that the level of a non-quality adjusted average price-to-average rent ratio is biased upward, unduly indicating housing market tension. But it also indicates that changes in that ratio, or a comparable index-to-index ratio which has no meaningful level, are disturbed by quality changes in the short term. Not only with regard to month-on-month changes but also at business cycle frequencies. For example, the average $\hat{Q}_T^h$ is 10.6% for the period from January 2011 to June 2015, but only 6.7% for January 2017 to December 2019, before rising back to 8.2% for the period from January 2020 to December 2022. In other words, if we wish to use the price-to-rent ratio in statistical analysis of housing market equilibrium or other types of macroeconomic analysis, it should be quality adjusted. This is a core result of this paper.

6.3 Variance decomposition

Variance decomposition of all 200 regression reveals the relative importance and explanatory power of different property characteristics. Unsurprisingly, apartment floor size is the most important price determinant by far, accounting for almost 44% of total variance on average. This is a reminder that "non-quality adjusted" is a misnomer for house price indices based on average per-square meter prices. They just aren't thoroughly quality-adjusted.

Second, location (by assessment area group and sub-assessment area group) is an im-

Figure 15. Variance decomposition



Note: Variance decomposition for each regression and rolling-window. For splined and locational variables, only the combined share of each regressor type, in explained variance, is shown. Time-axis indicates the month in which the rolling-window ends.

portant price determinant, accounting for 11.3% of total variance, on average, fluctuating between 18.7% and 5.9%. To some extent the development, over time, tells a story of a pre-crisis housing bubble more pronounced in central areas, a geographical flattening out of house prices as the bubble deflates, and of an uneven housing recovery during the post-crisis years, when central Reykjavík prices are resurrected first and peripheral areas follow suit with a lag. As demand growth continues in later years, housing affordability decreases and the policy of densification is pursued, peripheral areas catch up with the central areas as buyers compete fiercely for affordable housing. Thus, location only explains 6.5% of total variance in the last regression.

Third, building age also matters. Age, including the new building premium, accounts for 4.6% of total variance on average, fluctuating between 2.6 and 6.5% over time. Fourth, when general house price changes are rapid, irrespective of their direction, time matters. The portion of total variance attributable to time dummies is 1.7% on average, topping out at 8.7% for the window ending in December 2009. Thus, accounting for size, location, age and time seems indispensable, while other variables command much less explanatory power on the whole. On average, the combined explanatory power of building size, storage room size, garage size, balcony size, floor number, aesthetic features, house inpection scores, bathrooms and parking spots is only 4.9% of total variance, fluctuating between 3.2% and 6.1%.

These results can help guide the design of identical sale and rent price models, for the purpose of estimating a quality adjusted price-to-rent ratio. It could seem that if those models at least account for apartment size, location, building age and time, they can yield price-to-rent ratios largely free of omitted variable bias. But this also depends on our motives. For the purpose of estimating only the median price-to-rent ratio, this may apply. But if we wish to study property-specific price-to-rent ratios, they obviously matter. For example the highest observed value of the house inspection score variable is 0.3. An example of a coefficient estimated for that variable in a window containing an observed value of 0.3 is 0.8117. So, including that variable makes a 27.6% difference for that specific property's valuation, compared to a property with an observed house inspection value of 0.0. This, for a variable with negligible share in explaining total variance.

A likelihood ratio test comparing the model and a restricted version containing only time, location, apartment floor size and building age strongly rejects the restricted model in favor of the full model, at the 99% confidence level.

6.4 Quality-adjusted price indices

The indices presented here are not meant to replace official HMS or Statistics Iceland indices. Rather they are displayed as a straight-forward product of the model and to demonstrate its versatility and usefulness, from the standpoint of macroprudential policy.

The upper panel of figure 16 displays geometric double-imputation real price indices for the multi-dwelling market segment of the greater Reykjavík residential real estate market. As noted in section 2, the main index there is the Törnqvist index, a geometric average of the Paasche and Laspeyres indices. The accumulated difference between the latter two, at the end of the sample period, is quite small. This is not surprising as we only cover the multi-dwelling segment in one small city in a country with relatively tight income and asset distributions.

Figure 16. Geometric price indices

Note: Geometric double-imputation real price indices for the greater Reykjavík multi-dwelling market, excluding Álftanes. Lower panel shows breakdown of Törnqvist-index m-o-m changes into the contribution of the intercept and last time-dummy on one hand, and quality changes caused by changing marginal characteristics prices on the other.

As noted in section 2, the Paasche index grows more slowly than the Laspeyres index in the usual scenario where the quality of traded housing grows over time. The Laspeyres, however, temporarily undercuts the Paasche index in the aftermath of the financial crisis. This highlights that in the aftermath of the financial crisis, traded properties' quality deteriorated slightly for a number of years. In addition to a lower prevalence of new buildings, this may reflect a tendency for lower quality housing to enter the market throughout the recession of 2008-2011, as higher-income households withstood the onslaught of the recession whilst lower income groups were faced with default and foreclosure or the necessity to scale down their housing consumption.

