The dynamics of regional housing markets

Topics: Quality heterogeneity, sorting and housing affordability

Dynamikken i regionale boligmarkeder

Emner: Kvalitetsheterogenitet, sortering og boligkjøpekraft

Philosophiae Doctor (PhD) Thesis

Mari O. Mamre

Norwegian University of Life Sciences
Faculty of Business and Economics

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Supervisors and Evaluation Committee

PhD supervisors

Main supervisor: Dag Einar Sommervoll, Professor School of Economics and Business, Norwegian University of Life Sciences (NMBU)

Co-supervisor: André Anundsen, Affiliated Research Professor, Housing Lab, Oslo Metropolitan University (OsloMet)

Evaluation committee

Endre Jo Reite, Associate Professor, NTNU Business School, Norwegian University of Science and Technology (NTNU)

Brano Glumac, Lecturer, Henley Business School, University of Reading

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Science never solves a problem without creating ten more

George Bernhard Shaw

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Authors: Mamre, M.O and Sommervoll, D.E.

Paper II. "Search Ripples in Urban Housing markets: the Quality-Location Trade-off". *Submitted to journal.*
Authors: Mamre, M.O and Kivedal, B.K.

Paper III. "Income and Household Location Choice in Amenity-rich and Amenity-poor Cities".
Authors: Adams, Z., Liebi L., and Mamre, M.O.

Paper IV. "Housing Affordability of a Representative Local First-Time Buyer". *Tidsskrift for boligforskning* 4.1, 7-27 (2021). https://doi.org/10.18261/issn.2535-5988-2021-01-02.
Authors: Mamre, M.O.

Abstract

There are several reasons why housing markets are different from other economic markets. Housing markets are fundamentally local. The dynamics of these markets are significantly influenced by factors that vary spatially, such as local economic activity, regional policies, and the level of amenities. This is largely attributed to the immobility of houses, unlike many other goods. While housing markets are known to be aligned with macroeconomic factors like interest rates and local incomes, the microeconomic aspects of housing have become increasingly relevant in housing market research. Another prominent feature is that houses are vastly heterogeneous in their qualities, and many aspects of this quality is unobserved in research and economic models. Furthermore, housing markets primarily function as search markets, with households typically making choices based on housing quality rather than quantity.

This thesis addresses some of these aspects of housing markets. It measures the renovation quality of transacted houses and investigates whether households search more intensively for low-quality housing during booms. It also explores whether households sort differently by income in amenity-rich and amenity-poor cities compared to the larger urban area. Market frictions and fluctuations in buyer-seller ratios, location amenities, and policy measures can all contribute to the housing market equilibrium and the sorting of households. Moreover, housing affordability issues has become a main policy objective in many countries struggling with soaring housing prices.

Paper I aims to measure *the renovation level of houses* transacted using real estate listings and prospectuses in urban housing markets and estimate the market premium of renovation. We find a significant positive premium of 5-7 percent for renovated dwellings and a negative premium of 9-10 percent for unmaintained dwellings. Interestingly, these premiums vary significantly over time, exhibiting a counter-cyclical effect. Ignoring renovation information biases short-term house price growth estimates downward, a crucial insight for those monitoring housing market trends.

Building on this, Paper II studies *ripples of housing search* between different housing quality tiers during booms and busts. Overall, these findings point to a trade-off between quality and location. To maintain a better location quality, more buyers may be willing to reduce unit quality. Since most cities' housing markets are complex systems with spatial patterning of housing qualities and price levels, our findings support that variations in the demand for quality during booms and busts is a fundamental driver of variations in house price growth within and across neighborhoods and housing quality tiers.

Paper III investigates *household location choices by income within city regions*. Our approach emphasizes the importance of location quality differences and amenity concentration for hypotheses about the income-distance gradient. Although their concentration may be related in a complex way to other fundamental drivers, our findings reinforce the importance of amenities for household location choice. In line with theory, we estimate an inverse relationship between the degree of amenity-superiority of the city center and the income - distance gradient. Our estimates also support that more households respond by relocating to the city edge in response to increased access to public transportation and lower taxes at the city edges. These insights have significant implications for the amenity-based sorting literature and local urban planning.

Finally, Paper IV construct standardized measures for the *housing affordability* of representative first-time buyers in regional housing markets. This method provides multiple gains compared to simpler measures that are often used, such as price-income rates, and is also suited to regular updates. It also compares the estimates to actual first-time purchases in these markets. These results suggest that housing affordability has significantly decreased over the last decade, with many young people stretching their finances to enter the market.

Norsk sammendrag

Det er flere grunner til at boligmarkeder skiller seg fra andre økonomiske markeder. Boligmarkeder er grunnleggende lokale. Dynamikken i disse markedene påvirkes betydelig av faktorer som varierer geografisk, slik som lokal økonomisk aktivitet, regionale politiske virkemidler, og nivået av områdeattributter. Dette skyldes i stor grad boligers immobilitet, i motsetning til mange andre varer. Selv om boligmarkedene er kjent for å være i takt med makroøkonomiske faktorer som rentenivå og lokale inntekter, har mikroøkonomiske aspekter ved markedet blitt stadig mer relevant i boligmarkedsforskningen. En annen fremtredende egenskap er at hus er svært heterogene i sine kvaliteter, og mange aspekter ved denne kvaliteten er ikke observert i forskning og økonomiske modeller. Videre fungerer boligmarkedene primært som søkemarkeder, med husholdninger som vanligvis tar valg basert på boligkvalitet i stedet for kvantitet.

Denne avhandlingen tar opp noen av disse aspektene ved boligmarkedene. Den måler renoveringskvaliteten på omsatte boliger og undersøker om husholdninger søker mer intensivt etter boliger av lav kvalitet under perioder med sterk etterspørsel. Den utforsker også om husholdninger sorterer forskjellig etter inntekt i attributt-rike og attributt-fattige byer sammenlignet med det større byområdet. Markedsfriksjoner og svingninger i kjøper-selger-forhold, områdeattributter og politiske virkemidler kan alle bidra til boligmarkedets likevekt og sorteringen av husholdninger. I tillegg har økt boligkjøpekraft blitt et stadig viktigere politisk mål i mange land som opplever skyhøye boligpriser.

Artikkel I tar for seg å måle renoveringsnivået på omsatte boliger ved hjelp av eiendomsannonser og boligprospekter i urbane boligmarkeder og estimere markedspremien for renovering. Vi finner en betydelig positiv premie på 5-7 prosent for renoverte boliger og en negativ premie på 9-10 prosent for boliger som ikke er vedlikeholdt (oppussingsobjekter). Interessant nok varierer disse premiene betydelig over tid, og viser en mot-syklisk effekt. Å ignorere renoveringsinformasjon gir en skjevhet i estimatene for boligprisveksten på kort sikt, en viktig innsikt for de som overvåker boligmarkedsutviklingen.

På bakgrunn av dette studerer Artikkel II bølger av boligsøk mellom forskjellige boligkvalitetsnivåer under opp- og nedgangstider i boligmarkedet i fire norske byer. Samlet sett peker disse funnene på en avveining mellom kvalitet og beliggenhet. For å opprettholde en bedre beliggenhetskvalitet, kan flere kjøpere være villige til å redusere boligkvaliteten. Siden de fleste byers boligmarkeder er komplekse systemer med romlige mønstre av boligkvaliteter og prisnivåer, støtter våre funn at variasjoner i etterspørselen etter kvalitet under opp- og nedgangstider er en grunnleggende driver for variasjoner i boligprisveksten i og mellom nabolag og boligkvalitetsnivåer.

Artikkel III undersøker husholdningers lokasjonsvalg etter inntekt innen byregioner. Vår tilnærming understreker betydningen av forskjeller i stedskvalitet og konsentrasjon av områdeattributter for hypoteser om inntekt – avstand gradienten. Selv om deres konsentrasjon kan være relatert på en kompleks måte til andre grunnleggende drivere, forsterker våre funn viktigheten av områdeattributter for husholdningers lokasjonsvalg. I tråd med teori, estimerer vi et negativt forhold mellom graden av attributt-superioritet i bysentrum og inntekt – avstand gradienten. Våre anslag støtter også at flere husholdninger responderer ved å flytte til bykanten som svar på økt tilgang til offentlig transport og lavere skatter ved bykantene. Disse funnene har betydelige implikasjoner for litteraturen om attributtbasert sortering og lokal byplanlegging.

Til slutt konstruerer Artikkel IV standardiserte mål for boligkjøpekraften til representative førstegangskjøpere i regionale boligmarkeder. Den foreslåtte metoden gir flere fordeler sammenlignet med enklere mål som ofte brukes, for eksempel pris - inntektsrater, og er også egnet for regelmessige oppdateringer. Artikkelen sammenligner også estimatene med faktiske førstegangskjøp i disse markedene. Disse resultatene antyder at boligkjøpekraften er betydelig redusert i løpet av det siste tiåret, med mange unge som strekker økonomien sin for å komme inn på markedet.

Owning a home is keystone of wealth…both financial affluence and emotional security

Suze Orman

1 Introduction

1.1 Motivation

This thesis consists of four papers, where the first two are closely related. The objectives of this thesis are: (i) to enhance our understanding of housing quality heterogeneity and its impact on housing market models and (ii) explore how households may trade off housing quality and location during booms and busts. It also seeks to address (iii) location decisions and spatial sorting by income in cities with different relative amenity quality levels, and (iv) construct standardized measures for the housing affordability of representative first-time buyers in disparate regional housing markets.

This introduction outline important aspects of the theoretical background for the papers in this thesis such as hedonic theory, endogenous housing market search, and amenity-based sorting models. To motivate the economic mechanisms and empirical findings in Papers I-II, a simple matching model with heterogeneous housing qualities and household incomes is simulated in this introduction. Standard economic models assume that houses are homogeneous and determine a single equilibrium house price. As a result, equilibrium price growth for all houses will turn out identical, and the models cannot explain the differential effects typically found in the cross section of houses during booms and busts. The results of the simulations show that in this framework, a negative shock to the housing inventory during a boom will lead to a disequilibrium where higher-income households are matched with lower quality units, thereby contributing to higher price growth in these segments.

1.2 Theoretical background and implications

Paper I-II makes use of *hedonic valuation* and the theory that by observing actual location and housing choices, it is possible to find or *infer* demand for houses and location[1]. According to the theory, it is possible to estimate household's willingness to pay for specific hedonic characteristics, such as renovation quality (see Rosen, 1974). The hedonic model is also a useful starting point for the construction of house price indexes and provide an estimate of the growth in prices for houses of otherwise constant quality.

1.2.1 Hedonic valuation

The term hedonic valuation is commonly used for the branch of literature in the latter case when the interest concerns the willingness to pay for or value of specific attributes yielding utility or disutility to the residents. A second branch of this literature uses hedonic methods to conduct price valuations of individual houses and construct house price indices which aim to control for important differences in composition and quality over time and between areas. We begin with the classical contribution of Rosen (1974).

The classical hedonic model

The economy consists of $i = 1, \dots, N$ consumers with rational expectations. They derive utility from k housing characteristics (including location amenities) $\boldsymbol{Z}$, for $k = 1, \dots, K$, and other consumption, represented by a composite good C. They have a fixed income Y and face a price function $P(\boldsymbol{Z})$ that maps the characteristics of the various housing characteristics into a house price. Utility is represented by a time-separable utility-function $u(.)$ that satisfies standard regularity-conditions[2] $u = u(\boldsymbol{Z}, C, \boldsymbol{\alpha})$. Where $\boldsymbol{\alpha}$ is a vector of observed and unobserved factors which may characterize the idiosyncratic preferences of the household or other idiosyncrasies arising from poor matching or other violations of the strong assumption of the neo-

[1] Hedonic valuation is also popular frameworks in other commodity good areas such as industrial and consumer goods.

[2] Such as differentiability and convexity.

classical theory.[3] The household chooses a house with a bundle of characteristics, and consumption level to solve

$$\max_{\boldsymbol{Z},C} \; u(\boldsymbol{Z}, C, \boldsymbol{\alpha}) \;\; s.t. P(\boldsymbol{Z}) + C \; \leq y_i$$

Utility-maximization requires (for continuous characteristics)

$$\frac{\frac{\partial(\boldsymbol{Z}, C, \boldsymbol{\alpha})}{\partial Z_k}}{\frac{\partial(\boldsymbol{Z}, C, \boldsymbol{\alpha})}{\partial C}} = P_k \quad , \; \forall k$$

The derivative P_k is referred to as *the hedonic price* of characteristic k and $P(\boldsymbol{Z})$ is the hedonic price function. From this we can derive implicitly *the bid rent function* $\beta(\boldsymbol{Z}, C, \alpha, Y)$ which is the amount a household is willing to pay for the housing good as a function of the characteristics, and for given income and utility level of the household. Combined we get the well-known result that the optimal housing choice is characterized by equality between the slope of the bid rent and the hedonic price

$$\frac{\frac{\partial u(\boldsymbol{Z}, C, \boldsymbol{\alpha})}{\partial Z_k}}{\frac{\partial u(\boldsymbol{Z}, C, \boldsymbol{\alpha})}{\partial C}} = P_k = \frac{\partial \beta(\boldsymbol{Z}, C, \boldsymbol{\alpha}, Y)}{\partial Z_k}$$

There is also a supply side that constitute the basis for a market equilibrium, however the main interest in hedonic analysis often centers on the demand side. Estimation is based on parametric models in the classical approach, aiming to estimate $P(\boldsymbol{Z})$ on cross section microeconomic data on transacted dwellings where each house is noted by a i-subscript and where $i = 1, .., N$, with characteristics. The standard case is a linear regression model with an error term e_i: $P_i = \beta_0 + \sum_k \beta_k Z_k + e_i$.

[3] In particular, the assumptions of a market equilibrium and that sellers and buyers can find each other and match supply with demand.

Unbiased and consistent estimation of the marginal willingness to pay for individual attributes hinges on the model's capacity to align with the theory. This is particularly important if the purpose of the study is to make inference on demand and perform hedonic valuation estimation of willingness to pay for attributes such as renovation quality or amenities[4].

Challenges to classical approaches to hedonic estimation

A first difficulty that arises in applications of the hedonic model stems from the heterogeneity of housing and the fact that the household incorporates several factors into their housing choice, such as proximity to the workplace and neighborhood amenities. Other difficulties include standard problems of regression models such as finding the proper specification and non-normality of the errors. Moreover, parametric implementations often rely on quite strong assumptions, such as homogenous households and where any idiosyncrasies in preferences or deviations from market equilibrium (above denoted $\boldsymbol{\alpha}$) is captures by an error term. Lastly, a profound identification challenge may be expected to arise in the endeavor to estimate demand for the various characteristic if the model suffers from endogeneity issues. Several recent advances improve upon some of these pitfalls by use of non-parametric methods (see e.g., Bajari & Kahn, 2005),

Random Forest algorithms

In Paper I, we want to relax functional form restrictions and open for heterogeneous effects of renovation temporally. This is particularly appealing since our estimation period is so volatile, a clear violation of the classical assumptions of the hedonic theory presented, and we are dealing with a complex urban housing market. Random forest algorithms offer a non-parametric approach to approximating the statistical relationship between explanatory variables ($\mathbf{x}$), providing a robust alternative for modeling complex data structures. These algorithms work by

[4] There is a rich literature on hedonic valuation of environmental dis-amenities such as pollution or noise, and amenities such as green structures and sunlight.

creating a "forest" of decision trees, each built on a different subset of the data, and averaging their predictions for a more accurate and stable estimate.

Several studies highlight the superiority of random forest models in hedonic house price models (see Yoo et al., 2012; Ceh et al., 2018; Dimopoulos et al., 2018) and other challenging prediction problems. Auret & Aldrich (2012), in particular, demonstrate that random forest algorithms are superior at detecting non-linear relationships between variables using simulated data, outperforming classical linear regression models. Therefore, random forest models may provide more reliable house price predictions in cases where violations of the assumptions of the classical regression model are serious, or they may strengthen our confidence in the classical models if the results turn out to be similar. Other related machine learning algorithms, such as artificial neural networks (ANN) and non-parametric elements in hedonic time-dummy regressions, offer additional approaches for handling complex data structures (see e.g., Bao et al., 2004).

1.2.2 Endogenous housing market search

In Paper II, we study housing search intensity by quality tier, building on the model of endogenous housing search proposed by Williams (2018). In this model, buyers and sellers enter a housing market with imperfect elasticity. Buyers screen houses for sale across different quality tiers of the housing market, selecting a set of houses within each tier to further investigate. All houses within a tier share similar attributes on one or more dimensions, such as location, size, price, and renovation quality. As Williams elaborates, rational buyers control both their initial screening of listings and subsequent search intensities, such as house visits, to maximize their expected benefits from the search. However, in competitive housing markets, these benefits are influenced by the behavior of other buyers, thus search is endogenous in equilibrium.

The model predicts that surges in search activity will initially occur in the highest quality tier and then ripple outward into lower quality tiers. In the context of the Norwegian market, where the vast majority of buyers use the common electronic site Finn.no to screen houses for sale and house visits are typically open to all buyers, thus increasing the visibility of competitor buyers, this model offers particularly relevant insights. While empirical evidence of spatial ripple effects exists in the literature, evidence of a similar quality ripple and its effects is far less studied.

1.2.3 Simulations in a matching model of housing demand with different house qualities

The findings of Paper I-II of varying renovation premiums and cyclical shifts in search by quality tier implies that there is one or several driving mechanisms involved. In the following, a stylized model of housing demand is considered, as outlined in (Landvoigt et al., 2015)[5]. The purpose is to highlights important ways booms and busts in the housing market may affect demand and prices in various quality segments in the housing market differently. Based on this model, the affordability channel and a shock to the housing inventory, the number of houses available for purchase, is explored. This exposition separates from the framework presented there by incorporating income instead of wealth, and by considering a shock to inventory in a comparative statics analysis.

The model

A group of prospective buyer households faces an inventory of available houses. Houses are indivisible and come in different qualities indexed by $h \in [0,1]$. The quality index h summarizes characteristics of houses that households value (for instance size, location, interior or location). The inventory of houses by quality is described by a strictly increasing cumulative distribution function $G(h)$.

Every prospective buyer household buys exactly one house in this competitive market. In equilibrium, house prices adjust to match houses that differ by quality to households who differ by income. For every $h \in [0,1]$ the number of households who demand houses of quality less than h must equal the number of such houses in the inventory:

$$\Pr(h^*(p,i) \leq h) = G(h)$$

[5] This model is named *assignment model* in the paper.