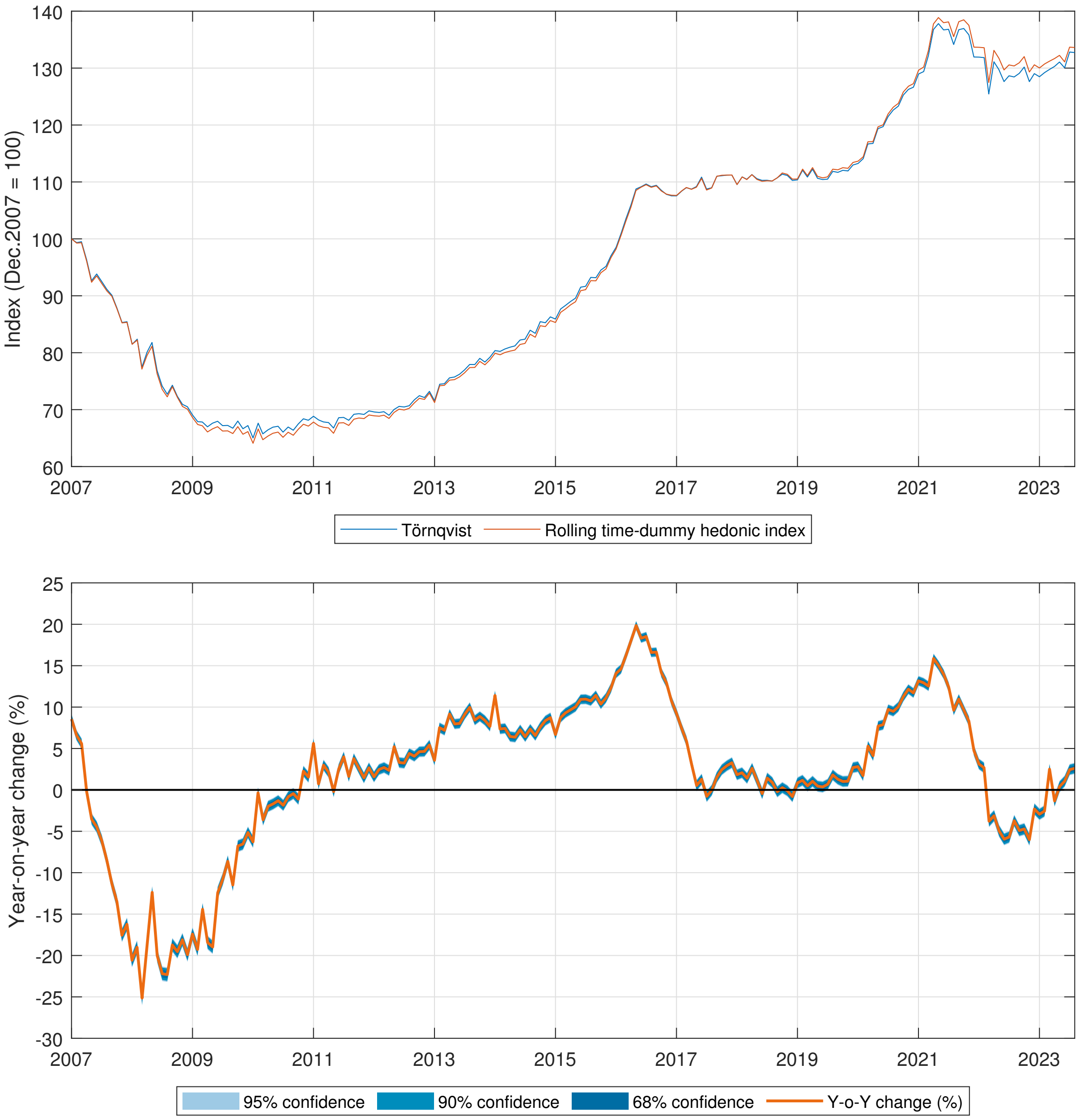
In the medium term, the Törnqvist index develops very similarly to the now discontinued non-quality adjusted HMS price index for greater Reykjavík multi-dwelling housing. The difference accumulated between December 2007 and January 2024, which can be labeled a quality-related bias in the HMS index, is only 3.7%.[42] This indicates that using the non-adjusted index to gauge medium term cycles in house prices, as has been done in the past, is not misleading. Month-on-month changes in the two indices are quite dissimilar, however. As the model is not designed specifically to produce price indices, a more thorough quality-adjustment could be achieved by adding more variables and interaction terms, while affording less consideration to multicollinearity. Then the accumulated quality bias would be greater.

The lower panel of figure 16 shows the breakdown of month-on-month changes in the Törnqvist-index, into the contributions of quality changes and quality-adjusted price level changes. In this context, changes in quality are due only to changing estimated marginal characteristic prices. The observed characteristics are unchanged between periods as the index measures the average price change between adjacent periods, of the same sample of properties. A shorter period and a simple breakdown are shown, simply to make the chart readable. As expected, the quality adjusted price-level emerges as the dominant factor. This applies most obviously to the years 2014 into 2017 and 2020 into 2021 as well as the short-lived period of decreasing prices from October 2022 to February 2023. This neat feature allows analysts to trace whether quality changes are important drivers of the index, and if so, which characteristics they relate to. The effect of new buildings is a good example of an effect that one might want to display as a separate contribution.

The most straightforward way to construct a price index from a rolling-window time-dummy hedonic model is not the Törnqvist index, but rather to use only the time-dummy coefficients to calculate the quality-adjusted price differential between the last and second-to-last period of each window, and then chain-linking those price differentials. This index is shown in figure 17. For the most part, it develops very similarly and sometimes identically to the Törnqvist index. This is appropriate as they are intended to measure the same thing.

[42] Also, part of the difference between the two can arise from different sample selection.

Figure 17. Rolling time dummy hedonic price index



Note: Rolling time-dummy hedonic real price index for the greater Reykjavík area multi-dwelling market, excluding Álftanes. Törnqvist-index for comparison. Lower panel shows y-o-y changes in the time-dummy index with confidence intervals constructed using the delta method.