The price function $p(h)$ describes a set of house prices at which households are happy to be matched to the available inventory of houses.

Consider a one-period problem. Households care for two goods. Non-housing consumption can be purchased in a frictionless market. Housing services are derived from indivisible housing units. Households have disposable income y and buy a house of quality h and other consumption c. A household maximizes utility

$$u(c, h)$$

s.t the budget constraint

$$c + p(h) = y$$

Let $F(y)$ denote the strictly increasing cumulative distribution function of income y.

The first order condition (FOC) becomes

$$p'(h) = \frac{u'_h(c, h)}{u'_c(c, h)}$$

It says that the marginal rate of substitution (MRS) of housing for consumption equals the marginal value of a house $p'(h)$ at quality level h. Note that the house price function does not need to be linear in quality.

Let h(p,y_i) denote the housing demand function of household i. It will depend on the house price function p as well as on household i's income. In equilibrium, the optimal house quality is unique and strictly increasing in income. Consider its inverse $y^*(h)$, which gives the income level of a household who is matched by a house of quality h. The market clearing condition becomes

$$F\big(y^*(h)\big) = G(h) \rightarrow y^*(h) = F^{-1}\big(G(h)\big), \qquad \forall h$$

The matching of income levels to house qualities depends only on the respective distributions and $G(h)$ describes the inventory of homes.

Assume separable log utility, $u(c,h) = log(c) + \theta log(h)$. The FOC becomes

$$p'(h) \;=\; \theta \frac{y^*(h) - p(h)}{h}$$

A household with income $y^*(h)$ must be indifferent between buying a house of quality h and spending $y^*(h) - p(h)$ on other consumption.

To obtain closed form solutions for equilibrium prices, we make the additional assumption that the distributions G and F are such that the matching function is a polynomial

$$y^*(h) = \sum_{i=1}^{N} a_i h^i$$

Where a_i is a household specific constant given by the ratio of income and house quality. The shape of $y^*(h)$ is determined by the relative dispersion within percentiles in the income and house quality distributions. The lowest-quality house in terms of total characteristics have a price p^o and is purchased by the household with income y^o. When $p^o = 0$, the particular solution to the differential equation become

$$p(h) = \int_0^h \left(\frac{\tilde{h}}{h}\right)^{\theta} \frac{\theta y^*(\tilde{h})}{\tilde{h}} d\tilde{h} = \sum_{i=1}^{N} a_i \frac{\theta}{\theta + i} h^i \,.$$

The price for a house of quality h is the weighted average of MRS for all agents who buy quality less than h, with the MRS evaluated at total income. Define the allocation $\{p_o, h_o\}$ as the marginal investor that will not be able to enter the housing market. This will play an important role in the interpretation later.

Equilibrium and comparative statics

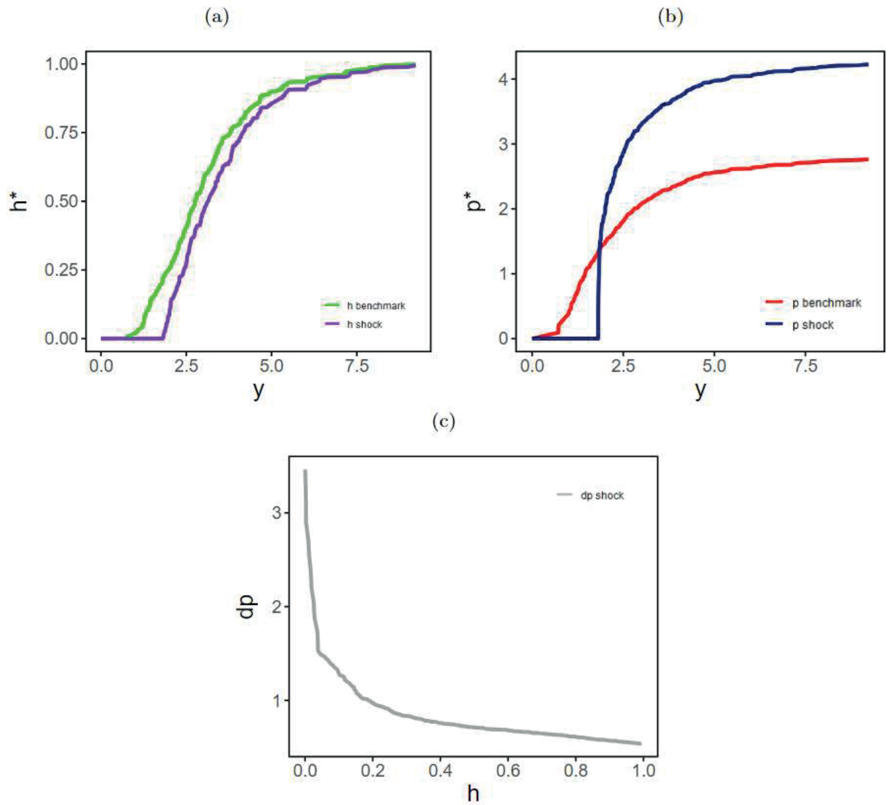
The model is simulated for $N = H = 500$. The income distribution of this model economy is log normally distribution with $\mu = 1$ and $\sigma = 0.5$ over the support [0,1] and with the additional condition that $y^o = 0$. Then y will vary over about (0,10). The quality inventory distribution is assumed to be uniformly distributed over the identical support [0,1], where also $h_o = 0$. Assume further that $\theta = 0.3$, that is all households spend 30 percent of period income on housing. In equilibrium, households are matched to houses of different qualities according to their income levels. Figure (1) gives the equilibrium quality match h^* and equilibrium price p^* for this case. As can be seen in the figures, both housing quality and price is an increasing and non-linear function of income.

Next, consider a shock to inventory where 100 units are removed from the market. Thus, now $N = 500$, $H = 400$. Excluded units are drawn randomly across the distribution of qualities $h \in [0,1]$. This shock could mimic the imbalance in a housing market boom that could arise due to high turnover, more rapid entry of households with no unit to sell, or if sufficiently many existing owners buy before they sell. In this market, houses will go to the households with the highest incomes by equation (6). In the new (dis-)equilibrium, the 100 lowest-income households become unmatched and the cutoff-household become marginal investor. A necessary condition for the price function (7) to hold is that $p^o = 0$, this will still be the case for our marginal investor. Otherwise, all unmatched households will not enter the price function in this case, $p(h) = \sum_{i=1}^{\widehat{N}} a_i \frac{\theta}{\theta+i} h^i$, where now $\widehat{N} = 400$.

Figure 1 also gives the disequilibrium quality match h^* and price p^* for this case. In the figure we have drawn all unmatched household with a zero price and zero house to ease comparison with the benchmark case. As can be seen in panel (a), this shock will affect the lowest-income household the most, which now either are left outside this market, or are matched with a significantly lower quality unit. Panel (b) shows the new equilibrium prices as a function of income, which become much steeper than before for the second quintile income group. Panel (c) considers house price growth for the houses that survived the shock to inventory as a function of quality level. Since the matched households have higher income than before, prices increase more for lower-quality units than higher-quality units. Moreover, since by the price function, the price for a house of quality h is the weighted average of MRS for all agents who buy quality less than h, this leads to higher prices for all higher qualities as well, with a non-linear decline in capital gain by quality.

Overall, these comparative statics emphasize how houses of different qualities can be affected differently in a housing market boom with a buyer-seller imbalance than in a balanced market. Since households are constrained by their budget, relatively low-quality units may become higher-in-demand and experience more rapid price appreciation if higher-income groups increasingly compete in these segments. In a housing market bust, we expect to see reversed results. Results are in line with (Landvoigt et al., 2015) who finds that relatively lower quality homes had to be matched to relatively richer households during a boom.

Figure 1 Matching model: Equilibrium outcomes



Notes: The figures show equilibrium results from a simulation of a matching model with log normally distributed income and uniformly distributed housing qualities. Panel (a) depicts equilibrium housing quality (h^*) as a function of household income. Panel (b) gives equilibrium house price (h^*) by household income. Both panels give results for a benchmark case with near market balance between market inventory and prospective buyers and a case with a significant reduction (20 per cent) of inventory relative to prospective buyers. Panel (c) gives house price growth (dp) by housing quality in the latter case.

1.2.4 Income, amenities and household location choice

The classical urban model of Alonso (1964), Mills (1967), and Muth (1969) provide a starting point for studies of city structure, household location choices and income sorting. This theory suggests that consumers living far from the central business district must be compensated for their costly commutes through lower housing prices relative to more central locations. This price decline can lead consumers to substitute towards city edges, resulting in larger dwellings at greater distances (Brueckner, 1987). However, the influence of amenities (and disamenities) on income-distance gradients has been widely recognized since the works of Roback (1982) and Rosen (1979). These authors provide a framework to investigate the effect of amenities on household location choice. It is posited that if proximity to amenities increases residents' utility, residents may be willing to accept lower income or higher rents to enjoy these amenities.

Empirical studies of cities typically find mixed results with large variations in the sign of the spatial income coefficient. Brueckner et al. (1999) noted that in French cities such as Paris, Lyon, and Nancy, household income tends to be higher in the city center. The authors develop a theory where the location of exogenous amenities can create a variety of household location choice patterns by income across cities. For instance, historic amenities in Paris's city center may serve as a pull factor for wealthier households. However, the lower housing prices in the suburbs could incentivize these households to live further from the city center. Therefore, unique city characteristics and developments may result in a variety of income-distance gradients across cities. This topic and theory are explored in Paper III.

The amenity-based sorting literature, although influential, is not without controversy. Alternative perspectives including those focusing on productivity differences (Albouy, 2016), agglomeration economies (Rosenthal et al., 2004) and consumption access (Miyauchi et al., 2021), complicate this picture. If amenity models fail to consider other important aspects, they risk overestimating the value of local amenities due to their likely correlation with e.g. productivity. As such, while the amenity-based sorting theory offers valuable insights, it is important to interpret the results of Paper III in the context of these diverse theoretical perspectives.

1.2.5 Actuarial model

Paper IV seek to estimate housing affordability by actuarial principles. In the actuarial framework, the bank offers time varying annuity flexible interest mortgages to potential owner-occupiers. The bank will approve a mortgage to a potential owner-occupier if it meets the standards of loan-to-value (LTV), loan-to-income (LTI), and affordability constraints given by the mortgage regulations. In Norway, these have consisted of: 1) Strict limits, e.g. a hard LTV limit of 85 % for all households from 2012. 2) 'Soft' limits, e.g. an LTI cap of 500 on new mortgage lending but allowing for 10 % of new mortgages above this limit in 2017 and reducing this exception-rate to 8% in 2019 in Oslo (see Table 1). Subject to these criteria, all demand is met in any period in the actuarial framework. The maximum principal loan amount for a FTB household is given by actuarial calculations incorporating the different rules and regulation.

Table 1: Guidelines and mortgage regulations in Norway between 2010-2020

	Guidelines I	Guidelines II	Regulations I	Regulations II
To - From	3.10-12.11	12.11-6.15	7.15-1.17	1.17-12.19
Maximal LTV	90%	85%	85%	85%
Maximal LTV Deductions	-	70%	70%	60%
Maximal LTI	300%	-	-	500%
Interest surcharge	-	5pp.	5pp	5pp.
Maximal excepted	-	-	10%	10%(8% in Oslo)

Source: Regjeringen.no

1.3 Empirical methodology

1.3.1 Classical econometric methods

Paper I-III employs classical econometric estimation techniques such as ordinary least squares (OLS), the negative binomial model and Pooled OLS panel data methods. Negative binomial regression is a generalized linear model where the dependent variable is a count of the number of times an event occurs. It is particularly useful when dealing with over-dispersed count data, where the variance is greater than the mean, a reasonable description of the search intensity data studied in paper II.

Pooled Ordinary Least Squares (Pooled OLS) is one of the methods used in panel data analysis, which is used in Paper III to study household location choice by distance to the city center. The choice of methodology is motivated by the large number of non-varying variables involved. In short, the Pooled OLS approach ignores the panel structure of the data and estimate a simple OLS regression, pooling all cross sections and time periods together. This technique assumes that there are no individual-specific or time-specific effects that need to be accounted for. If there are individual or time-specific effects that are correlated with the independent variables, Pooled OLS can lead to biased and inconsistent estimates.

1.3.2 VAR-models and Granger causality

In order to investigate the relationship between the housing cycle and search intensity by quality tier in paper II, we test for Granger causality between the house price index and search intensity. This is done both between these variables for the entire market and within and between the different spatial and quality submarkets. The strategy is to estimates VAR models for each price area and quality segment:

$$Y_t = \beta_o + \beta_1 Y_{t-1} + \cdots + \beta_p Y_{t-p} + \gamma_1 X_{t-1} + \cdots + \gamma_q Y_{t-q} + \varepsilon_t.$$

where Y_t and X_t represents the two variables being tested for Granger causality, alternating between house prices and housing search in all directions, for the city in total and within and between each quality and housing market segment. In this model it is essential to ensure stationarity of the series. Since stationarity is unlikely in this case, all variables are measured as first differences of their logarithms, and they are also seasonally adjusted. p and q are the number of lags for each variable, chosen by the Schwartz Bayesian information criteria which choose the optimal lag to include in the final VAR-model (Watanabe, 2013).

1.3.3 Random Forest algorithm

The random forests consist of individual decision trees and uses averaging to make predictions (see the seminal contribution of Breiman, 2001, for an outline). The decision trees and full forest ensemble partition the input data into subspaces such that each has a relatively homogeneous response variable. This locally fitted prediction allows for flexible modelling. In Paper I we estimate 1000 decision trees, where each tree is grown on a bootstrapped subsample with random variable selection. Compared to the classical OLS model, performance is improved in terms of R squared, however results are similar supporting that the classical regression model can capture much of the structure of the hedonic function. A particular advantage of the random forest in this application turns out to be the ability to capture time varying parameters without reducing sample size, yielding important insight into the timing of regime shifts. There are also notable improvements in the random forest predictions in more heterogeneous periphery locations associated with negative neighborhood amenities and relatively low prices (see Paper I).

1.3.4 Spatial aggregation with machine learning

Paper I-II also make use of spatial aggregation from the machine learning approach described in Sommervoll & Sommervoll (2019). This genetic algorithm relies on random variation and non-random selection in the search for larger areas with similar location premiums. The key advantage over simpler administrative areas is that this flexible aggregation method allows us to find areas that are potentially spatially far apart but have the same location premium. We think of such areas as belonging to the same housing submarket sharing the same location premium and use this to test for variations in search by housing quality tier by submarket in Paper II. Also, we use this methodology to construct spatial controls in Paper I.

As documented by Sommervoll & Sommervoll, the best aggregations found by the genetic algorithm outperform a conventional fixed effects model by postcode, even with fewer spatial controls. Similar gains are found in this thesis. As we show in Paper I where we test for spatial autocorrelation of residuals of hedonic models with different spatial controls based on a Moran's I test (see Moran, 1948), the specification using this spatial aggregation performs the best. The interpretation as submarkets sharing the similar location premium is also particularly beneficial in Paper II where the goal of the analysis is to study ripples of search in markets ranked by quality and location tiers.

1.4 Data

The analysis in this thesis uses a multitude of data sources:

Paper I

(i) The *listing data* used in this research contains the main text of the listing and a wide range of characteristics for 10,350 transacted dwellings in Oslo, Norway. The dataset is acquired from Eiendomsverdi ASA, a private company that collects all transactions in the Norwegian housing market and provides price valuations based on the automated valuation method (AVM) for banks and brokers, considered the best valuation by market agents and the government. In addition, the listing data includes zip codes, geographic coordinates, and both the transaction price and the AVM price valuation. It covers the period from primo 2014 to medio 2019. The renovation classification methodology is described in detail in section *Renovation classification* (p. 311-312 in the published paper). Incomplete information in the listings may result in dwellings being classified wrong. (ii) To address this concern, a second *dataset of prospectuses* with extensive detail is used to see if the distribution of renovation classifications differs greatly from the distribution based on the listing dataset

Paper II

(i) This paper uses the same listing dataset as Paper I, however for a total of four cities. (ii) The listing data is also coupled with information from the auction of each house from four large realtor organizations operating in the area. In the main analysis, we use data for the metropolitan market (Oslo) for 8,473 sales, compared to 5,278 sales in Trondheim, 335 sales in Tromsø and 1,600 sales in Drammen. The main variable describing the search intensity is the number of listed interested at the English sealed bid auction as well as the number of bidders.

Paper III

(i) Coordinates for a broad set of amenities in Switzerland is obtained from OpenStreetMap (OSM) for six categories of amenities: (i) entertainment facilities, such as art centers, casinos, cinemas, nightclubs, and theatres; (ii) eating out facilities including restaurants, pubs, bars, biergarten, and cafe's; (iii) outdoor recreation such as parks, playgrounds, firepits, and gardens; (iv) public services such as schools, kindergartens, clinics, dentists, doctors, and hospitals; (v) transportation points including all platforms where passengers are waiting for public transport vehicles; and (vi) sport facilities such as fitness centers, sport centers, and swimming pools as of 2020. Additionally, we retrieve information for further geographical features of interest such as lakes and national borders.

(ii) Detailed household characteristics from 1999 to 2014 for 16,940 households is sourced from the Swiss Household Panel (SHP). The SHP is an annual panel survey of households from all regions and across all population groups in Switzerland, with the main objective to measure social changes in Switzerland (Voorpostel et al., 2019). (iii) Fahrländer Partner Raumentwicklung provides data for house prices. Information from municipalities is combined with data on individual households.

Paper IV
(i) Register data for *home transfers* at individual level for first time buyers including among others the transaction price, location, ownership share, and buyers age from Ambita ASA between 2010-2020. (ii) *Home transactions* including a large set of housing attributes and fine scale location during the same period from Eiendomsverdi ASA. (iii) *Observational studies* on banks mortgage lending practices, household income data and macro-economic variables (Statistics Norway and various sources).