A robustness check is performed to check for unwarranted shifts in the time-dummy index. As described in section 2, $\exp(\hat{\delta}^{Th})/\exp(\hat{\delta}^{T-1,h})$ and $\exp(\hat{\delta}^{T-1,h+1})/\exp(\hat{\delta}^{T-2,h+1})$ are two estimates of the same quality-adjusted price level change between the same two periods. This way, the model provides up to 16 different estimates of each price level change between periods. On the whole, there is very little variability in different estimates of the same adjacent-period price differentials. Comparing the time-dummy index to an averaged version where the geometric average price differentials are chain-linked, there are only minuscule differences. The accumulated difference between the two from December 2007 to July 2024 is only 0.6%. That difference does not accumulate gradually though. It is mostly formed in February and March 2010, when the sample size is at its smallest. This indicates that there may be an unwarranted downward shift in the time-dummy index in those periods, and the averaged version may be preferred. But using the averaged version means that the non-revisability criterion is violated, and there will be small revisions to the index for up to 17 months after it is first published.

A feature of hedonic price indices is that confidence intervals can be constructed for changes in the index. The lower panel of figure 17 shows monthly year-on-year changes in the time-dummy index with confidence intervals.[43] This is useful for those who are not only interested in house price developments, but also in the uncertainty about what those developments are.

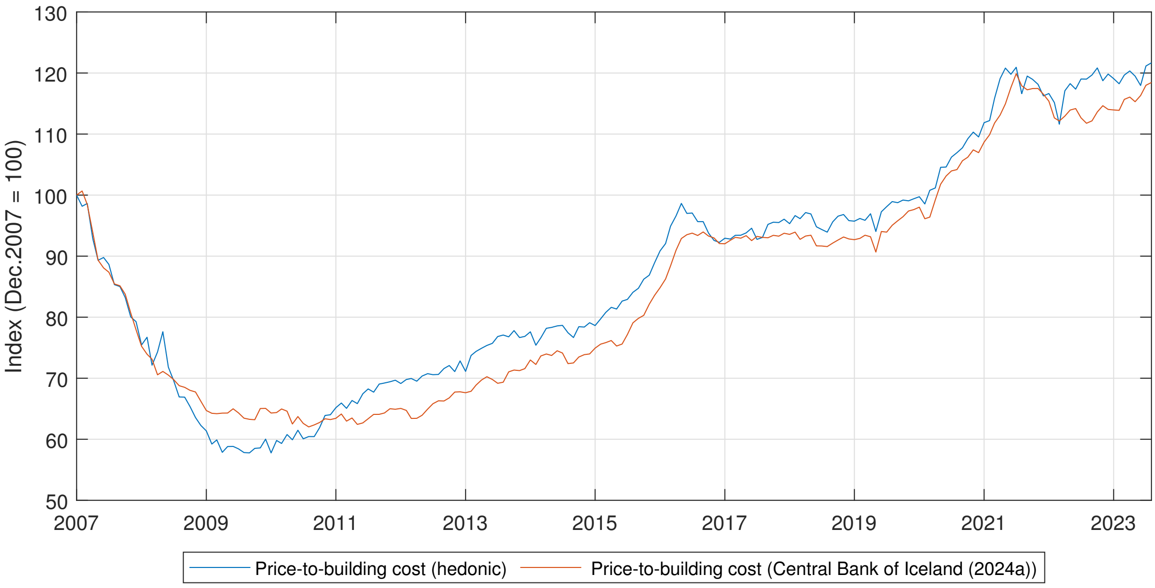
The results show very tight confidence intervals, indicating little uncertainty about the development of quality-adjusted house prices. It also provides a benchmark for how to describe price level changes. If the change is not statistically significant, then perhaps the price level is simply best described as relatively stable. This applies to the years 2019 and 2020. This approach may be particularly useful with regard to non-residential commercial property prices in the Reykjavík area, where the market is much more shallow and price level uncertainty is much greater. This is an avenue for future research.

As a last demonstration, the model is used to produce a price index which closely matches the building cost index provided by Statistics Iceland (2025). The reference building for the building cost index is a three-storied concrete multi-dwelling apartment building somewhere in the greater Reykjavík area. It has 18 apartments, an elevator and one dedicated parking spot for each apartment. Using this information, the price of an apartment which fits this description can be imputed for each period to construct a price index tailored to the building cost index.[44] For the characteristics included in the model, but not mentioned in the building cost index metadata, average values for new buildings for the whole sample period are used. This means the location price effect is a weighted average of area dummy price effects, where weights depend on area-turnover in new dwellings from 2006 to 2024. The reference dwelling

[43] In this case, the delta method (see e.g. Hayashi (2000), pp. 93-94) is applied to construct confidence intervals for year-on-year changes in the rolling time-dummy hedonic index. Diewert, Heravi & Silver (2009) show how confidence intervals can be constructed for changes in log-price hedonic imputation Paasche and Laspeyres indices as well.

[44] As fixed characteristics are used for the reference apartment the geometric Paasche, geometric Laspeyres and Törnqvist indices are identical.

Figure 18. Quality-adjusted price-to-building cost ratio



Note: Price-to-building cost ratio for the greater Reykjavík area multi-dwelling market. The hedonic ratio excludes Álftanes from the sample. Both ratios use Statistics Icelands' building cost index as the denominator.

is assumed to be located outside sub-assessment areas. It is of average size, is registered on the second floor (the average of the building cost index's reference building's three floors) with an elevator and carries one-third of the top-floor premium. It has the average aesthetics and inspection scores for new dwellings and the new dwelling-average combined number of toilets and bath fixtures.

Of course, the exact choice of characteristics for this sort of excercise is debatable. The hypothesis here is that building sector decisions on new investments depend on past sales prices of new dwellings rather than estimates of the general house price level, which places less emphasis on such effects as the new building premium and locational effects, when the median new dwelling is differently located than the median sold dwelling.