1.5 Main findings and limitations

Paper I
In this paper, we rely on novel textual analysis of real estate listings and identify renovated dwellings in a dataset of Norwegian transactions to estimate the renovation premium in an urban housing market. We estimate a significant positive renovation premium of 5–7 percent for renovated dwellings and a negative premium of 9–10 percent for unmaintained/neglected dwellings. These averages mask significant variations in these premiums over time, particularly, a counter-cyclical effect. Omitting renovation information also has implications for estimated short-term house price growth. Unmaintained dwellings tend to transact more in the fourth quarter, indicating that parts of the seasonal price variation reported in the literature are due to compositional variation with respect to renovation. This composition effect bias price movement estimates downward, if uncontrolled for, as unmaintained dwellings transact at significantly lower prices. Existing evidence (e.g., Bogin & Doerner, 2019) concludes that a higher renovation activity in central areas is the primary explanation for biased HPI estimates. In contrast, our results

show that the renovation bias tends to be higher in less central areas, driven by a higher frequency of unmaintained dwellings transacted. These results could be explained by changes in the composition of buyers over the housing cycle, in line with the predictions of Chernobai and Chernobai (2013). Another candidate driving factor is affordability effects. This may result in less competition for expensive dwellings, including fully renovated for otherwise constant characteristics. Unmaintained dwellings allow for a future renovation and, as such, involve a potential investment smoothing.

On a higher level, our analysis of online listings points to a way to control for renovation. Other ways, for example, using computer vision (Yencha, 2019), may prove an even more powerful way to measure the degree of renovation and get closer to quality-adjusted price levels and price indices for the housing market. In this sense, our analysis is an early contribution that shows controlling for renovation is feasible and involves significant rewards.

Paper II

Based on a multitude of data sources such as auction-based search intensities and listings information, we find that search for low-quality housing in most of the cities studied is significantly pro-cyclical, while search for high-quality housing is counter-cyclical, and that these effects are stronger for more attractive locations. During major housing market booms, the dispersion is greater, while during busts this ripple is reversed. In the metropolitan market, there is a hierarchy in order of magnitude from prime to distressed locations based on price zones, where high-to-low quality dispersion is estimated at 42.2 percent during booms in both prices and buyer-seller ratios, while this is estimated at 30.4 per cent in secondary locations, and insignificantly different from zero in distressed locations. This sorting is not as clear when we use an alternative spatial aggregation, supporting that the spatial premium play an important role for search ripples during booms.

Overall, these findings point to a trade-off between quality and location. In order to maintain a better location quality, more buyers may be willing to reduce unit quality. The results are largely consistent with predictions from theory. Williams (2018) shows how average prices increase with search intensity, from the preferred segment outwards to secondary segments and beyond. Empirical evidence tends to focus on ripple effects in the spatial dimension. The results are also in line with studies such as Landvoigt et al. (2015) and Ho et al. (2008), although there are some important differences in the scope and dynamics considered. Additionally, this paper highlights the value of including aggregate search intensity directly in the analysis of market phases. We can consider the average number of searchers per unit for sale as a measure of the inventory (im)balance and a parameter for the likelihood of crowding-out effects.

We relate this to housing market outcomes in two ways. First, our findings suggest that search by quality tier is related to housing turnover and price growth in the expected way. Second, based on VAR-analysis and Granger causality tests, we see a positive relationship between search intensity and overall price development by quality tier, where changes in search tend to lead changes in house prices. One limitation of the analysis is that we lack identifying information about the searchers across auctions and study volumes. Further work could benefit from studying search at the individual level to disentangle the effects of existing homebuyers and clientele effects. Finally, more work could be done to disentangle the effects of supply and demand.

Paper III

By extracting data from a geographic database, we distinguish between amenity-rich and amenity-poor city centers relative to the larger urban area in eight Swiss cities. Although their concentration may be related in a complex way to other fundamental drivers, our findings reinforce the importance of amenities for household location choice. In line with the theoretical predictions of (Brueckner et al., 1999), we estimate an inverse relationship between the degree of amenity-superiority of the city center and the income - distance gradient. Similar are found in other European and Latin American cities (Hohenberg & Lees, 1995; Ingram & Carroll, 1981). Our study also examines how households respond to increased access to amenities such as public transportation at the city edge, as well as local variations in taxes.

Our results contribute to the limited existing research on European cities. Swiss cities are small relative to cities in the U.S. and several other European cities, are in close proximity, and tends to be well-connected by an efficient public transportation network. One limitation of our analysis is that we measure amenities at a single point in time, six years after the end of the household data spell. While the supply and composition of amenities in a city change rather slowly over time (Duranton & Puga, 2015), this approach might overlook significant changes in amenities and their value over time. To handle endogeneity, we consider alternative specifications with additional variables and amenities that are more likely to satisfy the exogeneity assumption, arriving at similar main results. Although we do not have access to instruments for house prices, the inclusion of area level prices and our approach of distance-weighting is expected to mitigate the endogeneity problem. Results are also similar and even more pronounced when we relax other simplifying assumptions of the canonical model, such as full mobility of households. Future research could improve the amenity measurements and additionally aim to find suitable instruments for transportation and urban amenities to better handle the endogeneity issues of household location choice, income and amenities.

Paper IV

To arrive at a measure of annual housing affordability, paper IV estimates the purchasing power index of average local first-time buyers in 43 Norwegian municipalities. Results are compared with the development in actual first-time purchases annually and may indicate that many young people go far beyond what the limits for their own finances dictate. While a typical single first-time buyer would be able to afford 29 percent of homes sold in the six largest Norwegian cities in 2010, the corresponding figure is 7 percent of homes sold in 2019. Although there are important differences in scope and methodology, results on the weakening of housing affordability are broadly in line with other Norwegian studies (Lindquist & Vatne, 2019; Lund, 2018), while also adding the comparison to actual purchases.

The methodology proposed provides multiple gains compared to simpler measures that are often used, such as price-income rates, and is also suited to regular updates. In the actuarial model employed, a pro-cyclical lending practice increases maximum borrowing during boom periods and weakens maximum borrowing during bust periods. Further work could benefit from implementing various first-rime buyer household types and better incorporate household wealth.

1.6 Concluding remarks

This thesis contributes to the empirical literature on the dynamics and microstructure of housing markets, specifically within the understudied areas of housing and location quality. By using novel data sources and combining them in innovative ways, this research has provided new insights into quality differentials, quality sorting, and spatial sorting within housing markets. Each article in this thesis is grounded in relevant literature and theory and offers estimates and empirical results that broaden our understanding of these aspects of housing markets. However, it's important to note that these findings are conditional on the quality of the data, the chosen methodologies, and the research design. As with all research, there is always room for refinement and improvement in these areas.

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3 Paper I

Our overall conclusions are surprisingly consistent across sources and eras, that the Consumer price index (CPI) bias was roughly -1.0 percent prior to the methodological improvements in the CPI due to quality change in rental housing over the twentieth century.

Gordon & VanGoethem, 2005

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Coming of Age: Renovation Premiums in Housing Markets

Mari O. Mamre[1] · Dag Einar Sommervoll[2]

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Abstract
We rely on novel textual analysis of real estate listings and identify renovated dwellings in a dataset of Norwegian transactions to estimate the renovation premium in an urban housing market. The renovation premium is estimated in a hedonic framework by classical regression approaches and a random forest algorithm. The strength of the latter is that it allows for a more complex interplay between the renovation premium and explanatory variables. We estimate a significant positive renovation premium of 5–7 percent for renovated dwellings and a negative premium of 9–10 percent for unmaintained/neglected dwellings. These averages mask significant variations in these premiums over time, particularly, a counter-cyclical effect. Omitting renovation information also has implications for estimated short-term house price growth. Unmaintained dwellings tend to transact more in the fourth quarter, indicating that parts of the seasonal price variation reported in the literature are due to compositional variation with respect to renovation. This composition effect bias price movement estimates downward, if uncontrolled for, as unmaintained dwellings transact at significantly lower prices.

Keywords Renovation · Hedonic estimation · House price indexes · Real estate listings · Random forest

JEL Classification O18 · R30 · E60 · E31

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✉ Mari O. Mamre
mari.olsen.mamre@nmbu.no

Dag Einar Sommervoll
dag.einar.sommervoll@nmbu.no

[1] Norwegian University of Life Sciences, Aas, Norway

[2] Norwegian University of Life Sciences and NTNU Trondheim Business School, Aas, Norway

Introduction

The housing market is of keen interest to households and policymakers alike. Real estate constitutes the major wealth component for most households. The last financial crisis made us painfully aware that the housing market is not a passive receiver of shocks; it can be the originator of an economic downturn with dire consequences (e.g., Leamer, 2015). However, houses transact infrequently and are highly differentiated with respect to their characteristics. An important dimension of this heterogeneity is related to variations in the quality of the structure. Quality heterogeneity can arise in markets for durable goods, such as real estate, where consumers have a choice of new or used goods that have deteriorated to a lower quality (Sweeney, 1974). Owing to this, monitoring the housing market is far from easy, a recurrent issue within macroprudential policy.

Economic models of house prices have various strategies to control for heterogeneity. Hedonic models, where house prices are explained by a wide array of house characteristics, such as location, size, number of bedrooms, etc., date back to Rosen (1974). Models of repeated sales tackle the issue of heterogeneity by considering same-house sales (e.g., Case & Shiller, 1989). The fundamental assumption of both workhorse house price models is the ability to control for quality variation, either directly (hedonic) or indirectly by assuming the house quality does not change between sales (repeated sales). Failure of these assumptions will likely lead to biased inference if the omitted information is essential. For instance, the dwelling size and location are typically found to be more important for the transaction price than a fireplace and an extra bathroom (see Xiao, 2017). In this hierarchy of price determinants, renovation is likely to be high on the list but seldom included due to data limitations. The listing of dwellings for sale online may change this.

Online listings often state that a dwelling is newly renovated as this information is likely to attract interested parties. A wide range of positive words is used to describe newly renovated units (gorgeous, flawless, exclusive, lavish) along with information on the extent of renovation. Online listings also include photos, and poorly maintained dwellings are easy to spot. The wording, in this case, tends to focus on a unit's potential and attract interested parties that are comfortable with a major renovation. Hence, these listing texts shed information about the renovation and the maintenance level of the dwelling for sale.

We study the renovation premium in a hedonic framework for an urban housing market over five years (2014–2019). The period contains a boom followed by a bust and thus allows us to address the potential time variation of the renovation premium, particularly whether it is pro- or countercyclical. The analysis relies on two novel datasets, mainly a listing dataset and in addition a detailed prospectus dataset of transacted dwellings in Oslo, Norway.[1] We pair transaction data with their listings text and, through text analysis, classify dwellings into four groups, unmaintained, partially renovated, fully renovated, and none of the first three.

[1] The listing dataset contains a brief description of the house for sale. The prospectus dataset used for validation contains detailed information about the characteristics of the house and any renovations done.

It is important to stress that the incentive to renovate is higher in attractive areas since the expected gain from renovations exceeds the cost by a greater margin (Gyourko & Saiz, 2004). In other words, one may expect a spatially clustered vintage effect (Randolph, 1988b) that creates challenges for estimations of the renovation premium. We address this concern by applying flexible random forest techniques as well as classical hedonic- based regression approaches. The major takeaway from our analysis is the importance of renovation as a price determinant. Failure to control for renovation leads to significant biases of housing price levels and indices. Unfortunately, these are not only considerable but also tend to vary over time and across space.

We find a premium for the fully renovated (in the 5 to 7 percent range) and a negative premium for the unmaintained (in the 9 to 10 percent range). Our estimates can be interpreted as a lower bound of the renovation premium. These average effects gloss over interesting temporal variation. In particular, heated housing markets diminish both the positive premium of the fully renovated dwellings and the negative premium of the unmaintained. The counter-cyclical effect is especially strong for the fully renovated. In a heated market, buyers, on average, do not distinguish renovated from non-renovated dwellings in terms of pricing.

These results could be explained by changes in the composition of buyers over the housing cycle, in line with the predictions of Chernobai and Chernobai (2013), leading to variations in the bargaining process between buyers and sellers on certain characteristics (Bourassa et al., 2009). A second candidate explanation is the income-mortgage effect. The market heat is like a tide that lifts all boats, but the attractive and expensive in several market segments to a lesser extent due to income and mortgage financing limitations. This may result in less competition for expensive dwellings, which include the fully renovated for otherwise constant characteristics. In contrast, unmaintained dwellings allow for a future renovation and, as such, involve a potential investment smoothing.

Another notable finding is a systematic quarter-to-quarter variation, where the 4th quarter sees more unmaintained dwellings changing hands. This composition effect has implications for the seasonal variation observed in house price indices and tends to bias price movement estimates downward, if uncontrolled for, as unmaintained dwellings transact at significantly lower prices. Finally, our results show that the renovation bias tends to be higher in less central areas, driven by a higher frequency of unmaintained dwellings transacted.

The literature on renovation and renovation premiums in the housing market is sparse. The lion's share of academic contributions concerns neighborhood effects. These may be related to externalities or positive spillover effects (e.g., Wilson & Kashem, 2017). One form of externality regards sustainability, that renovation may have a negative impact on the environment, at least in the short run (Liu et al., 2020). In the case of the Taiwanese market, Lee et al. (2017) estimate the renovation premium per area unit (ping[2]) to 10.0 percent (14,880 NTD), but the focus is spillover effects of urban regeneration. Another branch of literature concerns the renovation premium through energy-efficiency-related

[2] 1 ping = 3.305 m^2.

renovations. McLean et al. (2013) estimate a renovation premium of 9.4 percent from increased energy efficiency for the Hungarian housing market. Therefore, little is known about the isolated impacts of general renovations. Our paper, in contrast, considers small-scale, household-initiated renovation or lack thereof. Spillover effects are likely to play a minor role in our case.[3] The direct impact of a renovation that involves improved energy efficiency is likely to be part of the renovation premium.

The literature on renovation and repeat sales indices is more extensive and points to a significant difference in estimated house price growth with and without renovation information. McMillen and Thorsnes (2006) estimate a repeat sales index (median quantile) for Chicago for the period 1993–2002 and find that the index overestimates price growth by 9 percent without renovation information. Bourassa et al. (2013) arrive at an even larger overestimate (14 percent) for Louisville, Kentucky (1988–2010) for their repeat sales index. Furthermore, Bogin and Doerner (2019) asserts that overestimation tends to be severe in central areas due to an uneven concentration of renovation activity. Our paper contrasts this literature by the renovation information used[4] and by studying the renovation premium and renovation bias in a hedonic framework. The two main reasons for the choice of the hedonic methodology are, firstly, the ability to estimate implicit prices. Secondly, we do not observe the renovation status of the dwellings at previous sales. For the broader role of housing quality, early contributions appeared at the same time as the seminal work on attribute prices of bundled goods. Two of these are Sweeney (1974) and Cubbin (1974).

The remainder of the paper is organized as follows. Data Description and Renovation Classification describes the data and classification details. Methodology for Assessing the Impact of Renovation discuss measurement and outline empirical strategies. Results Empirical Analysis reports results for the renovation premium. Temporal Variation in the Renovation Premium consider temporal heterogeneity in the renovation premium, and Renovation Bias in House Price Growth estimates the "renovation bias" in short term house price growth. Additional Tests and Robustness Analysis perform additional tests. Conclusion and Discussion concludes.

Data Description and Renovation Classification

Institutional Detail and Data Description

Most real estate transactions in Norway are arm's length brokered sales. The seller contacts a broker who puts the house on the market. The broker is also responsible for preparing the sales prospectus and listing, and when the house is placed on the market, the listing and sales prospectus are available online. Moreover, the broker organizes an open house and manages the ascending-bid auction, which usually

[3] The subset of renovations that are external fixes and where the condition of the unit was severely distressed before the renovation is a candidate for neighborhood spillover effects. However, our sample consists mainly of apartments where most renovations are inside the structure.

[4] We extract renovation information from the real estate listings and additionally consider unmaintained dwellings.

takes place on the first business day after the open house. Bids are submitted by telephone or electronically, and each bid is legally binding.

The *listing data* contains the main text of the listing and a wide range of characteristics for 10,350 transacted dwellings in Oslo, Norway. The dataset is acquired from Eiendomsverdi ASA, a private company that collects all transactions in the Norwegian housing market and provides price valuations based on the automated valuation method (AVM) for banks and brokers, considered the best valuation by market agents and the government. In addition, the listing data includes zip codes, geographic coordinates, and both the transaction price and the AVM price valuation. It covers the period from primo 2014 to medio 2019. Table 1 provides summary statistics for the main variables. The dwellings have a mean age of 54.6 years, mean size of 79.7 square meters, and the majority of transactions are apartments (85.5 percent).

Renovation Classification

The main focus of this paper is quality-enhancing renovations in the context of real estate sales. In contrast to most previous work, information on renovations within the structure, such as a new kitchen and bathroom, is also extracted.[5]

One challenge in creating a renovation classification is that it is essentially a continuous variable. A new house is "renovated" and begins its journey toward “unmaintained”. As a dwelling age, its quality deteriorates in two ways. First, everything from plumbing fixtures to window frames is subject to natural tear and wear. Second, after a certain amount of time, the materials and construction become outdated and no longer reflect the current zeitgeist. To offset or dampen these effects, owners may decide to do a partial or full renovation. To distinguish these cases, a renovation variable with two positive values for partial renovation (1) and full renovation (2) and one negative value for unmaintained (-1) or neglected units in need of renovation is constructed. Dwellings that are neither renovated nor unmaintained but somewhere in between are labeled neutral (0). Since we are unable to estimate renovation more precisely for the entire dataset, a scale is used as a proxy.

A combination of machine search and a careful reading of all listings was undertaken to assign one of the values 2, 1, 0, or -1 to the renovation variable. About half of the units classified as renovated (48 percent) had "renovated" in their list text.[6] Whether the renovation is interpreted as full or partial depends on whether it includes the most expensive rooms to renovate, as well as the timing of the renovation, and the overall impression of the extent of the renovations. For instance, units with a new kitchen, floors, and bathroom or that is described as "fully renovated" receive a score of 2. In contrast, units with new paint and a kitchen installed seven years ago or described to have "some renovations" receive a score of 1. Only new paint and no further renovation signaling information receive the score 0. As much as 89 percent of dwellings classified as unmaintained had "unmaintained" in their list text. These and similar wordings are assigned the score -1. Thus, incomplete information in the listings may result in many dwellings being classified

[5] This allows us to capture more renovations than in studies that only capture remodeling renovations in the form of additional rooms or additional living space or renovations that require a building permit.