Figure 17 shows a price-to-building cost ratio calculated this way, compared to the price-to-building cost ratio published in Central Bank of Iceland (2024a) where the numerator is an official HMS non-quality adjusted multi-dwelling price index. In both cases, the denominator is the building cost index from Statistics Iceland. The medium-term development is similar, but short-run dynamics are quite different. The hedonic ratio indicates a sharper drop from December 2007 to the trough. The fall measures 42% for the hedonic version, compared to 38% for the other ratio. In addition, the hedonic ratio hits the trough much earlier. The recovery in the hedonic ratio is also sharper, reaching a higher peak in 2017. In the post-covid years, as the new building premium shoots up, the hedonic ratio flatlines excluding a short-lived drop in early 2023. Thus, the hedonic ratio indicates a more persistent incentive to build in the post-covid years.

7 Conclusion

In this paper, it is argued that hedonic modeling is an advantageous approach to residential real estate market analysis for the purposes of macroprudential policy making in Iceland. The quality of traded dwellings in the greater Reykjavík market is shown to be variable, stemming both from changing property characteristics in both the sales and rental markets, and from time-varying marginal characteristics prices in the multi-dwelling sales market. This is shown to call for quality-adjustment methods, particularly with regard to the comparison of house prices to fundamentals, a mainstay of systemic risk analysis. In order to obtain a price-to-rent ratio with a meaningful level, and thus applicable for equilibrium analysis, and meaningful development over time unbiased by quality changes, hedonic methods are needed. Hedonic methods can also provide the means to obtain a more meaningful price-to-building cost ratio, both in terms of new dwelling-prices, but potentially also with regard to land prices, an important component of building cost, currently omitted from the measure. Also, hedonic methods provide a way to make meaningful geographical analysis of the real estate market, which could potentially underpin geographically differentiated application of macroprudential tools. Furthermore, the development over time of individual estimated coefficients in a hedonic model can provide valuable insights into supply and demand dynamics in the market.

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Appendix A: Dataset treatment

7.1 Sales contract data

The HMS dataset on residential real estate sales contracts, has a sample size of 155,974 spanning the period from 1st July 2006 to 31st July 2024.[45] For each contract, the dataset contains information on prices, transaction dates, contract characteristics, property characteristics and various property registry information.

The building type is an important category; whether each property belongs in the detached market segment or the multi-dwelling segment. Within the detached segment it matters further if the property is semi-detached and if so whether it is a duplex, terraced, or is part of a two-dwelling house. Within the multi-dwelling segment it matters if the apartment is serviced and whether it is unsanctioned or in a building designed as non-residential. In order to make these distinctions the dataset has different variables, which are mostly in agreement, but occasionally in contradiction. They are the "Housing type" variable and the IST120 variable, a categorization based on the ÍST120-standard for registration and classification of geographic information. To ascertain the correct classification of property types, the following procedure is followed:

1. All observations where "Housing type" and IST120 are in accordance and clearly indicate the property type are kept without manual inspection. This represents around 97% of the dataset.

2. New dummy variables are created for each of the following: Detached house, duplex, terraced house, apartment in a detached or semi-detached house where the apartment is either unsanctioned or the building is categorized as (non-residential) commercial real estate, apartment in multi-dwelling building, serviced apartment in multi-dwelling building and, lastly, apartments in multi-dwelling buildings where the apartment is either unsanctioned or the building is categorized as non-residential. Each observation out of the 97% in step 1 is assigned a value of 1 on one and only one of these new variables, 0 on the others.

3. The remaining observations are manually inspected using various online information systems, such as Google Maps, Reykjavík's online City Viewer and fastinn.is, a free

[45] The data is retrieved from the HMS database with only minimal filtering. Only contracts marked as "usable" by the HMS and only contracts marked as pertaining to exactly one property are retrieved. The same applies to the data on rent contracts.

online database of for-sale listings. For each unique combination of values on “Housing type” and IST120 a decision on the property categorization according to the new variables created in step 2, or elimination, is made at the group level.[46]

In this process 160 contracts are eliminated from the sample. Unwanted and imperfect observations are then discarded based on the following criteria, and in the following order:

1. The variable “Housing type”, which assigns a building type to the property underlying each contract, is restricted to the categories “Detached house”, “Semi-detached house” and “Multi-dwelling building”.[47] With this restriction, nine commercial properties, garages without accompanying apartments and stand-alone sheds are eliminated from the sample. Detached and semi-detached houses are kept in the sample for the purpose of descriptive statistics in section 4, although the model presented in section 5 is estimated exclusively on the multi-dwelling segment.

2. A tax category identifier, which indicates the property’s classification for the purpose of levying property taxes is restricted to class A, which includes only residential property, summer cabins, inheritance lands and farm-related real estate. This restriction eliminates 263 contracts. They are kept in the sample for the purpose of descriptive statistics in section 4, but discarded in section 5.

3. A variable which identifies the property’s location by municipality is restricted to the six municipalities in the capital city area. Those are Reykjavík city and five suburbs; Kópavogur, Hafnarfjörður, Garðabær, Mosfellsbær and Seltjarnarnes. As of 2023, these six municipalities were home to almost 64% of the country’s population and contained almost 65% of the country’s total number of dwellings.[48] With this restriction, 50,425 contracts are eliminated.

4. The six municipalities in the sample cover both urban and rural or uninhabited areas. A locational variable which indicates the location of each property within a list of assessment areas is restricted to urban and suburban areas. Thereby, 731 contracts relating to inheritance lands and farm-related real estate are eliminated.

[46]The manual inspection in step 3 reveals, first, that making decisions at that group level is largely appropriate. Second, IST120 is generally the more reliable variable and in most cases where the two variables contradict each other, IST120 is verified as the correct one.

[47]The Icelandic terms, used in the database are “Einbýlishús”, “Sérbýlishús” and “Sambýlishús” respectively.

[48]See Statistics Iceland (2024c) and HMS (2024).

5. A utilization descriptor variable is restricted to descriptions indicating that the property is a dwelling.[49] This eliminates 299 contracts, e.g. for parts of properties and for unsanctioned housing. They are kept in the sample for the purpose of descriptive statistics in section 4, but discarded in section 5.