[6] Other much-used markers are "completely new kitchen, bathroom and floors", or just a recent year (“kitchen, bathroom and floors from 2018”).

with a renovation score of zero. To address this concern, a second dataset of prospectuses with extensive detail is used to see if the distribution of renovation scores differs greatly from the distribution based on the listing dataset.[7]

Classification Results

In total, we find a share of 12.4 percent renovated (7.0 percent fully renovated) and 8.7 percent unmaintained transactions, based on information in the listings. Our results for the share renovated are roughly comparable to those of McMillen and Thorsnes (2006), who estimates a renovation share of transactions associated with issued building permits in Chicago of 10.7 percent over 1993–2002. However, these results are significantly larger than those of Bogin and Doerner (2019).[8]

In addition, we can shed some light on the development of renovated transactions over time. Figure 1 shows the quarterly distribution of sales by renovation class. The highest combined renovation share of sales for a single quarter is 26 percent in 2016-Q4 (neutral non-renovated units, denoted R0, account for 74 percent), and the lowest is 13 percent in 2018-Q3. There is evidence of systematic quarter-to-quarter variation, where the 4th quarter (Q4) sees more unmaintained dwellings changing hands, with an average of 11 percent of sales compared to 7–8.5 percent in Q1-Q3.[9]

Finally, there are notable differences in dwelling age and price per square meter by renovation class. For instance, older dwellings are increasingly likely to be renovated (Table 2).[10] This accords with the result in Lee et al. (2005) that the renovation (redevelopment) propensity increases with the age of the dwelling. Since older dwellings tend to be located in more attractive parts of this urban area, one might expect a spatially clustered vintage effect (Randolph, 1988b) that creates challenges for estimation of the renovation premium. This age-renovation patterning may partly be driven by a pure age effect caused by the extent of depreciation. Partly by an investment effect caused by higher incentives to renovate in attractive areas since the expected gain from renovation exceeds the cost by a greater margin (Gyourko & Saiz, 2004).

Methodology for Assessing the Impact of Renovation

The *observed renovation premium* is defined as the expected increase in the equilibrium house price for an average renovation, derived from the well-known hedonic equilibrium price function $P = f(X, \varepsilon)$. The price function maps the

[7] See details in Table 12 in Appendix 1.

[8] The authors find a 0–2 percent renovation share for transacted dwellings in large U.S. cities. Their study likely measures extensive renovations, such as whole-unit remodeling, so we expect the estimates to be lower.

[9] The details can be found in Table 11 in Appendix 1. The sample length used in this analysis should preferably be extended to conclude confidently.

[10] By contrast, the highest proportion of unmaintained dwellings are found to be between 31 and 50 years old, and this proportion is subsequently lower for younger and older units, resulting in a reversed u-shape for the share of unmaintained units by age.

Table 1 Summary Statistics for prices and key housing characteristics for listing data. Prices in million NOK. $N = 10,350$

Statistic	Mean	St. Dev	Min	Max
Transaction price	4.5	2.3	1.0	33.0
AVM price valuation[a]	4.6	2.2	1.1	20.1
Size in m^2	79.7	49.0	14	757
Dwelling age	54.6	36.5	-2[b]	214
Average area income	4.34	0.68	2.80	5.99
Average area education	0.47	0.11	0.27	0.76
	No. of obs.		Percent	
Dwelling type:				
Apartment	8,845		85.5	
Single family	554		5.4	
Multi family	851		8.2	
New	100		1.0	
Ownership type[c]				
Regular owner	5,448		52.6	
Coop	4,384		42.4	
Regular owner in part	518		5.0	
Location[d]				
Central	3,921		37.9	
West	4,403		42.5	
East	2,026		19.6	
Total	10,350		100	

The table shows summary statistics for the full data set. The three subsets of this full dataset used in the analysis are summarized in Appendix 1. 1 NOK = 0.11 USD on January 7, 2022. Notes: a. The AVM price is produced by Eiendomsverdi ASA and available for a smaller set of the data (N = 5,809). b. New dwellings sold two years before completion. c. In a coop, the purchaser own a right to live in her unit. A regular owner owns her unit. d. See Table 13 for the list of Oslo suburbs in each of the three categories

relationship between the observed and unobserved to the economist attributes, respectively (X, ε), and the house price P. The implicit price reflects the marginal willingness to pay for renovation (Rosen, 1974).

We build on Randolph (1988a) and Randolph (1988b) in our understanding of how renovation combines with closely related attributes such as residential depreciation and overall quality of a unit in the price function. In this view, residential depreciation can be defined as the value of the portion of unmeasured quality change caused by aging alone. A renovation is a discrete upward shift in the aging/quality depreciation curve. The interpretation for the hedonic relationship is that any measurements of age depreciation are expected to capture renovations that are unobserved to the economist in addition to age-only depreciation. This is consistent with Diewert et al. (2015) who defines the net depreciation rate as the "true" gross depreciation rate of the house less an average renovation appreciation rate.

The following sections presents empirical strategies for identifying and examining the renovation premium. Because the fraction of measured age depreciation that is attributable to renovation or quality of materials is unobserved, and for simplicity, our

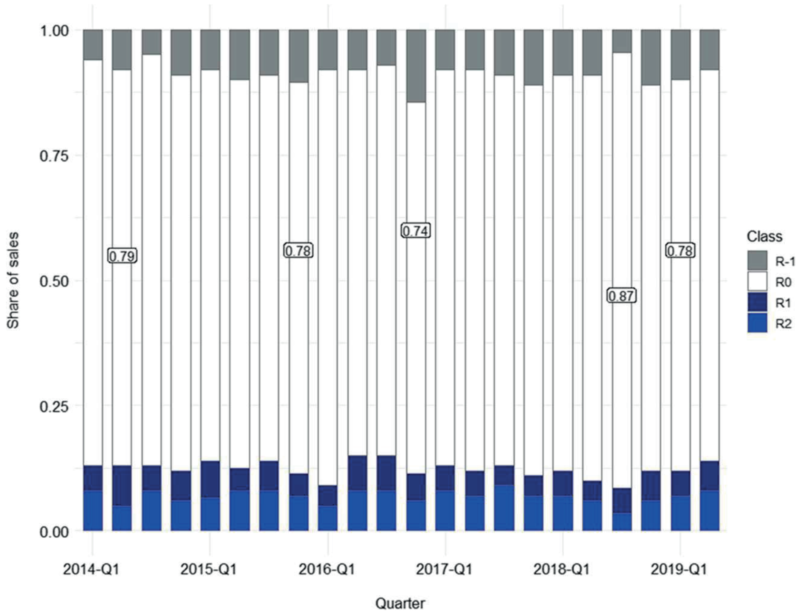


Fig. 1 The Renovation Class of House transactions by share of sales between 2014-Q1 and 2019-Q2. N = 10,350. The figure shows the quarterly results of a classification of sales by renovation level based on real estate listings in Oslo, Norway. Notes: R-1 ~ unmaintained, R0 ~ neutral, R1 ~ partially renovated, R2 ~ fully renovated

analysis focus on the observed renovation premium (according to our classification), which is referred to below as the *renovation premium*. However, it should be inferred from this discussion that there are potentially important interactions, correlated characteristics, and nonlinear effects in the hedonic relationship, especially when considering the isolated impact of renovation/neglect on the house price. We address these concerns by applying flexible random forest techniques as well as classical hedonic-based regression approaches. As a measure of the gain in house valuation performance from our renovation information, the loss in predictive performance with and without renovation information included as characteristics is compared.

A classical Linear Regression Model

As a benchmark specification, a classical log-linear regression that has become standard in the hedonic house price literature (see Xiao, 2017, for a recent review) is estimated. The house price model includes dummies for renovation class, along with a set of characteristics. Subsequently, the benchmark specification is extended to include interaction terms between characteristics such as renovation and location and location and age of the unit. These regressions with interactions highlight

Table 2 Classification Results. The number of House transactions in each Renovation class (frequency in percent) in the listing dataset (top) and the Age distribution by Renovation class (bottom). N = 10,350

Description	Renovation class	No. of obs. (percent)		
Fully renovated	2	723 (7.0%)		
Partially renovated[a]	1	558 (5.4%)		
Neutral	0	6,736 (65.1%)		
Unmaintained	-1	902 (8.7%)		
Less than 10 years old		1,431 (13.8%)		
Age group	Price[b] per m^2	Unmaintained	Renovated[c]	No. of obs
< 11	69.3	0.000	0.008	1,784
11–30	60.3	0.050	0.056	1,198
31–50	46.7	0.149	0.109	1,775
51–60	53.8	0.120	0.153	1,522
61–70	59.9	0.110	0.132	1,114
71–90	69.4	0.106	0.178	1,394
91–120	69.3	0.083	0.246	940
> 120	73.8	0.074	0.236	623

The table summarizes our results for renovation shares in real estate transactions. Notes: a. Partial renovation usually includes costly rooms such as kitchen and bathroom, but not a full renovation. Neutral units are neither renovated nor unmaintained. b. Price per m^2 in 1,000 NOK. c. *Renovated* combines partially and fully renovated units

spatial variation in the renovation premium and the age distribution of dwellings. Our regression specification is, $\forall i \in (1, N_T)$:

$$\log P_i = \beta_0 + \beta_1 \log(Size_i) + \sum_{\forall s \in S} \beta_S D_{is} + \sum_{\forall l \in L} \beta_l L_{il} + \sum_{\forall k \in K} \delta_k R_{ik} + \varepsilon_i. \tag{1}$$

where P_i is the house price, $Size_i$ is the area (in sqm.), D_{is} are either dummy variables or dummy interaction variables, $s \in$(dwelling type, ownership type, dwelling age cohort, sales quarter, administrative area dummies and/or price zone dummies), L_{il} are administrative level fixed effects, $l \in$(income level, education level), and R_{ik} are renovation classes $k \in$(-1, 1, 2). The delineation of the age cohorts and log-form of house size is proposed in a preliminary analysis by a random forest estimation.[11] ε_i is an error term. The coefficients of primary interest are estimates of the renovation premium, δ_k. The dataset[12] is split into an estimation set S_T containing 70 percent of the data and an out-of-sample set S_O containing 30 percent.

A Random Forest Algorithm

The hedonic theory provides little guidance about the functional form of the relationship between the house price and various characteristics. This is especially relevant

[11] Details are available upon request.

[12] See Table 14: (3) Hedonic Model data (1) with price zones.

when there are likely to be non-linear effects or complex interactions among characteristics. To address this concern, a growing body of literature uses more flexible methods to value real estate; among these, non-parametric random forest algorithms.[13] Many studies conclude that a random forest improves predictive performance relative to more standard approaches to house price modelling (e.g., Bogin & Shui, 2020; Čeh et al., 2018; Yoo et al., 2012) or when dealing with other challenging prediction problems (Auret & Aldrich, 2012), although several caveats remain when interest concerns consistent and stable coefficient estimates (Mullainathan & Spiess, 2017).

The random forest algorithm is a particularly interactive class of models that builds a random ensemble of decision trees by bootstrapping. Specifically, we use the methodology described in (Breiman, 2001) with cross-validation to select an optimal complexity level that maximizes prediction accuracy without overfitting. Candidate variables for each decision tree split are drawn randomly from the complete set of variables, making each tree distinct.[14] The random forest and classical regression models use the same set of independent variables to ensure comparability of inferences.

Predictive performance is compared out-of-sample (O). The squared correlation coefficient (R^2 and adjusted R^2) and root mean square error (RMSE) are among the most commonly used measures of accuracy, where $RMSE = \sqrt{\frac{1}{N_O}\sum_i\left(\log\left(P_i\right) - \log\left(\hat{P}_i\right)\right)^2}$, and weights larger errors more heavily than smaller errors.

Spatial Aggregation

A well-documented challenge in regression methods such as hedonic house price estimation arises from spatial dependence and spatial heterogeneity when models do not adequately capture spatial structure or omits essential variables (Anselin, 1990; LeSage & Pace, 2009). To obtain robust estimates of the spatial price premium, both standard administrative area districts from zip codes and noncontiguous *price zone* dummies are constructed. The price zones are estimated with the methodology described by Sommervoll and Sommervoll (2019).[15] This flexible aggregation method allows us to find spatially distant areas with similar location premiums.

The prize-zone algorithm can be summarized as follows:

1. Estimate an auxiliary hedonic house price regression.
2. Use a grid to partition Oslo into rectangular cells.
3. Restrict the number of submarkets to be fixed at 12.
4. Search for maxima for the auxiliary hedonic regression (here R^2) by varying the spatial aggregation of the cells using a genetic algorithm, a variant of gradient ascent.
5. The final result is an aggregation of 370 zip codes to 12 submarkets, represented by a 370-dimensional vector $(7, 2, 7, 1, 12, \dots)$ with cells estimated to have the highest location premium in price zone nr. 12 and the lowest in price zone nr. 1.

[13] Alternatively, neural networks and gradient boosting algorithms are also often adopted within the recent machine learning literature.

[14] See details in Appendix 2.

[15] The method employed is described in 4.1 Genetic algorithm, p.243-.

The administrative areas and price zones should be interpreted differently. For instance, while administrative areas capture the aggregated value of neighborhood amenities such as the quality of schools and area reputation, the price zones capture the aggregated value of amenities *across space* such as the extent of view, hours of sun and transportation access.[16] Any aforementioned unexplained spatial clustering of dwelling vintages (different construction vintages may imply variations in the quality of materials etc.) is also expected to be captured to some extent in the price zones.

To evaluate the spatial implementation and compare regression models, spatial autocorrelation is tested for by estimating the global Moran's I statistic on model residuals (LeSage & Pace, 2009; Moran, 1948). It uses the location of dwellings, where location is a pair of latitude and longitude coordinates $\{lat_i, lon_i\}$, and is defined:

$$MI = \frac{N_T}{S}\frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum_i z_i^2}.$$

where N_T is the number of units in the estimation data, $z_i = \hat{\varepsilon}_i - \overline{\varepsilon}_i$ is the deviation from mean of residual i, w_{ij} is the spatial weight that defines the spatial relationship between pairs of observations i and j and S is the sum of all weights. The definition of w_{ij} is crucial for measuring spatial autocorrelation, as it implies a conjecture of how observations are related in space. We assume that local autocorrelation is the main potential issue and construct a set of $N_T \times N_T$ spatial weight matrices W_r of different ranges within 0.1–1.5 km as contiguity matrices[17] using the great circle distance around each dwelling as calculated by the Haversine formula. Dwellings within each cutoff distance receive an equal weight in the final row-standardized W_r, $\forall r \in (0.1, 0.5, 1.0, 1.5)$.

Results Empirical Analysis

The Renovation Premium in the Classical Model

Table 3 reports results for the effects of three levels of renovation on price. Included is a comparison for the classic regression model with area dummies and area fixed effects (column 1) and one that also includes the price zone dummies (column 2).[18] Column 3 shows the results for the model in column 2 without the renovation variable. Column 4 shows the results with interaction terms between dwelling age and area, and column 5 also adds interactions between renovation class and area.[19]

[16] Maps showing both spatial aggregations are documented in Fig. 7 in Appendix 1.

[17] Dwellings outside the cutoff distance receive the weight zero.

[18] The generalized variance inflation factor (VIF) scores remain low for all coefficients, and about 1.05–1.08 for the renovation coefficients.

[19] All models are estimated with robust standard errors (White). The Breuch Pagan $\sim \chi^2_p = 432.7$ in column (2) with $p = 59$ degrees of freedom.

Table 3 Regression Results: Classical linear model

	Linear and Interaction models				
	Dependent variable: log(Price)				
	LIN A (1)	LIN AP (2)	LIN AP No R (3)	INT 1 (4)	INT 2 (5)
log(Size)	0.698*** (0.006)	0.695*** (0.006)	0.689*** (0.006)	0.698*** (0.006)	0.697*** (0.006)
R-1	–0.100*** (0.007)	–0.096*** (0.007)		–0.097†	–0.098†
R1	0.006 (0.007)	0.012 (0.007)		0.014* (0.007)	0.015* (0.007)
R2	0.053*** (0.007)	0.055*** (0.007)		0.059†	0.051†
Age (8)					
Age2	–0.081*** (0.008)	–0.074*** (0.007)	–0.077*** (0.007)		
Age5	–0.123*** (0.007)	–0.109*** (0.007)	–0.117*** (0.007)		
Age8	–0.082*** (0.008)	–0.082*** (0.008)	–0.084*** (0.009)		
Rk × Area (12)					
R-1 × A4 (Central)					-0.102*** (0.014)
R-1 × A7 (West)					-0.085** (0.029)
R2 × A4 (Central)					0.052*** (0.015)
R2 × A7 (West)					0.080** (0.027)
Time, structural	x	x	x	x	x
Area (A)	x	x	x	x	x
Price zone (P)	–	x	x	x	x
Area × Age	–	–	–	x	x
Robust errors[a]	x	x	x	x	x
Est. parameters	52	63	60	130	154
Observations	5,742	5,742	5,742	5,742	5,742
Adjusted R	0.892	0.902	0.896	0.906	0.906

The table presents results for classical hedonic models including the effects of three levels of renovation, R-1, R1, and R2. Each column represents a separately estimated regression. Notes: Includes Administrative area dummies (A), Administrative area and Price zone dummies (AP), No Renovation variable (No R), Area-Unit Age interaction terms (INT 1), and in addition Area-Renovation interaction terms (INT 2). †These are average marginal effects (AME) in the interaction regressions. a. White standard errors. Significance level: $*p<0.1; **p<0.05; ***p<0.01$

Across the different specifications in columns (1)-(5), these results suggest a significant positive average renovation premium[20] in the range of 5.4–6.1 percent for fully renovated (R2) dwellings, and a negative premium in the range of 9.1–9.5 percent for unmaintained (R-1) dwellings. The following adjustment is used to interpret the coefficients as the percent change in price: $\left[\exp\left(\hat{\delta}_k\right) - 1\right] \times 100$. The coefficient for partial renovation (R1) is slightly positive but close to zero in most cases. This could be due to the difficulty distinguishing "somewhat" renovated from neutral (R0).

To interpret the economic magnitude of the average renovation premium, we focus on the results in column 2. Expressed in market prices, a renovation premium of 5.7 percent implies a premium of NOK 255,800 (USD 28,100) for the average-priced dwelling sold in the middle of the period. A negative premium of 9.2 percent for unmaintained units implies a discount of NOK 414,100 (USD 45,600). These are substantial sums for the average working person, who earned an average of NOK 522,700 per year before taxes in the middle of the period.[21]

When excluding the renovation variable in column 3, this is seen to scale the other model coefficients, in particular the age coefficients. This is consistent with age-renovation correlations. A similar effect is seen for the age coefficients when including the price zones in column 2, suggesting spatial clustering of dwelling vintages is captured to some extent in the price zones. Including dwelling age and area interactions in column 4, the average marginal effect (AME) renovation premium for fully renovated is estimated to 5.9 percent. The AME estimate for unmaintained units is similar to the previous. Column 5 displays area-specific renovation premiums, suggesting spatial variation.[22] In addition to the possibility of heterogeneous "treatment effects" of renovations, such patterns may be due to systematic geographically heterogeneous "treatments," i.e., the size and monetary value of the renovation. It is likely that investments are larger in high-end areas due to more expensive tastes and higher expected resale values, so fully renovated does not mean the same on average for different locations.