6. The sample is restricted to properties at building stages 7, signifying fully constructed buildings, and 8, signifying fully constructed buildings without a fully finished lot, e.g. without pavements, soil and vegetation. Newly built apartments in multi-dwelling buildings are sometimes sold while in building stage 8, although the seller makes a commitment to finish the lot at a later date. By this restriction, 2,714 contracts for properties at lower building stages are discarded.

7. 67 contracts where the year of construction is missing are eliminated.

8. Total floor area in square meters is restricted at the upper tail of the distribution. 34 contracts pertaining to property larger than or equal to $500m^2$ in floor area are filtered out. The truncation occurs exclusively in detached houses.

9. Five contracts where balcony floor is registered as a negative number are eliminated.

10. The selling price variable is only filtered with respect to missing and extreme values which are highly likely to be errors. 151 contracts with a missing selling price are eliminated. Two contracts with implausibly high prices are filtered out, in addition to five contracts with a registered price of zero.

11. A variable measuring the per-square meter price by dividing the price variable by total floor area is filtered with regard to abnormally high and low values. By setting the maximum allowed per-square meter price to ISK 2.5 million, 17 contracts are filtered out. 15 out of those 17 are contracts where total floor area is registered as $0m^2$, so the per-square meter price is registered as infinite. By setting the minimum allowed per-square meter price to 120,000 ISK, 89 contracts are discarded.

12. Lastly, 48 contracts where building age, i.e. the year of the contract date minus the registered year of construction, is < -2 are discarded. Where building age is registered as -1 or -2 it is recoded as 0.

[49] The descriptions allowed are “Detached house”, “Duplex”, “Terraced”, “Apartment and garage”, “Apartment on floor”, “Apartment in basement” and “Apartment in attic”.

After filtering, the sample contains 100,955 observations and has been reduced by roughly 35%, mostly based on geographical location. 78,420 observations relate to the multi-dwelling market and 22,535 observations to the detached and semi-detached market. The average quarterly sample is 1,074 observations for multi-dwelling buildings, and 302 for detached and semi-detached houses.

7.2 Rent contract data

The HMS dataset on residential rent contracts has a sample size of 105,004 observations spanning the period from 1st January 2011 to 31st December 2022. Like the sales contract data it is retrieved from the database with only minimal filtering.

The rent contract data is filtered in the same way as the sales contract data with regard to location, building category, utilization description, tax class, size and prices. Furthermore, filtering occurs on two important criteria. First, 855 rent contracts marked as between related parties are filtered out as they are not certain to represent market prices. Second, a variable which categorizes landlords by operating motive is applied to discard contracts where the landlord operates on a social welfare motive. Contracts where landlords are individuals, legal persons operating on a profit motive or non-profit legal persons which are nonetheless deemed likely to charge market rent are retained. 5,471 contracts where landlords are municipalities, municipal agencies, housing co-operatives or other entities intended to offer below-market rent prices and receive endowment capital from the government are discarded.

The same procedure as with the sales contract data is performed to ascertain the correct classification of property types. In this procedure, 991 rent contracts are eliminated from the sample and close to 1,000 contracts' property types are either verified or recoded according to the new variables created in step 2 of the procedure. After filtering, the rent contract sample contains 56,354 observations, split between 43,194 for dwellings in multi-dwelling buildings and 13,150 for detached and semi-detached houses.

Appendix B: Grouped assessment areas

Column	HMS area identifiers	Description	Avg. $\hat{\beta}_k$
0	11, 20, 25-27, 31	Rvk. Miðbær, Vesturbær n. Hringbrautar	N/A
1	70-72, 74-75, 400, 402-405	Rvk. Vesturbær s. Hringbrautar, Seltjarnarnes	-0.0284
2	80-81, 94	Rvk. Hlíðar, Suðurhlíðar, Valsreitur	-0.0422
3	90, 92-93	Rvk. Holt, Tún, Háteigsvegur, Hlíðar	-0.0614
4	95, 100-102	Rvk. Laugarneshverfi, Vogar, Teigar	-0.1015
5	110, 120	Rvk. Grafarvogur s., Bryggjuhverfi	-0.2223
6	130, 140, 180, 181	Rvk. Grafarvogur n., Grafarholt, Úlfarsárd.	-0.2376
7	150	Rvk. Seljahverfi	-0.2893
8	160, 161, 170, 171, 172	Rvk. Breiðholt n. Breiðholtsbrautar	-0.3011
9	200, 210, 220, 270	Rvk. Árbær, Norðlingaholt	-0.2292
10	85, 91, 280-284	Rvk. Fossvogur, Kringla, Leiti, Réttarholt	-0.0864
11	300, 320, 330	Kópavogur vestan Reykjanesbrautar	-0.1735
12	340, 350-351	Kópavogur austan Reykjanesbrautar	-0.2072
13	500, 510-512, 520, 530, 540, 550, 560	Garðabær	-0.1169
14	600-602, 650	Hafnarfjörður norður, vestur, Setberg	-0.2483
15	620, 630, 640, 680	Hfj. Ásland, Börð, Hvaleyrarholt, Vellir	-0.2800
16	800, 810, 820, 840, 850	Mosfellsbær	-0.2227

Table 2: Column refers to column in the $AREA^h$ matrix. Column number 0 refers to the base area which is omitted. HMS areas refer to the geographical areas defined by the HMS for the purpose of property valuation.