Improvements in Prediction Performance. Comparison of the Random Forest and the Classical Model

The random forest algorithm achieves moderately higher overall performance than the classical regression model out-of-sample, such as a decrease in RMSE from 0.128 to 0.115 in Table 4 Panel B, columns 1 and 7. R squared increases from 0.898 to 0.918. However, the random forest is also found to reduce spatial dependence in the residuals for all sets of spatial variables, indicating its superiority in capturing spatial structure and heterogeneous effects. This is in accordance with McMillen

[20] A joint heteroskedasticity robust linear F-test of regression model (1) rejects the null hypothesis that all renovation coefficients are zero by a large margin: $F = 6.447$ (p-value < 0.001).

[21] Official income data is gathered from Statistics Norway: https://www.ssb.no/en/arbeid-og-lonn/lonn-og-arbeidskraftkostnader/statistikk/lonn.

[22] The table includes a few interaction terms to illustrate.

Table 4 Moran's I (in-sample) and Model performance (out-of-sample)

Panel A: Moran's I[a]. Spatial autocorrelation of residuals/prediction errors
In-sample ($N_T = 5,742$)

	Linear			Random Forest (RF)			Neighbors	
Dist.[b]	A, P	A	No spatial	A, P	A	No spatial	Mean	Min, Max
0.1	0.162	0.227	0.415	0.117	0.174	0.392	6.6	(0, 39)
SD	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)		
0.5	0.081	0.175	0.452	0.044	0.107	0.356	95.2	(0, 254)
SD	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)		
1.0	0.043	0.107	0.408	0.020	0.060	0.322	318.4	(2, 820)
SD	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		
1.5	0.026	0.066	0.369	0.012	0.034	0.290	643.6	(3, 1508)
SD	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)		

Panel B: Model performance[c] with/without renovation (R).
Out-of-sample ($N_O = 2,461$)

	Linear R		Linear No R		RF R		RF No R	
Metric	Overall	P25, P75	Overall	P25, P75	Overall	P25, P75	Overall	P25, P75
R^2	0.900	0.638, 0.761	0.896	0.614, 0.750	0.921	0.678, 0.776	0.915	0.661, 0.757
Adj. R^2	0.897	0.629, 0.755	0.893	0.604, 0.744	–	–	–	–
RMSE	0.128	0.127, 0.154	0.131	0.132,0.158	0.115	0.103, 0.138	0.118	0.106, 0.143

The table reports the results from Moran's I tests on regression residuals for the classical model and prediction errors for the random forest algorithm in Panel A. Panel B shows results for model performance. Notes: a. Panel A reports Moran's I test statistics and their standard deviation (SD). The expected Moran's I-values ≈ 0.000 and p-values < 0.001 in all cases. b. The Haversine distance in kilometers. This spherical distance is based on a radius r of the earth of value $r = 6,378.137$ km. All neighbors within the given distances are given equal weight in the contiguity weight matrix. The mean number of neighbors within the relevant distance is reported under *Neighbors*, along with the min and max. c. Performance measures are reported for the overall case and the top ($P75$) and bottom ($P25$) quartiles of the house price distribution

(2010), who argues that problems with functional form may lie behind any observed spatial autocorrelation and suggests the use of flexible methods. The random forest achieves slightly higher out-of-sample performance than in-sample,[23] consistent with that the predictor is not overfitting to the estimation data (Hastie et al., 2009).

The inclusion of the price zone dummies is found to reduce spatial dependence, as evidenced by lower spatial autocorrelation of the residuals (see the results of the Moran's I test in Panel A).[24] The spatial autocorrelation is estimated to be positive and strongest at a radius of 100 m around each dwelling. Although significantly different from its theoretical mean (close to zero) under the null hypothesis of no spatial autocorrelation, Moran's I test statistics between 0.026–0.162 (first column) and 0.012–0.117 (fourth column) are considered low.[25]

When excluding the renovation variable in the linear model, there is a modest decrease in adjusted R squared overall, from 0.902 to 0.896 (columns 1 and 4). RMSE increases from 0.128 to 0.131. Model performance for the random forest changes to a similar extent. Because of well-known issues with the interpretation of "coefficients" or derived partial effects as consistent estimates for the random forest algorithm (e.g., Mullainathan & Spiess, 2017), we restrict attention to the magnitude of the estimated parameters in the classical models.

The marginal improvement in adjusted R squared by including the renovation variable is larger in the upper and lower quartiles (P75 and P25, respectively) of the house price distribution, as seen for the linear model when comparing the second and fifth columns of Table 4 where it increases from 0.604 to 0.629. This larger tail effect bears resemblance to McMillen and Thorsnes (2006) who also points to larger effects from omitting renovation information in the upper and lower quartiles.[26]

Overall, Table 4 shows that spatial dependence is not expected to be a major concern for our preferred model specifications in columns 1 (classical) and 4 (random forest). This supports our results for the renovation premium obtained previously. Second, the gains in model performance from including the renovation variable is similar for the classical model and the more flexible random forest, with larger gains in the tails of the house price distribution.

A Model with Professional AVMs

A challenge to hedonic valuation is that unobserved factors may be correlated with the house price and characteristics of interest. This is relevant for the probability of renovating a house and could lead to inconsistent estimates of the renovation premiums (see a discussion in Bajari et al., 2012). To illustrate, omitting unit-specific characteristics such as a fireplace and balcony may be correlated with expected resale value and thus, the decision to renovate or not renovate prior to sale. To

[23] Not reported for brevity.

[24] Note that we use a test based on fine-scaled spatial aggregations (100 m-1.5 km circle around each dwelling) and expect some shortcomings of the spatial dummies.

[25] The Moran's I statistic ranges from -1 to 1, with 1 indicating perfect positive spatial autocorrelation.

[26] The authors study house price appreciation and not house price levels, as is the case here.

address this issue, we collect external price valuations used by market participants and produced at the time of sale. The AVMs are based on all transactions in the Norwegian housing market (including those outside Oslo) and a more comprehensive set of hedonic characteristics. The following strategy is used, $\forall i \in \left(1, \ldots, N_V\right)$:

1. Regress the valuation price $logP_{AVM,i}$ on our set of hedonic characteristics. Variable interpretations are the same as for model (1):

$$\log P_{AVM,i} = \overline{\beta}_0 + \overline{\beta}_1 \log\left(Size_i\right) + \sum_{\forall s \in S} \overline{\beta}_S D_{is} + \sum_{\forall l \in L} \overline{\beta}_l L_{il} + \sum_{\forall k \in K} \overline{\delta}_k R_{ik} + \overline{\varepsilon}_{AVM,i}. \quad (2)$$

2. Calculate the vector of residuals, $\hat{\overline{\varepsilon}}_{AVM,i}$.
3. Estimate the hedonic classical model including the orthogonalized residuals, $\hat{\overline{\varepsilon}}_{AVM,i}$, our estimate of unobserved price-determining factors:

$$\log P_i = \overline{\overline{\beta}}_0 + \overline{\overline{\beta}}_1 \log\left(Size_i\right) + \sum_{\forall s \in S} \overline{\overline{\beta}}_s D_{is} + \sum_{\forall l \in L} \overline{\overline{\beta}}_l L_{il} + \sum_{\forall k \in K} \overline{\overline{\delta}}_k R_{ik} + \hat{\overline{\varepsilon}}_{AVM,i} + \epsilon_i. \quad (3)$$

Table 5 Regression Results: A model with professional AVMs

	Dependent variable: log(Price)		
	LIN (1)	AVM (2)	VAL (3)
R-1	–0.095*** (0.007)	–0.095*** (0.005)	–
R1	–0.005 (0.007)	–0.005 (0.006)	–
R2	0.043*** (0.007)	0.043*** (0.006)	–
$\hat{\overline{\varepsilon}}_{AVM}$	–	0.768*** (0.022)	–
AVM	–	–	0.990*** (0.004)
Time, structural	*x*	*x*	–
Area (A)	*x*	*x*	–
Price zone (P)	*x*	*x*	–
Robust errors (White)	*x*	*x*	*x*
Observations	5,809	5,809	5,809
Adjusted R^2	0.909	0.945	0.935

The table contains results for the hedonic model with an instrument for omitted characteristics. Each column represents a separately estimated regression. Notes: *LIN* is the same specification as *LIN AP* in Table 3, *AVM* includes the residual from an auxiliary regression of a model with external valuations as the dependent variable, *VAL* is the regression of price on the AVM alone. Significance level: $*p<0.1$; $**p<0.05$; $***p<0.01$

Table 5 display results with the AVM instrument for omitted characteristics. Due to dataset variations[27] the classical model is re-estimated in column (1), resulting in a lower premium for full renovation estimated at 4.4 percent. Results for the other premiums are similar. Column 2 contains the results of model (3) estimated with OLS. These results strengthen our previous findings for the renovation premiums. The coefficients are identical up to two decimal places and more stable, suggesting that our estimates are robust when the extensive price-determining characteristics in the AVM valuation is controlled for. The quality of the AVM valuation is also reflected in the large increase in adjusted R squared from 0.909 to 0.945 (0.935 without our hedonic characteristics in column 3).

Temporal Variation in the Renovation Premium

The period for which we have access to renovation information contains a boom followed by a bust. This section examines the temporal variation in the renovation premium and compare the trajectory of the premium with the housing market cycle. In addition to the benchmark linear hedonic model and the nonparametric random forest considered earlier, a rolling-window version of model (1) is estimated. For this purpose, the estimation sample is split into three adjacent parts. Each estimator is used to predict the identical time window out-of-sample.[28] The adjacent window approach is useful for studying parameter variation. The random forest index results are used to determine breakpoints for the rolling window model.

To study temporal variations in the renovation premium, our procedure is to trace out the renovation premium over time by estimating the HPI by renovation class and computing their ratios. Since interest lies in level movements for a bundle of characteristics, it is convenient to consider a Laspeyres price index.[29] Each price index, defined as $I^{0-t}_{x_i \in S_B}$ for any period t relative to period 0, is obtained by predicting the classical linear, rolling-window, and random forest models on a fixed set of house transactions at the beginning of the period, $S_B\left(N_B = 954\right)$, named the base period. The characteristics of the base period, $x_i \in S_B$ where $B = 2014$–2015, are held constant and reassessed subsequent periods. It is essential that the composition of the characteristics is reasonably evenly distributed and that the base period set is sufficiently large.

[27] Details in Appendix 1. A notable difference is that the AVMs are dominantly in place for regular owner-dwellings and that a smaller share is located centrally.

[28] This can be regarded as an extreme case of a rolling window approach, which typically builds overlapping estimation windows in each model (see Hill, Melser, and Syed, 2009).

[29] There are several other candidates, but not all are equally appropriate for models estimated on hedonic characteristics and for comparison across regression models. For example, the Paasche index involves changing the actual bundles and their prices. Thus, the movement of the index is determined in part by changes in the prices of the characteristics and in part by composition effects. For instance, to what extent the house price increases in part because the price per square meters increases and in part because the "median" house is 3 square meter larger is considered a concern, depends on the analysis at hand. In this analysis, the Laspeyres index seems to be the most appropriate.

Fig. 2 Renovation Premiums in a housing market (left). Separate hedonic House price Indexes by Renovation class (right) (**a**) Random Forest Renovation premium (**b**) Random Forest Index (**c**) Linear Renovation premium (**d**) Linear model Index (**e**) Linear Rolling window Renovation premium (**f**) Linear Rolling window Index. The figure displays results for the temporal variation in the renovation premiums. Notes: The renovation premium in period t (figures on the left) is defined as the difference between the estimates of the HPI level of fully renovated (R2) and neutral (R0) units at t, for out-of-sample HPI predictions (right-hand side). Similarly for R-1. The confidence interval for the renovation premium is twice the standard error of the differences in the average predictions. The random forest uses the jackknife median standard errors of the predictions ▶

Fortunately, both the renovation classes and the other characteristics appear to be largely balanced in S_B and later periods, with some small variations.[30]

Figure 2 shows separate house price indexes by renovation class (right) and the corresponding renovation premium (left). One notable result is that the premiums vary considerably in this volatile market period when considering the random forest model (a), allowing for such variability. Panel (e) and Table 6 columns (1)-(3) gives results for the rolling window model that support the time variation trend in the renovation premium found by the random forest model. During the boom-bust period, the premium on full renovation is not significantly different from zero. As a result, when excluding the boom- bust periods in the rolling window model, the average premium on fully renovated units increases to 6.7–7.0 percent. The discount on unmaintained units is also reduced during the boom-bust period, although the reduction is smaller in magnitude. Panel (d) shows the equivalent index for the classical linear model, where the price development by renovation class are multiplicative shifts from each other, a consequence of the log-linear form of the model.

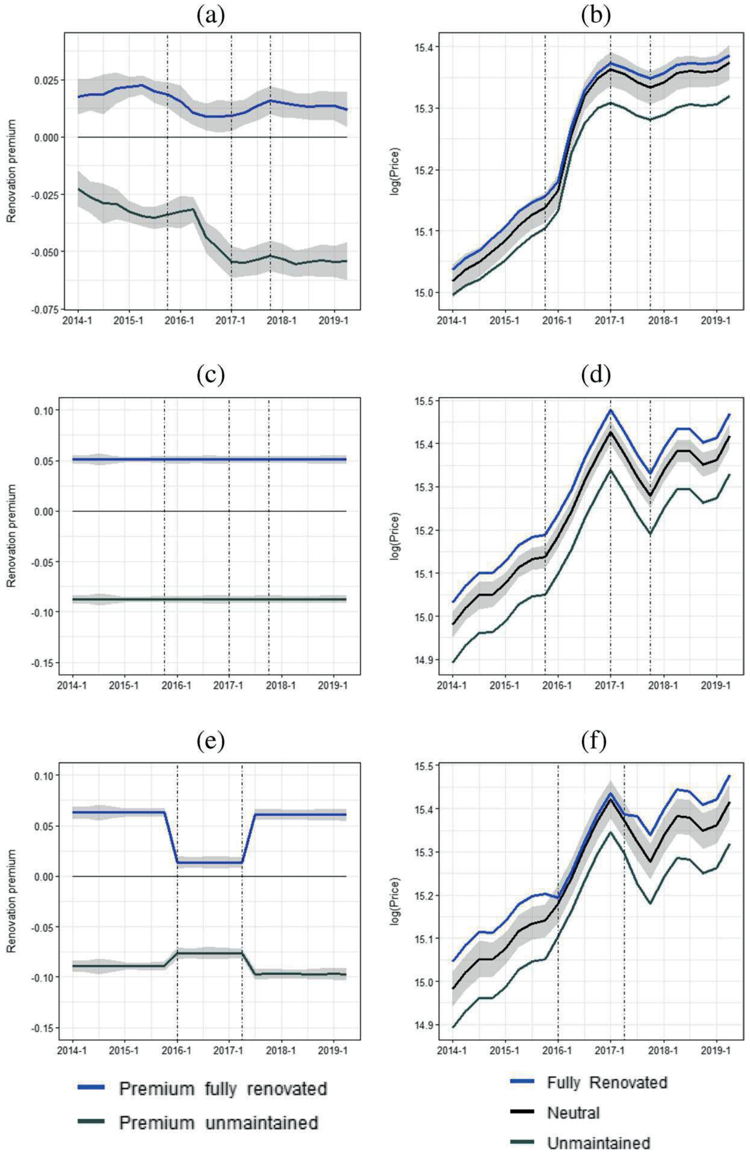
Figure 3 show the renovation premium predictions of the random forest model (Fig. 2a) along with macro-variables providing information on the housing cycle, as measured by house price growth and housing investment growth.[31] These results suggest the renovation premium is counter-cyclical during the boom and bust. This finding is consistent with Zabel (2015) who estimates a counter-cyclical variation in hedonic implicit prices for other housing quality characteristics for Boston, US. The result of a counter-cyclical premium for unmaintained houses also resembles the findings of Bourassa et al. (2009) who asserts that the values of atypical homes rise at higher-than-average rates in strong markets, whereas the reverse holds in weak markets.

Renovation Bias in House Price Growth

This section examines the impact of omitting renovation information on the HPI. The previous sections document evidence of differences in the composition of renovated dwellings over time. Moreover, that the renovation premium is significant. This may have implications for estimated house price growth.

[30] Variations include a gradual increase in the mean age of the dwellings and a slight tendency toward a more central location in later periods.

[31] *Housing investments* consists of investment in new construction and aggregate renovations of existing houses (the entire dwelling stock).



The difference in the house price growth estimates for the classical linear model is calculated. The quarterly house price growth for the Laspeyres HPI described earlier is computed, including, and excluding the renovation variable. The results in columns 2–3 in Table 3 is used. The absolute deviation in the house price growth estimate is defined as the *renovation bias*:

Table 6 Regression Results: Rolling window model[a]

	Dependent variable: log(Price)		
	LIN Normal Q1.14-Q4.15 (1)	LIN Boom, Bust Q1.16-Q2.17 (2)	LIN Normal Q3.17-Q2.19 (3)
log(Size)	0.715***	0.655***	0.702***
	(0.009)	(0.010)	(0.010)
R-1	-0.098***	–0.084***	–0.106***
	(0.011)	(0.012)	(0.011)
R1	0.012	0.008	0.012
	(0.010)	(0.015)	(0.013)
R2	0.068***	0.015	0.065***
	(0.011)	(0.012)	(0.012)
Time, structural	x	x	x
Area (A)	x	x	x
Price zone (P)	x	x	x
Robust errors (White)	x	x	x
Observations	2,132	1,552	2,058
Adjusted R^2	0.900	0.896	0.895

The table contains results for hedonic regression models. Each column represents a separately estimated regression. Notes: a. The Rolling Window model is estimated for three adjacent time periods in each column. Significance level: $*p<0.1; **p<0.05; ***p<0.01$

$$\left|\Delta log I_R^{t-(t+1)} - \Delta log I_{None}^{t-(t+1)}\right|, \forall t \in (1, \ldots, T). \tag{4}$$

The average absolute deviation in estimated house growth for the city total and smaller strata is displayed in Fig. 4 Quarterly House Price Growth, with and without Renovation informationand summarized in Table 7. Evident in the figures is a systematic fourth quarter effect. Since the frequency of unmaintained dwellings is considerably higher in the

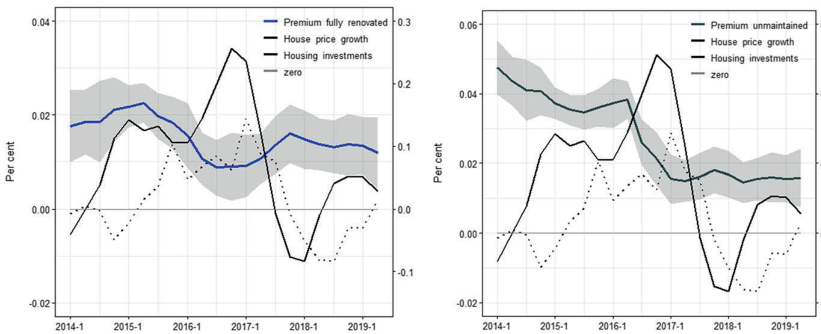


Fig. 3 Renovation premium, House price growth and Housing investment growth. The figures display results for the renovation premiums compared to the housing market cycle. Notes: House price and residential investment growth are official estimates from Eiendomsverdi ASA and Statistics Norway, respectively. The premium for unmaintained dwellings is shifted up by 0.07 percentage points for ease of interpretation

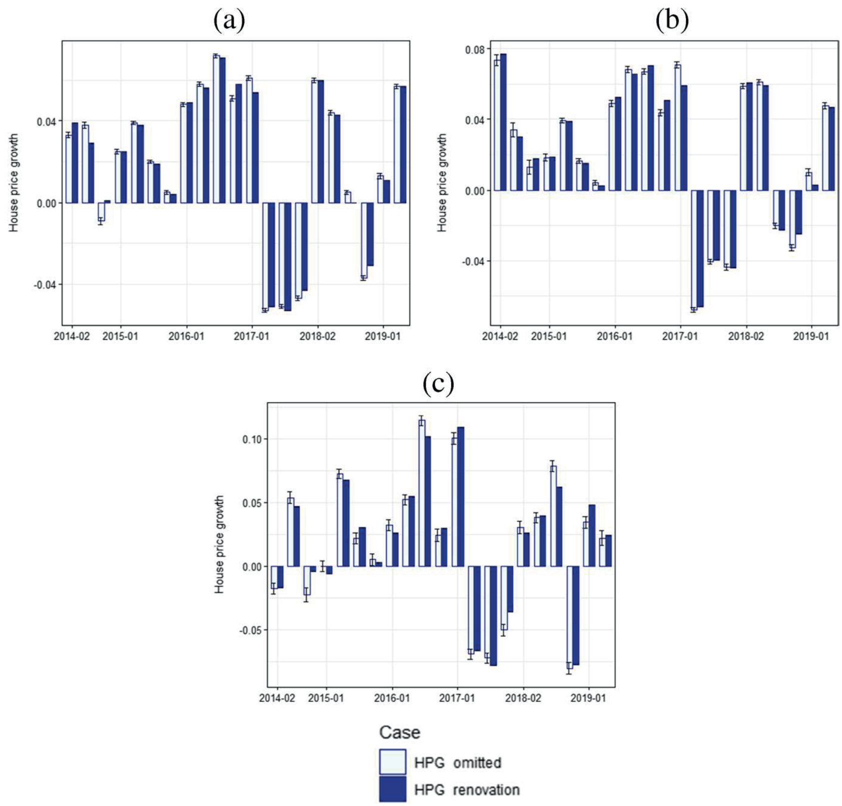


Fig. 4 Quarterly House Price Growth, with and without Renovation information (**a**) City total (**b**) Central (**c**) East. The figure displays results for the quarterly absolute renovation omission bias (%) of the linear classical hedonic model for the *City total*, the *Central* strata, and the *East* strata. Notes: *HPG omitted* omit renovation and *HPG renovation* includes renovation in the hedonic regression

fourth quarter, this tends to bias the fourth quarter price movement estimates downward, if uncontrolled for, as unmaintained dwellings transact at a significantly lower price. For the *City total* the renovation bias is estimated to 0.32 percentage points per quarter, which is 8.08 percent of the average absolute quarterly growth over this period. The results for the *Central* region are similar. In the less affluent *East*, omitting renovation information leads to a larger deviation in estimated price growth, 0.70 pp. on average, equivalent in absolute terms to 14.83 percent of average quarterly growth.[32] This finding contrasts with Bogin and Doerner (2019) who proposes the bias in the HPI is greatest in downtown areas of large cities. Most, but not all, quarterly differences are statistically significant (Fig. 4).[33]

[32] The direction of the bias is largely in line with differences in the composition of renovation classes.

[33] Alternatively, one could consider "renovation-adjusted" house price growth, where the different renovation classes are regarded as separate strata weighted by their transaction shares. This method is common practice in the literature on house price indices for type, location, etc. when different segments evolve at different growth rates.

Table 7 Renovation bias in quarterly house price growth

Strata	Bias[a] (pp.)	Share quarterly	Bias boom[b] (pp.)	Share quarterly boom
Full city	0.32	8.08	0.43	10.78
East	0.70	14.83	0.75	15.89
Central	0.34	8.0	0.61	14.4

The table reports results for the quarterly renovation omission bias (%) of the linear classical hedonic model. See Table 13 for the list of Oslo suburbs in each of the categories. Notes: a. This is defined as the average absolute change in the quarterly house price growth estimates due to omission of renovation information. The bias is measured in percentage points. b. The two right columns show results for year 2016 only (boom)

Additional Tests and Robustness Analysis

This section addresses a shortcoming of the renovation classification and tests if a change in demand for centrality could confound the results. The main takeaway from these analyses is that our results for the renovation premium and counter-cyclical variation largely hold. However, as there are likely to be renovations not reflected in the online-listings texts, this is expected to create a downward bias in the estimates of the renovation premium. As such, our estimates can be interpreted as a lower bound of the renovation premium.

Adjustments for Shortcomings of the Renovation Classification

Comparing the classification based on listings with a classification based on complete prospectuses, we expect that too few units are classified with renovation class R1 and R2.[34] The discrepancy is estimated to be 8 points of transactions for the fully renovated. In the repeat-sales framework, researchers often aim to address unobserved factors such as renovations and remodeling by approximate methods such as truncating the tails in the error or price change distribution. For instance, Bajari et al. (2012) and Harding et al. (2007) removes observations in the top appreciation rate percentiles. In the hedonic framework, it is common to remove units based on outlier prices and characteristics, such as very large or very expensive dwellings (e.g., Xiao, 2017).

Similarly, two observations based on our renovation classification are exploited to roughly target undetected renovated units. First, one can observe that a larger share of the detected renovated units would end up in the top right tail of the error distribution. Table 8 reports results for each renovation class by residual percentile based on the classical linear hedonic model without renovation information. While 11.5 percent of the detected fully renovated units appear in the upper P80-P100 percentile residual distribution, only 2.1 percent appear in the bottom P0-P20 percentile. Second, renovated dwellings tend to be dated. As many as 24–25 percent of dwellings

[34] See Table 12 in Appendix 1.

Table 8 Renovation class (share) by Price Residual percentile

Residual percentile	Unmaintained	Partially renovated	Fully renovated
P0-P20	0.186	0.042	0.021
P20-P40	0.103	0.056	0.042
P40-P60	0.056	0.075	0.068
P60-P80	0.039	0.060	0.081
P80-P100	0.033	0.051	0.115
P90-P100	0.036	0.046	0.121
P95-P100	0.038	0.050	0.125

The table reports the transaction-shares of renovation classes in the estimated price residual distribution. The estimates are based on a hedonic linear model without renovation information included, summarized in Table 3 column 3

above 90 years are detected renovated, while this is the case for less than 1 percent of dwellings aged 10 years or younger.[35] Specifically, we restrict candidate dwellings to units initially assigned renovation class R0 in the right tail of the price error distribution based on the linear hedonic model specification that *includes* the renovation information from the listings.[36] Sales from the boom year 2016 are excluded since any large unexplained price may be related to, among others, market tightness rather than renovations.

Four different dataset truncations are tested, and the linear models are re-estimated on each corresponding adjusted dataset (Table 9). Columns 1–2 adjust the samples solely on upper price residual criteria. When truncating the upper six percentile (P94) and four percentile (P96) error distribution, the coefficient on partial renovation increases to 2.0–2.4 percent and is highly significant. The coefficient on full renovation increases to 6.7–7.1 percent and the discount on unmaintained units reduces to 7.5–7.9 percent. Noting that the detected renovated units are not as right skewed in the error distribution as in the dwelling age distribution, columns 3–4 consider a broader part of the error distribution and add age criteria. Column 3 excludes units in the top 30 error percentile (P70) if they are more than 70 years. In column 4, this reasoning is taken even further, where units in the top 50 percentile (P50) error distribution are excluded if they are more than 90 years. Results for the renovation premiums are similar, although the increase in the premium estimates for partial and full renovation is even more substantial. Columns 5–7 displays the results of the rolling window model for scenario *P70 Age I*. The pattern of temporal variation in the renovation premium is still evident, with R1-R2 premiums declining sharply in the boom-bust years.

Overall, the reductions in the right tail of the price error and age distributions have resulted in larger implicit price estimates for renovation. However, this

35 Summary statistics in Table 2.

36 See the model specification in column (2) in Table 3.

Table 9 Adjusted sample Regression Results: Classical and Rolling window model

	Dependent variable: log(Price)						
	LIN P94 (1)	LIN P96 (2)	LIN P70 Age I (3)	LIN P50 Age II (4)	LIN Normal[a] Q1.14-Q4.15 (5)	(6)	LIN Normal Q3.17-Q2.19 (7)
log(Size)	0.678^{***}	0.678^{***}	0.694^{***}	0.691^{***}	0.720^{***}	0.649^{***}	0.701^{***}
	(0.005)	(0.005)	(0.006)	(0.006)	(0.009)	(0.010)	(0.010)
R-1	-0.078^{***}	-0.082^{***}	-0.079^{***}	-0.084^{***}	-0.079^{***}	-0.084^{***}	-0.075^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.012)	(0.011)
R1	0.024^{***}	0.020^{**}	0.036^{***}	0.031^{***}	0.040^{***}	0.015	0.049^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)	(0.015)	(0.013)
R2	0.069^{***}	0.065^{***}	0.077^{***}	0.073^{***}	0.097^{***}	0.026^{*}	0.092^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.012)	(0.012)
Time, structural	*x*	*x*	*x*	*x*	*x*	*x*	*x*
Area (A)	*x*	*x*	*x*	*x*	*x*	*x*	*x*
Price zone (P)	*x*	*x*	*x*	*x*	*x*	*x*	*x*
Robust errors (White)	*x*	*x*	*x*	*x*	*x*	*x*	*x*
Observations	5,514	5,590	5,417	5,464	1,998	1,510	1,909
Adjusted R^2	0.915	0.912	0.905	0.903	0.906	0.895	0.900

The table contains results for hedonic regression models on adjusted datasets according to four different adjustment criteria in columns 1–4 and a rolling window model in columns 5–7. Each column represents a separately estimated regression. Notes: a. The Rolling Window model uses the specification *LIN P70 Age I* and is estimated for three adjacent time periods. Significance level: $*p<0.1; **p<0.05; ***p<0.01$

approach probably involves removal of dwellings that are old but not renovated or receive an unexplained high price (by our model) for reasons unrelated to renovation. Although we suspect that our renovation premium estimates are somewhat biased downward, it is plausible to expect that these rough adjusted sample-estimates are biased upward. Thus, our results can be interpreted as a lower bound of the renovation premium. Moreover, we gain support for the finding of counter-cyclical temporal variation.

Testing if Variations in the Renovation Premium are Driven by Variations in the Implicit Price for Centrality

Based on hedonic theory, it could be argued that all implicit prices may exhibit a similar pattern to the renovation premium in times of disequilibrium. More importantly, movements in one implicit price may be confounded by movements in another if not accounted for. Using the random forest, HPIs segmented by other hedonic characteristics (such as size and type) are examined for similar patterns of temporal variation. Potential heterogeneity in implicit prices for apartments vs. single-family units has received some attention among practitioners. We find that the temporal variation in size- and dwelling type coefficients are considerably more modest.[37] However, the average HPI by geographical strata follows a similar, but less pronounced, pattern where the centrality premium reduces temporarily during the boom.

From this finding, there is the possibility that our results for the variations of the renovation premiums may in part be driven by shifts in the centrality premium. To test this contingency, the temporal variation of the renovation premium for more homogeneous urban strata is examined. The most central urban area around the CBD (Central), an affluent western suburb (West), and a less affluent eastern suburb (East),[38] although this distinction is not exact. Figure 5 displays the renovation premium for the Central and East regions. The renovation premium shows similar patterns with considerable cyclic variation over the period, implying that our results are robust to lower geographical segmentation.

Conclusion and Discussion

The housing market involves transactions of dwellings that differ with respect to hedonic characteristics. A fundamental assumption of workhorse house price models is the ability to control for quality variation. Failure of this assumption is likely to lead to biased inference if the omitted information is essential. This paper addresses the price determinant renovation, which is of unknown importance, being seldom included in house price estimation due to data limitations.

[37] Results are similar for regular owner vs. coop dwellings.

[38] See Table 13 in Appendix 1.

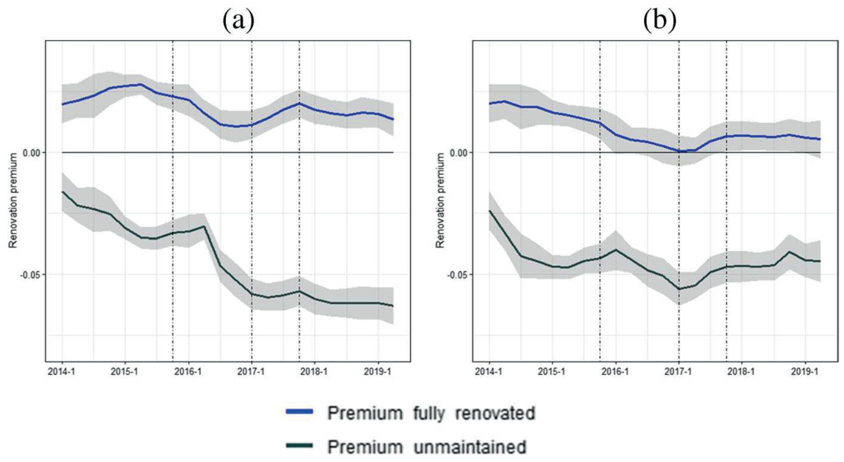


Fig. 5 Strata: Random Forest Renovation premiums (**a**) Central (**b**) East. The figure displays our results for the temporal variation in the renovation premiums in two urban strata, the most central urban area around the CBD (Central) and a less affluent eastern suburb (East). Note: The methodology is identical to Fig. 2. The out-of-sample dataset for 2014–2015 for the Central region is of size $N_{central,O\in(Q114,Q415)} = 493$, whereas the estimation dataset is of size $N_{central,T} = 3,212$. Similarly for the East, $N_{east,O\in(Q114,Q415)} = 172$ and $N_{east,T} = 1,098$

Texts of online listings of houses transacted in the Oslo market for the period 2014 to 2019 are used to sort dwellings according to four renovation classes.[39] We find that the renovation premium (fully renovated) is in the 5 to 7 percent range. The negative premium for unmaintained dwellings is somewhat higher, estimated at 9 to 10 percent. Our results for fully renovated dwellings are lower than the estimates in McLean et al. (2013) of 9.4 percent for Hungary. However, when comparing our point estimates with other studies, the differences in the renovation data should be kept in mind.[40]

Nevertheless, one limitation of this study is that it relies on less than perfect identification of renovation class for the dwellings in question. This creates a downward bias, and as such, our estimates can be interpreted as a lower bound of the renovation premium. However, the importance of renovation as a price determinant is an undeniable takeaway from our analysis. Failure to control for renovation leads to significant biases of housing price levels and indices. Moreover, these are unfortunately not only considerable, but they also tend to vary over time and across space.

The time dimension is important for two reasons. First, it appears to be a variation with the business cycle, where the renovation premium is considerably lower in

[39] These are unmaintained, partly renovated and fully renovated. The fourth is the reference category, dwellings that are neither renovated nor unmaintained.

[40] See the discussion in the Introduction.

a more heated housing market. This effect is the opposite for unmaintained dwellings, where the negative premium is reduced in a heated housing market. These results could be explained by changes in the composition of buyers over the housing cycle, in line with the predictions of Chernobai and Chernobai (2013), leading to variations in the bargaining process between buyers and sellers on certain characteristics (Bourassa et al., 2009). A related explanation is shifts in investment motives and levels of exuberance. Depken et al. (2011) estimates that in a boom phase, a large percentage of transactions are speculative or "flips" in Las Vegas, US, while this share is highly reduced in a bust.

Another candidate driving factor is the income-mortgage effect. The market heat is like a tide that lifts all boats, but the attractive and expensive in several market segments to a lesser extent due to income and mortgage financing limitations. This may result in less competition for expensive dwellings, including fully renovated for otherwise constant characteristics. Unmaintained dwellings allow for a future renovation and, as such, involve a potential investment smoothing. Future research extends this analysis by incorporating micro data on housing search and the holding times of each renovation class to study if variations in renovation premiums are matched by variations in search and the extent of flipping.

Second, our analysis indicates that part of the well-known seasonality in house price indices is partly due to composition effects. The frequency of unmaintained dwellings is considerably higher in the fourth quarter. This composition effect has implications for the seasonal variation observed in house price indices and tends to bias price movement estimates downward, if uncontrolled for, as unmaintained dwellings transact at a significantly lower price. Adding to this, the systematic temporal variation in renovation premiums may also bias estimates for price indices and house price growth.

Finally, this study observes significant spatial variation in renovation classes. Existing evidence (e.g., Bogin & Doerner, 2019) concludes that a higher renovation activity in central areas is the primary explanation for biased HPI estimates. In contrast, our results show that the renovation bias tends to be higher in less central areas, driven by a higher frequency of unmaintained dwellings transacted. We ascribe the differing results mainly to variations in the information sets used, mainly that our study also includes the unmaintained characteristic. There are reasons to believe that both higher renovation frequency in central areas and higher propensity to not undertake necessary maintenance in more distant areas from the city center apply to most cities. As both effects lead to a smaller price difference between central and non-central areas when adjusting for renovation (or lack thereof), this finding has implications for the literature regarding beta and sigma convergence in metropolitan areas (see e.g., Wood et al., 2016).