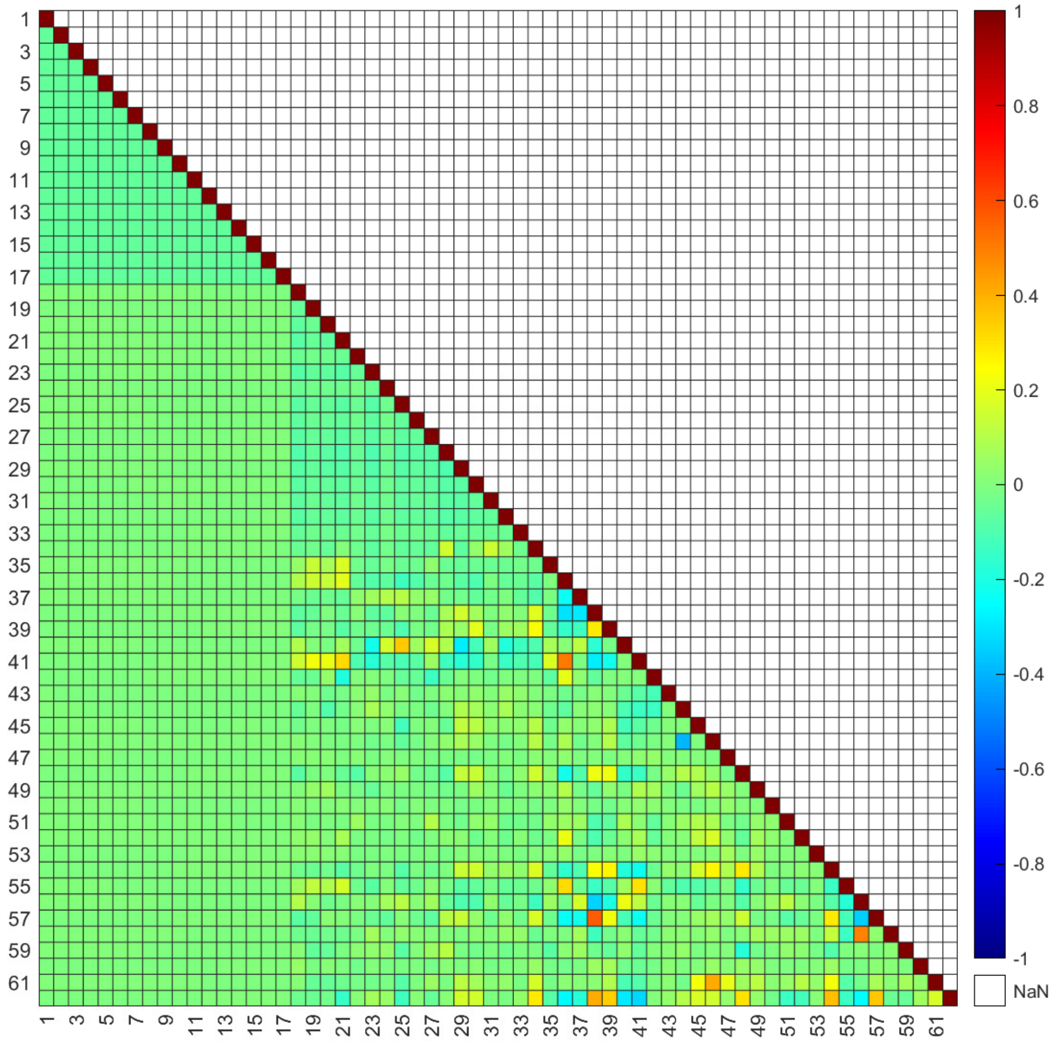
Appendix C: Grouped sub-assessment areas

Column	HMS area identifiers	Description
1	31, 65, 15, 16	Proximity to green areas
1	6, 10, 11, 18, 32, 33, 34, 41, 47, 49, 50, 51, 53, 54, 60, 64, 66, 105, 106, 116	Ocean front, lake front
1	44, 52, 58, 121, 122	High-quality and luxury buildings
2	1, 2, 3, 17, 35, 36, 39, 40, 56, 63	Proximity to strongly negative environmental factors, mostly heavy traffic

Table 3: Column refers to column in the $SUBAREA^h$ matrix. HMS areas refer to the geographical areas defined by the HMS for the purpose of property valuation.