At a higher level, our analysis of online listings points to a way to control for renovation. Other ways, for example, using computer vision (Yencha, 2019), may prove an even more powerful way to measure the degree of renovation and get closer to quality-adjusted price levels and price indices for the housing market. In this sense, our analysis is an early contribution that shows controlling for renovation is feasible and involves significant rewards.

Appendix 1

Table 10 Data Preparation prospectus data and Summary Counts listings and prospectus data. Averages and totals

Panel A: Data Preparation prospectus data	
Data stage	No. of transactions
Raw data	7,212
(1) Data after removal of errors in price variable	7,205
(2) Data after adjusting (1) for age cohort and time-of-sale[a]	3,485
Panel B: Summary Counts listings data ($N = 10,350$) and prospectus data ($N_p = 3,485$)	
Data counts	No. of words, sections, or bytes
Average no. of words per listing text[b]	15.2
Words in total listing texts	156,878
Bytes total listing texts	1,768,700
Sections per prospectus[c]	51.5
Bytes total prospectus texts	16,634,488

Panel A provides a brief overview of the data preparation. Panel B provides a comparison of text length. The listing data have less text available for text analysis. This makes text analysis easier because the texts are more standardized. There is also the possibility that renovation/poor maintenance is not reflected in the text. A similar classification based on exceedingly richer information in prospectuses is performed for a smaller subset of dwellings to address this. Notes: a. Stratified re-sampling of transactions by age cohort of dwellings and time-of-sale, matching the distribution of listings. b. The listing text is written in the form of keywords. These typically contain condensed information or highlights of the unit, often including information about recent renovations. Summary statistics are based on a full count. c. The prospectus texts include, in most cases, an extensive description of the unit and a list of maintenance and renovations

Table 11 Frequent Words in listing texts and Summary Statistics by Renovation class $N = 10,350$

Renovation class	2	1	-1	0	age < 10 yr	All
No. of obs	723	558	902	6,736	1,431	10,350
Percent	7.0	5.4	8.7	65.1	13.8	100
+Renovation indicators[a]						
Renovert (Renovated)	482	128	0	35	7	552
Påkostet (Lavish)	68	16	0	8	37	129
Kjøkken (Kitchen)	106	358	20	382	12	–
Baderom (Bathroom)	126	284	108	842	81	1,441
Lekker (Gorgeous)	230	100	3	707	303	1,343
Høy standard (High Standard)	62	34	1	360	71	528
Strøken (Flawless)	45	6	0	83	51	185
– Renovation indicators						
Oppussingsobjekt (Unmaintained)	0	0	803	3	0	807
Potensial (Potential)	0	0	145	22	0	167
Sjarmerende/Hyggelig (Charming/Nice)	20	28	19	418	9	494
Moderne (Modern)	37	32	213	202	122	606
Dwelling characteristics						
Transaction price (10^6 NOK)	4.5	3.9	4.7	4.4	5.3	4.5
Transaction price per m^2 (10^3 NOK)	65.5	64.9	51.9	61.2	68.5	61.9
Size in m^2	74.8	63.8	98.7	78.6	81.1	79.7
Dwelling age	74.8	77.8	63.5	60.0	4.4	54.6
Location						
Central	335	265	283	2,515	523	3,921
West	245	213	412	2,921	612	4,403
East	143	80	207	1,481	115	2,026
Quarter of sale (share)						
Q1	0.07	0.055	0.085	0.79	–	2,749
Q2	0.07	0.055	0.085	0.79	–	3,324
Q3	0.07	0.055	0.07	0.80	–	2,230
Q4	0.065	0.050	0.11	0.77	–	2,047

The table provides details on the word frequencies for the different renovation groups in our classification. This can be seen as a first check of the classification since the keywords signaling full renovation should be almost absent for the unmaintained ones and vice versa. The table is encouraging because it shows the desired separation of signaling words. To some degree, these listing texts are essentially advertisements, so there is considerable creativity that presents a challenge for text analysis. A wide range of positive words is used to describe newly renovated units (gorgeous, flawless, exclusive, lavish). Since most of these words could be cheap talk, a careful reading of all listing texts was undertaken to assess the degree of renovation they reflect. Listings for unmaintained units generally use a different vocabulary. "Potential" and "charming" are widely recognized as positive ways to describe a poorly maintained dwelling. Notes: a. The classification is based on both automated word search and manual control

Table 12 Validation: Renovation Classification Results between 2017-Q2 and 2019-Q2. Shares and volumes. Prospectuses (P) and Listings (L)

	R-1 (P)	R-1 (L)	R0 (P)	R0 (L)	R1 (P)	R1 (L)	R2 (P)	R2 (L)
Shares								
2017-Q2	0.10	0.08	0.58	0.80	0.15	0.05	0.17	0.07
2017-Q3	0.08	0.09	0.54	0.78	0.20	0.04	0.18	0.09
2017-Q4	0.12	0.11	0.62	0.78	0.13	0.04	0.13	0.07
2018-Q1	0.12	0.09	0.52	0.79	0.19	0.05	0.16	0.07
2018-Q2	0.10	0.09	0.59	0.81	0.16	0.04	0.15	0.06
2018-Q3	0.12	0.04	0.58	0.87	0.15	0.05	0.15	0.03
2018-Q4	0.19	0.11	0.55	0.77	0.11	0.06	0.15	0.06
2019-Q1	0.08	0.10	0.60	0.78	0.14	0.05	0.18	0.07
2019-Q2	0.09	0.08	0.58	0.78	0.20	0.06	0.14	0.08
Total	0.11	0.09	0.57	0.80	0.16	0.05	0.15	0.07
Volumes								
2017-Q2	20	47	110	472	29	29	32	44
2017-Q3	12	41	80	357	30	19	27	42
2017-Q4	18	50	92	352	19	17	19	33
2018-Q1	18	41	78	364	29	22	24	32
2018-Q2	20	52	114	480	31	25	28	35
2018-Q3	21	23	100	452	26	27	25	18
2018-Q4	24	41	68	290	14	23	18	24
2019-Q1	11	46	85	343	20	21	25	31
2019-Q2	10	30	67	274	23	21	16	28
Total	154	371	794	3,384	221	204	214	287

The table compares the renovation classifications for the listing and prospectus datasets. To make the comparison valid, the transactions in the prospectus data are adjusted for differences in the timing of sales and the age distribution of the units. The shares of R-1, the unmaintained units for sale, are reasonably similar overall. Thus, the listing text appears to be adequate for capturing dwellings needing renovation. The story for R1 and R2 is less reassuring. In the case of fully renovated units, the proportion in the prospectus data set is 15 percent, compared to 7 in the listing dataset. Although these are different data sets, they are from the same area and cover the same period. Notes: In the validation stage, a fixed share of 40 (20 percent $\times$ 2 with replacement) of the transactions in the adjusted prospectus data ($N_p = 3,485$) is randomly selected each quarter and classified by the same criteria as for the listing data

Table 13 Administrative areas in Oslo by Strata

Strata	Administrative area with area number
Central	1. Frogner, 2. Günerløkka, 3. Sentrum, St. Hanshaugen, 4. Sagene, 5. Gamle Oslo
West	6. Ullern, 7. Vestre Aker, 8. Nordre Aker, Marka, 11. Nordstrand
East	9. Bjerke, 10. Alna, 11. Østensjø, 12. Søndre Nordstrand, Stovner, Grorud

Notes: To achieve a sufficient volume of transactions in each area, Sentrum, Marka, Søndre Nordstrand, and Stovner are merged with nearby areas or areas with similar location premiums

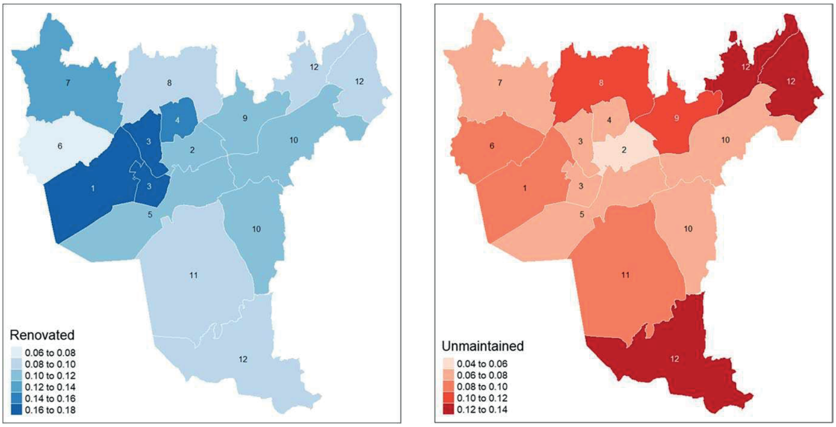


Fig. 6 The share of Renovated transacted dwellings by administrative area between 2014-Q1 and 2019-Q2. Left: Renovated (R1-R2). Right: Unmaintained (R-1). The figure maps the spatial distribution of the share of renovated transacted dwellings for the five-year period. According to these findings, renovation shares R1-R2 are positively associated with urban location (left graph), with the highest shares in central, high-end suburbs. Unmaintained sales are more common in low-income southern and eastern suburbs (right panel). For instance, renovated dwellings are more frequent in area 3 which includes the city center. Unmaintained units are more frequent in area 12, the cheapest housing areas in the city. The numbering corresponds to Table 13. Notes: Oslo's large most Northern administrative area, including mainly recreational zoning areas, is excluded from the map (Marka)

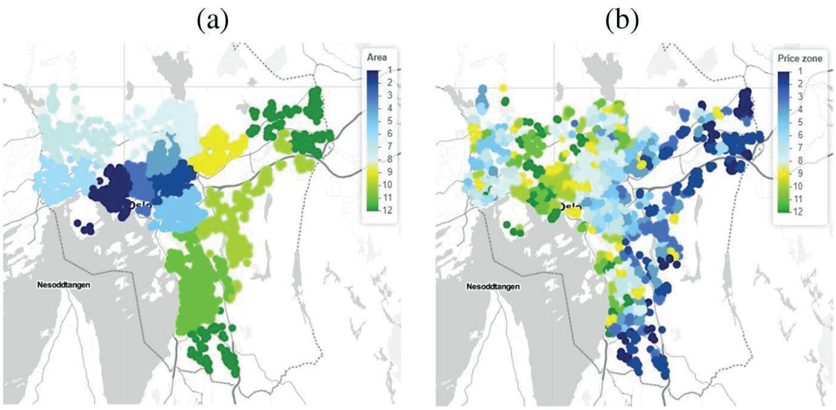


Fig. 7 Transactions in Administrative areas (by color) and non-contiguous Price zones (by color). $N = 8,203$ Notes: The administrative areas in (**a**) are described above. The price zones in (**b**) are constructed based on the methodology described in Sommervoll and Sommervoll (2019)

Table 14 Data Preparation listing data

Data stage	No. of transactions
Raw data	11,683
Hedonic data after removal of non-housing transactions	
(commercial, vacation-property, contracts, lots, whole buildings)	11,372
Hedonic data after removal of data with errors in price-variables[a]	11,284
Hedonic data after renovation classification[b]	10,842
Hedonic model data after removal of missing model variables	10,642
(1) Hedonic model data after excluding 2013-transactions[c]	10,350
(2) Hedonic model data (1) with geographical coordinates	9,186
(3) Hedonic model data (1) with price zones	8,203

Notes: a. 90 transactions recorded with very low transaction prices are removed. b. 442 transactions are removed because the text of the listings contain very limited information, and classification by renovation status is not possible based on the information reported. c. 2013-data is removed due to few transactions per quarter

Table 15 Checks for Balances: Summary Statistics estimation data, out-of-sample data, and data with AVMs. Prices and Key housing characteristics. Prices in million NOK

Statistic	Mean	St. Dev	Min	Max
Estimation data. $N_T = 5,742$				
Transaction price	4.5	2.25	1.1	32.5
Dwelling age	75.7	46.0	14	757
Size in m^2	57.1	37.7	1[a]	176
Sold before 2016 (share)	37.1			
Apartments (share)	88.7			
Regular owner (share)	54.7			
Located centrally (share)	55.9			
Out-of-sample data. $N_O = 2,461$				
Transaction price	4.4	2.1	1.1	21.0
Size in m^2	74.6	44.5	15	397
Dwelling age	57.9	37.4	0	188
Sold before 2016 (share)	38.8			
Apartments (share)	89.7			
Regular owner (share)	54.5			
Located centrally (share)	55.4			
Data with AVMs. $N_V = 5,809$				
Transaction price	4.65	2.3	1.0	33.0
AVM price[b]	4.6	2.2	1.1	20.1
Size in m^2	80.2	49.0	14	757
Dwelling age	53.5	36.5	−2	214
Sold before 2016 (share)	39.7			
Apartments (share)	85.7			
Regular owner (share)	74.8			
Located centrally (share)	47.1			

Notes: 1 NOK = 0.11 USD on January 7, 2022. a. New dwellings sold before completion. b. The AVM price is a professional price estimate from Eiendomsverdi ASA

Appendix 2

Random forest details

Random forest algorithms require hyperparameters that control how many decision trees are grown, how many variables are included in each split (mtry), and how small each terminal node of the tree can be (node size). The chosen performance measure minimizes the predictions' root mean squared error (RMSE). To find the optimal set of hyperparameters, we run a loop of hyperparameter combinations using fivefold cross-validation.

Although regression tree models often use categorical data in their natural form, it is worth considering whether alternative coding can improve performance. In this case, including all variables in numerical form produces the best predictive results. The best performing models, in the sense of no significant gains in model performance (R squared or RMSE) from altering the hyperparameters, is found around the parameter set where the number of trees is about 1,000, as this is demonstrated to be sufficient to achieve a stable error rate in our case (see the discussion in Breiman, 2001), *mtry* is 5–6, and the final *nodesize* is 5. With a node size beyond 6, performance is reduced. The final hyperparameters used are $mtry = 5$, $nodesize = 5$, $trees = 1,000$. The infinitesimal jackknife for bagging is used to estimate the standard errors. The *Ranger*, *Caret* and *RandomForest* packages in *R* are used to estimate the models. Reported estimation results are based on the Ranger package (see Wright & Ziegler, 2015).

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4 Paper II

Williams (2014) develops a model of "focused search" that moves beyond a purely random search process. The key assumption in his focused-search model is that the pre-search results in a truncation of the distribution of idiosyncratic match values with the new truncated distribution being well-approximated by a power law distribution. The use of a power law approximation has been shown to have strong microfoundations in other applications.

Han & Strange, 2015

Search Ripples in Urban Housing markets: the Quality-Location Trade-off

Mari O. Mamre[a], Bjørnar Karlsen Kivedal[b]

[a] *Oslo Metropolitan University and Norwegian University of Life Sciences, Norway*
[b] *Oslo Metropolitan University and Østfold University College, Norway*

Abstract

This article investigates ripples of search across different housing quality tiers empirically, using fine-scale data on housing search activities and transactions. This is the first paper to study ripples of housing search in the quality dimension using data from housing auctions. Consistent with theory, our findings indicate that search for low-quality housing in a city is significantly pro-cyclical, while search for high-quality housing is countercyclical. These effects are amplified in more attractive locations. During major housing market booms, the dispersion is greater, while during busts this ripple is reversed. We relate this to housing market outcomes in two ways. First, our findings suggest that search by quality tier is related to housing turnover and price growth in the expected way. Second, based on Vector Autoregression (VAR) analysis and Granger causality tests, we document a positive relationship between search intensity and aggregate price development by quality tier, where shifts in search tend to lead changes in house prices.

Keywords:
Housing market search, housing quality, house price ripples
JEL: O18, D10, D83, R21

1. Introduction

Housing markets are frictional in nature, characterized by costly search processes and variable arrival of potential trading partners. During housing market booms, buyers enter the market more rapidly, increasing the buyer-to-seller ratio in a spatially defined market, leading to higher turnover, accelerated house price growth, and spatial ripple effects. While the existence and direction of such ripple effects are disputed, many studies suggest a price ripple from prime to secondary locations. Location, however, is not the only attribute that buyers care about when considering potential homes. Housing is a highly composite good that varies in a wide range of qualities, such as size and interiors. In light of this heterogeneity, any spatial spillover may be paralleled by quality spillovers, since another

Email addresses: `corresponding author: mari.mamre@oslomet.no` (Mari O. Mamre), `bjornar.k.kivedal@hiof.no` (Bjørnar Karlsen Kivedal)

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viable strategy for budget constrained households is to reduce the quality of the home, which is the focal point of this study.

Recent theoretical work by Williams (2018) suggests that the choice of housing among home searchers may depend on the level of competition across different housing quality segments. Search is defined as the activity that follows the initial screening of listings, such as visiting the house. The combination of costly crowding-out effects and inflated price growth in preferred quality segments during booms may induce more buyers to reassess their optimal match value, the unique buyer's valuation of the home, and search in less preferred segments. However, there is little direct empirical evidence of such ripples in housing search activity.[1]

Informed by this theoretical model and a growing related body of literature, we empirically investigate how aggregate search intensity in the cross-section of houses changes with market phases. In essence, we seek to answer: Do the masses of searchers tend to search for high- or low-quality houses, and are these decisions correlated with the market cycle? Our analysis is based on fine-scale data from residential auctions combined with a rich set of transaction data for four urban areas, with a primary focus on Oslo, the largest metropolitan market in Norway. These urban areas, where the vast majority of households are homeowners, are particularly suitable for this analysis. Moreover, Norwegian auctions, conducted as English auctions, often lead to heated bidding wars, driving up prices and creating crowding-out effects.

As the previous literature demonstrate, there is no universally accepted concept of quality. In its broadest definition, it refers to all characteristics that a potential buyer is likely to value. Sweeney (1974b) and Cubbin (1974) emphasized the importance of houses as distinct substitute goods that could be divided into quality hierarchies, but defined quality in a broad sense. Leishman (2001) further argued that housing can be segmented both spatially and by quality and that it must be considered as a set of interrelated submarkets. Although the combination of space and quality dimensions is challenging to implement, we include both to some extent throughout the analysis. In this study, we define housing quality tiers based on size, age, and a measure of the renovation status of the house at the time of sale described in Mamre and Sommervoll (2022). To separate the market into spatial segments, we construct both price zones and search zones. We show that search intensity have a clear monocentric structure in the metropolitan market.