Appendix D

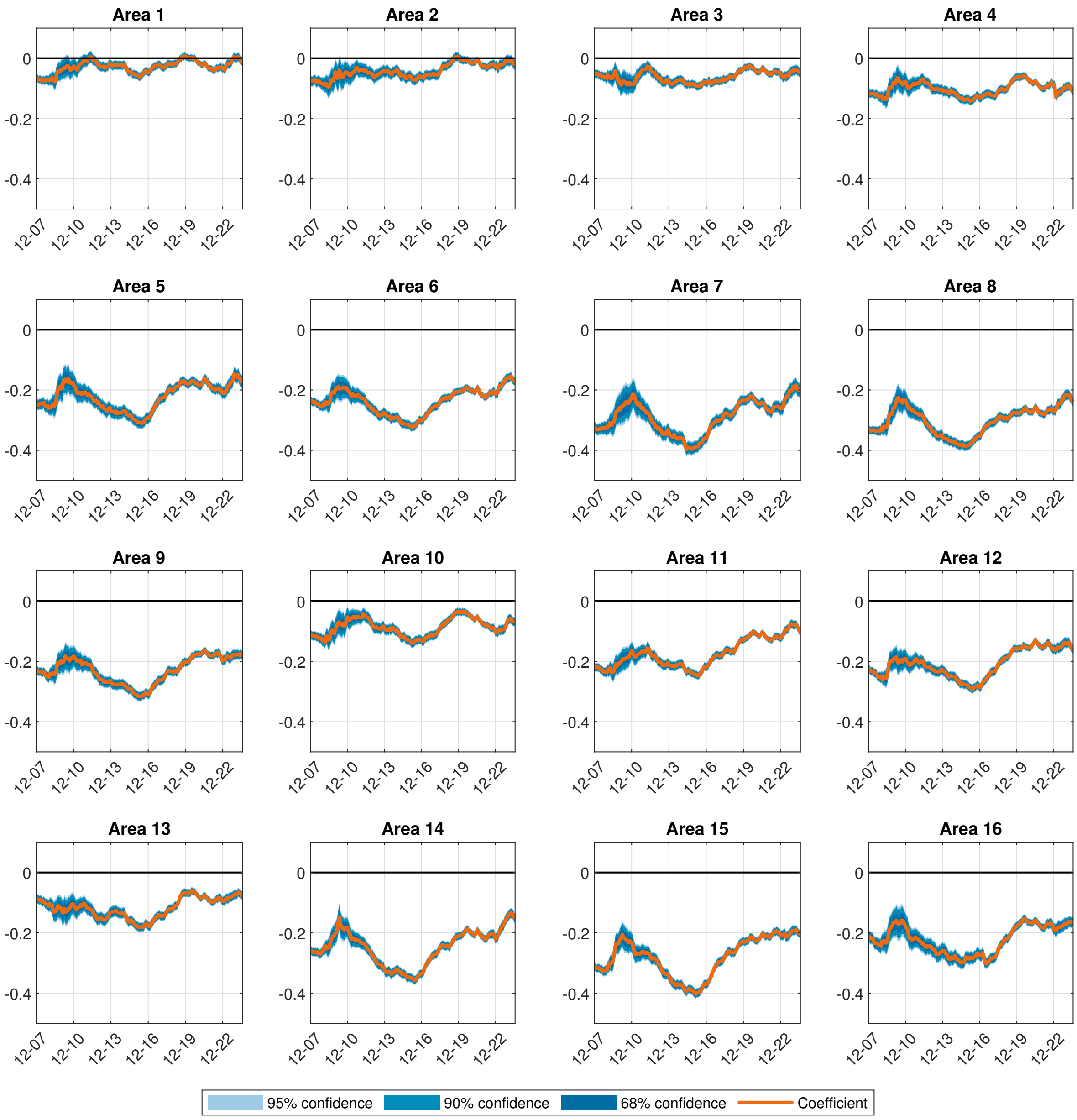
Figure 19. Average pairwise regressor correlation matrix



Note: Each element in the lower triangular part is the arithmetic average of the respective elements in the pairwise correlation matrices for all 200 windows.

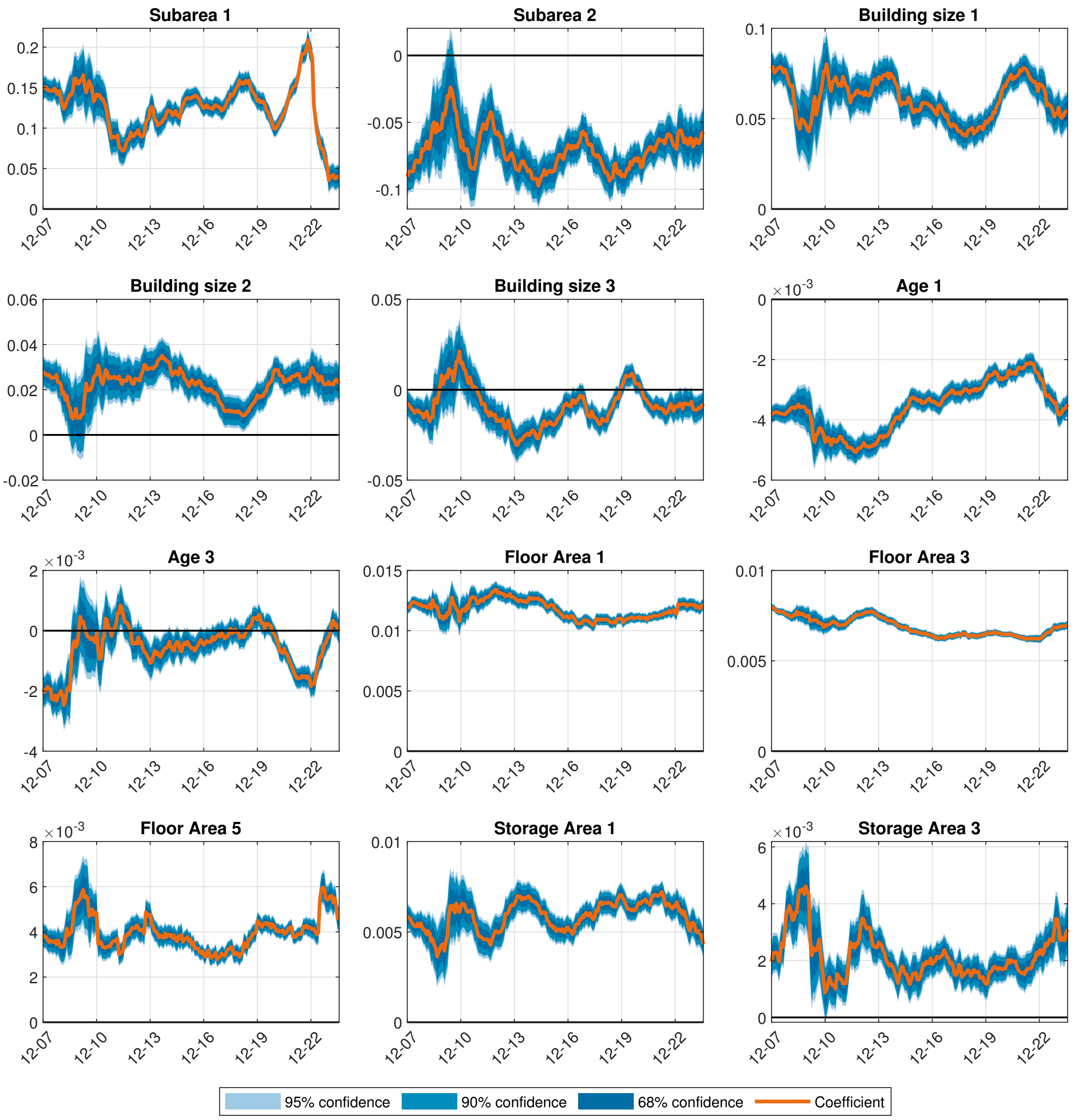
Appendix E

Figure 20. Estimated log-real price effect of area dummy variables



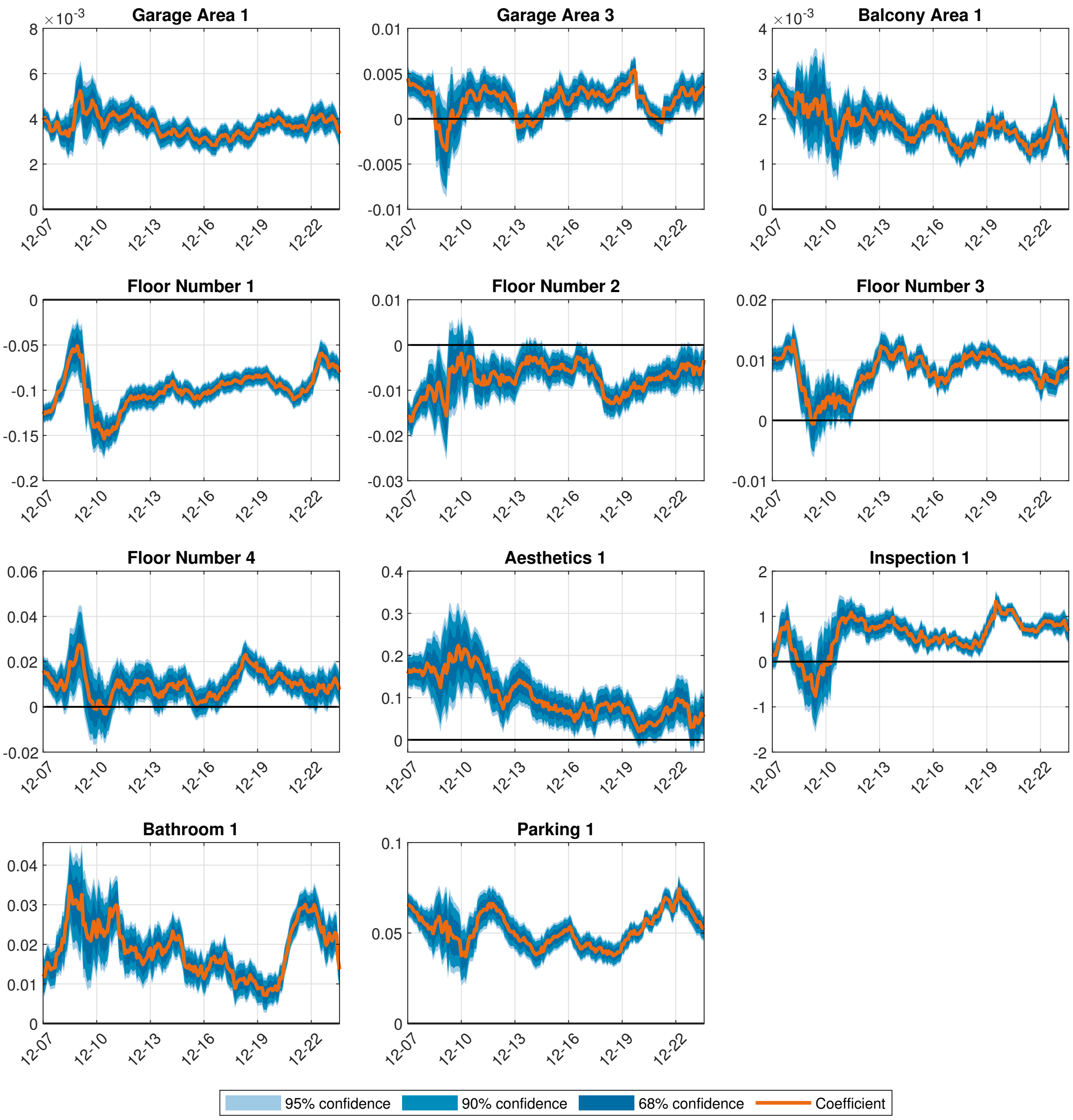
Note: Log-real sales price effect compared to the base area, which is central Reykjavík city. Each coefficient is estimated using an 18 month rolling-window ending in the month indicated by the horizontal axis. Greater Reykjavík area multi-dwelling market, excluding Álftanes, July 2006 - July 2024. Confidence intervals are constructed using the Student's t-distribution with $N_h - 62$ degrees of freedom, where N_h is the sample size in a given rolling-window.

Figure 21. Estimated marginal log-real characteristics prices



Note: Each coefficient is estimated using an 18 month rolling-window ending in the month indicated by the horizontal axis. Greater Reykjavík area multi-dwelling market, excluding Álftanes, July 2006 - July 2024. Only slope coefficients are shown for splined variables, not bucket-specific intercepts. Confidence intervals are constructed using the Student's t-distribution with $N_h - 62$ degrees of freedom, where N_h is the sample size in a given rolling-window.

Figure 22. Estimated marginal log-real characteristics prices



Note: Each coefficient is estimated using an 18 month rolling-window ending in the month indicated by the horizontal axis. Greater Reykjavík area multi-dwelling market, excluding Álftanes, July 2006 - July 2024. Only slope coefficients are shown for splined variables, not bucket-specific intercepts. Confidence intervals are constructed using the Student's t-distribution with $N_h - 62$ degrees of freedom, where N_h is the sample size in a given rolling-window.