Consistent with theory, the key finding is that the dispersion in aggregate search intensity by house quality tier displays clear variations over the housing cycle. Most notably, we find that search for low-quality housing is significantly pro-cyclical while the search for high-quality housing is counter-cyclical, albeit to a lesser extent. During major housing market booms the dispersion is greater, while this search ripple is reversed during busts. These effects are particularly strong in prime locations, while they are almost non-existent in distressed locations. Specifically, these estimates show that the dispersion in

[1]Exceptions are found in Genesove and Han (2012) and Han and Strange (2016), which do not consider the cross-sectional dimension, and Piazzesi et al. (2020) which considers cross-sectional variations in online screening.

search intensity from medium to low quality housing (medium-to-low dispersion) in the metropolitan market is estimated at 19.9 percent during the phase of boom where both prices and the ratio of buyers to sellers increase. In the same market phase, the even more extreme measure of high-to-low quality dispersion is estimated to be 27.8 percent. Both estimates are important in magnitude and statistically significant. The tendency for a higher relative search for lower quality housing during booms is found in three out of four cities studied, while it is not significant in one city. In the metropolitan market, there is a hierarchy in order of magnitude from prime to distressed locations based on price zones, where high-to-low quality dispersion is estimated at 42.2 percent during booms in both prices and buyer-seller ratios, while this is estimated at 30.4 per cent in secondary locations, and insignificantly different from zero in distressed locations. This sorting is not as clear when we use an alternative spatial aggregation, supporting that prices and location play an important role for search ripples during booms

We relate these finding to housing market outcomes in two ways. First, our findings document that search by quality tier is related to housing turnover, the number of bids received, and price growth in the expected way. Second, based on VAR analysis and Granger causality tests, the paper also documents a significant relationship between search intensity and price growth by quality tier, where changes in search tend to lead changes in house prices. Theoretical models with bargaining between buyers and sellers provide a possible explanation for why changes in search intensity can lead to changes in prices (e.g. Krainer (2001); Piazzesi and Schneider (2009)). Such bargaining are likely in these housing auctions. These findings indicate a trade-off between quality and location. In order to maintain optimum location quality, more buyers may be willing to reduce unit quality. Our findings also align to some extent with realtors' claims that buyers are more selective during busts, while "anything goes" in booms. Since most cities' housing markets are complex systems with spatial patterning of housing qualities and price levels (see e.g., Piazzesi and Schneider (2009)), our findings support that variations in the demand for quality during booms and busts is a fundamental driver of variations in house price growth within and across neighborhoods (see Ferreira and Gyourko (2012)) and housing quality tiers. Additionally, this paper highlights the value of including aggregate search intensity directly in the analysis of market phases. We can consider the average number of searchers per unit for sale as a measure of the inventory (im)balance and a parameter for the likelihood of crowding-out effects. By looking only at price measures, as is common in the literature, we would not see the interesting variation in dispersion between the parts of the boom where search intensity expands and contracts, and get more muted results.

However, changes in search activity of potential home buyers during booms and busts are not the only plausible mechanism at work. A shortcoming of the analysis is that we lack identifying information about searchers across auctions and study volumes. For instance, Chernobai and Chernobai (2013) show that there is also expected to be a clientele effect, with professional investors in particular entering the market to a greater extent during booms and disappearing during busts. Although the size of the clientele effect is unknown there is, however, strong theoretical support for quality ripples of search among ordinary home buyers as well. Moreover, several of the markets considered here have a small and stable share of buy-to-let houses during the time period studied.

The remainder of the paper is organized as follows. Section 2 review previous literature on how quality can direct search in booms and busts. Section 3 describes the data, the quality segmentation, and the spatial and temporal aggregation of submarkets and housing market cycles. Section 4 empirically studies the evidence for quality ripples of search intensity in cross-section models. Section 5 empirically studies implications for housing market outcomes and test for ripple effects by VAR analysis and Granger causality. Section 6 contains a robustness analysis, and section 7 concludes.

2. Literature: How Quality can direct Buyer Search in Booms and Busts

This paper relates generally to the literature addressing the microstructure of housing markets (see Han and Strange (2015) for a review), herein a large literature on buyer search activity and its impact on housing market dynamics (Wheaton (1990); Ngai and Tenreyro (2014); Guren and McQuade (2020); Carrillo (2012), Anenberg and Bayer (2020)) as well as the effects of shocks (see e.g., Ortalo-Magne and Rady (2006). Specifically, our paper adds to the body of empirical research analyzing buyer search activity in the cross-section of houses.

It is well acknowledged in parts of the housing search literature that buyers are not equally inclined to search for all the houses in a market, leading to a tendency for search to be segmented. In their study of the San Francisco Bay area, Piazzesi et al. (2020) demonstrate that online screening, often preceding any search or visit, primarily occurs along the three dimensions: location, price and house size. They also highlight the importance of buyer differences and market integration levels for housing market outcomes. Similarly, Rae and Sener (2016) document that most of the online screening in London is fairly local and is also segmented by price and size.

It has been shown that booms have an impact on housing search (Novy-Marx (2007); Albrecht et al. (2007); Han and Strange (2016)) and that booms or shocks to key household-specific variables, such as income or wealth, can affect the cross-section of houses differently. As Sweeney (1974a) pointed out, this happens because buyers in a housing market face a choice of quality rather than a choice of quantity. Positive income shocks for low-income buyers can facilitate trading-up, causing units to "filter" down the quality hierarchy of houses to buyers with even lower incomes, which in turn leads to house price ripples. Similar effects are observed when low-wealth buyers experience wealth shocks (Ho et al. (2008)). Furthermore, differences in price growth in the cross-section of houses during a boom can be explained by wealth and credit channel mechanisms (Landvoigt et al. (2015)). Increased dispersion may arise from increased costs to enter the housing market. Factors such as first-time buyers, poorer households, migration, sellers' strategies, and clientele effects play significant roles in shaping the distribution of housing search during booms (Ortalo-Magne and Rady (2006); Landvoigt et al. (2015); Anenberg and Bayer (2020); Meen (1999); Moen et al. (2021); Novy-Marx (2007); Peng et al. (2020); Piazzesi et al. (2020)).

Search intensity can also vary significantly during the cycle due to sellers' strategies and clientele effects. Although most buyers are also sellers in the market (see e.g. Wheaton (1990)), an important observation is that a boom can generate a buy-first market, while a bust can generate a sell-first market (Moen et al., 2021). If sufficiently many buy before they sell, in the short term there may be a significant reduction in the inventory available to each potential buyer, which can contribute to crowding-out effects and heated bidding wars. Finally, this paper relates to an extensive literature on spatial ripple effects measured by house prices (see e.g. Alexander and Barrow (1994); Meen (1999); Gupta and Miller (2012); Grigoryeva and Ley (2019); Hu et al. (2020)) and an emerging literature considering heterogeneity in house price developments within cities (Zhang and Yi (2017); Bogin et al. (2019); Zhu et al. (2022); Ferreira and Gyourko (2011)), both likely outcomes of redirected buyer search.

In summary, variations in search and matching between buyers and houses of different quality during booms and busts may stem from factors such as affordability, buyer/seller ratios, and clientele effects. These variations can generate ripple effects, resulting in cross-sectional and within-city heterogeneity in housing market outcomes. The closest antecedents to our study are reported in table (1), along with their definition of housing quality segments, type of shocks considered, and outcome variables studied. While there is no universal strategy for studying these issues, the typical approach compares market outcome measures, such as prices, turnover, and time on market, across housing market segments (Liu et al. (2014); Ho et al. (2008)).

Our paper closely aligns with the theoretical model of Williams (2018) as it posits that search activity is both endogenous and segmented. The following section considers a simpler version of this model and discusses the properties of the buyer's choice problem for optimal search activity in different housing quality tiers. The full model captures important aspects such as affordability and variations in the buyer/seller ratio. Our purpose is to discuss some of the intuitions of this model in a simpler framework and relate this intuition to the predictions of the full model.

Table 1: Literature on the Cross-section of Housing Markets

Research	**Model**	**Quality definition**	**Shock**	**Outcomes**
Sweeney (1974a)	Filtering model with quality segments and heterogeneous households. Theoretical model	Quality hierarchies defined generally	Income	Demand, prices
Ho et al. (2007)	Dynamic stock-flow model with quality segments and heterogeneous households. Granger causality tests. Theoretical model with empirical support	Size	Wealth	Demand, prices, transaction volumes
Ortalo-Magne and Rady (2006)	Life-cycle model with quality segments and heterogeneous households. Theoretical model with empirical support	"Starter-homes" and "trade-up" homes	Wealth	Demand, prices, transaction volumes
Piazzesi, Schneider, and Stroebel (2020)	A new dataset on listing screening. A search model with quality segments, segmented search, and heterogeneous buyers Theoretical and quantified model	Location, price and size	Moving shocks	Search intensity, inventory, turnover, prices
Williams (2018)	Search model with quality segments and endogenous search. Theoretical	Location, price, size, and more^{a}	Booms and busts in terms of search intensity and prices	Search intensity, prices, rents
Landvoigt, Piazzesi, and Schneider (2013)	Assignment model with quality segments and heterogeneous buyers. Theoretical and quantified model	Price	Credit	Demand, prices, transaction volumes
Liu et al. (2014)	Optimization model with quality segments. Repeat sales methods. Theoretical and empirical support	Size	Booms and busts in prices	Prices, turnover, supply

Notes: The table lists research that focuses on cross-sectional differences in outcomes, and in two cases buyer search intensity, in housing markets. It reports the model and methods used, the quality definition employed to segment houses in the cross-section, the sources of shocks, and the outcome variables used. a.The segments are similar along *one or more* dimensions.

3. Theoretical Foundations: A Model with Endogenous Search

The housing market under study comprises buyers and sellers of homes, however we abstract from sellers in this exposition to focus on buyer's search problem. Buyers are searching for a housing unit for their households.[2] Homes in this market are divided into one of three quality tiers, $i = P, S, D$, denoted as primary (P), secondary (S) or distressed (D). Buyers can search for homes within each of these tiers. Every home within a tier shares similar attributes across one or more dimensions, such as size, price, location, and unit quality.

Buyers initially screen houses for sale on a public site and then decide the tier in which to direct their search. The quality tiers are differentiated by their *common values*, which are identical among all buyers. During the initial screening, only the common value is observable. For tier i the common value is the mean of the truncated distribution, $m_i \equiv E(x|x > a_i) = a_i \frac{\eta}{(\eta-1)} > 0$, where $1 < \eta < \infty$. The largest feasible minimum match value, α_i, has the associated common value $\mu_i = E(x|x > \alpha_i) = \frac{\alpha_i \eta}{(\eta-1)}$. This can be associated with the buyer's most preferred segment of affordable homes in i.

The primary tier P has the largest feasible common value, followed by the secondary tier, with the distressed tier having the smallest feasible common value, $\mu_P > \mu_S > \mu_D$. Buyers differ solely by their idiosyncratic *match values*, which are revealed upon visiting the house. Buyers screen houses for sale optimally by controlling their minimum *match values*. This screening truncates below the lower end of the distribution of possible match values x between a buyer and the homes. The truncated distribution D_i in segment i is assumed to be power law: $D_i(x) = 1 - (a_i/x)^\eta$ for all $x > a_i$ with $1 < \eta < \infty$ and $i = P, S, D$. For each tier i, each buyer selects the minimum acceptable match value a_i from the feasible set $a_i \in \{1, ..., \alpha_i\}$.

3.1. Screening and Search

Houses appear on this market according to some independent process. Once all houses for sale across all tiers have been screened, each buyer chooses one or more tiers for subsequent search. Buyers selecting i inspect houses within that tier, drawn randomly from its distribution of residual match values. Between inspections, the buyer continues their search, expending effort per unit of time: $q_i \geq 0$. This search effort incurs an opportunity cost per unit of time of $OC_i = \gamma m_i q_i^\delta$, with $\gamma > 0$ and $\delta > 1$. The increasing marginal cost reflects each buyer's rational prioritization of alternative activities. Homes with higher common values m_i are proportionally more costly to inspect.[3] Each buyer's search in their preferred tier follows an independent Poisson process. If a buyer searches in i with the intensity q_i, they inspect one listing during the next short time interval Δt with the probability, $q_i \Delta t + (\Delta t)^2$, and two or more listings in the same tier with a much smaller probability $(\Delta t)^2$. Thus, each buyer inspects listings at the average rate q_i. The auction

[2] This model abstracts from the dual role of buyer/seller as described in works by Moen et al. (2014) and Moen et al. (2021).

[3] For instance, because buyers with higher incomes have higher opportunity costs of time and because larger houses are more costly to inspect.

follows any bargaining structure with an expected buyer gain from trade g_{bi}. The buyer solves the recursive problem:

$$V_{bi} = max_{q_i \geq 0} e^{-t\Delta t}\{V_{bi} + (m_i q_i g_{bi} - OC_i)\Delta t + (\Delta t)^2\}, \tag{1}$$

This can be solved for V_{bi} to give:

$$V_{bi} = max_{q_i \geq 0} \beta^t \{(m_i q_i g_{bi} - UC_i)\Delta t + (\Delta t)^2\}, \tag{2}$$

for $i = P, S, D$ and where $\beta^t := \frac{e^{-t\Delta t}}{1-e^{-t\Delta t}} \geq 0, \forall t$. In equation (2), the buyer searches over time to maximize the present value of the expected gains from search minus the costs of search. The solution to this problem is the buyer's optimal search intensity q_i^* in tier i. Anticipating this search, each buyer first selects the optimal screens for all tiers and then the tier for search with the highest expected present value of search, V_{bi^*}.

Properties of equation (2) include, for each i: (i) $\frac{\partial V_{bi}}{\partial g_{bi}} > 0$. An increase in the expected buyer gain from trade in i increases the expected present value of search in this tier. (ii) $\frac{\partial V_{bi}}{\partial a_i} < 0$. A negative shift in buyers' minimum match values a_i, this decreases the expected present value of search in this tier since by the truncated distribution assumption, $m_i = a_i \frac{\eta}{(\eta-1)}$. c) $\frac{\partial V_{bi}}{\partial OC_i} < 0$. An increase in the opportunity cost of search in i, for instance due to increases in common values m_i, reduces the expected present value of search in this tier.

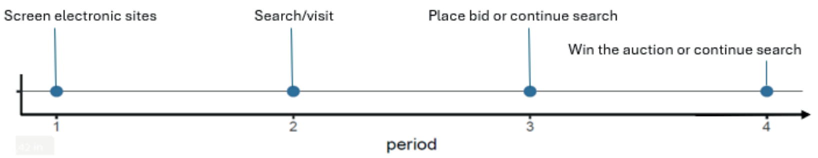
3.2. Discussion: Steady State

In this model, we have demonstrated that the value of, and hence the choice of, quality tier in which to search is contingent upon the expected buyer gain from trade, the minimum match values, and the opportunity cost of search. Under additional assumptions and with inelastic entry of buyers and sellers, Williams (2018) describes the steady state. With a rapid entry by buyers inthe primary tier, the premium paid for preferred homes in the prime tier relative to the secondary tier eventually decreases. In steady state, the optimal set in each segment has the tightest feasible truncation of match values and thereby the highest affordable common value. Consequentially, during booms when buyers enter relatively more rapidly, they initially search more in their preferred tier and later in progressively less liked tiers, while during busts this ripple is reversed. These results follow from the same properties outlined above, where this ripple and ripple effect is propagated by buyers re-evaluating relative minimum match values, changes in the opportunity cost of search, and differences in the expected buyer gain from trade. Empirical implications include; (i) higher average search and prices in preferred tiers and (ii) spatial and qualitative ripples of search intensity and prices across tiers.

The following sections describe the data and segmentation into quality tiers and aim to empirically test these implications. In line with the intuition from the model, we also define booms and busts in terms of both prices and buyer/seller ratios, which allows for empirically testing these predictions.

4. Data Description

Figure 1: Timeline of Search in the Housing Market



Notes: The figure illustrates the typical timeline of search in the housing market from screening to purchase or continuation of search.

The analysis employs a cross-sectional dataset of housing transactions in four Norwegian cities, sourced from Eiendomsverdi ASA, coupled with the house listing text from the main real estate portal Finn.no. The transaction data is also coupled with information from the auction of each house, obtained from four large realtor organizations operating in the area. In the main analysis, we use data for the metropolitan market (Oslo) for 11,683 sales, which is reduced to 8,473 sales after excluding transactions that lack information about the house auction and the asking price, as well as some additional key variables. Missing variables are handled through listwise deletion, resulting in minimal data loss. Comparable data operations have been performed for the other urban areas (see the summary statistics in Appendix).

The main variable representing search intensity is the number of listed interested at the English sealed bid auction. Additionally, the number of bidders in each auction is used to describe buyer search intensity. To be listed as an interested party or to place a bid, potential buyers must contact the realtor at the auction or via email or phone. The number of listed interested parties differs from the number of bidders in terms of purchase commitment. We also have data on the number of bids in each auction, which depends on the number of bidders and the bidding strategies of the involved parties. Thus, it can be considered an outcome variable rather than a measure of search intensity. The number of bids and time on market (TOM) are regarded as measures of market outcomes, alongside the final transaction prices. On average, transacted houses in the metropolitan market had 16.7 potential interested buyers, 3 bidders, 9.6 bids, spent 58 days on the market, and sold at a price of USD 420,000.

4.1. Quality Segmentation

The ideal approach would construct fine-scale housing quality segments. However, for tractability in our quantitative approach, each transacted house is segmented into three quality tiers Q, where Q:={low,medium,high}. Quality is defined by size, age and level of renovation and is considered to be a measure of the common value component of housing quality, as opposed to the unobserved idiosyncratic component. As discussed, previous literature has tended to use size (see table 1) and see a discussion in Liu et al. (2014)), price, and/or location to segment houses. Newer and fully renovated units also tend to be

Table 2: Summary Statistics

Variable	Mean	Median	SD	Min	Max
Interested	16.70	13.0	14.7	1	166
Bidders	2.98	2.0	2.1	1	20
Bids	9.60	8.0	7.3	1	72
TOM^a	58.13	35.0	74.5	1	1,254
Transaction price	0.42	0.36	0.21	0.10	3.06
Ask price	0.40	0.34	0.21	0.09	4.23
Size^b in m^2	72.96	65.0	40.3	14	503
Dwelling age	57.32	58.0	37.6	0	188
Distance to Center (km)	3.92	3.19	2.3	0.27	12.3
Fully renovated	0.096				
Unmaintained	0.085				
Newly developed^c	0.055				

Notes: The table shows summary statistics for the main variables for the metropolitan market Oslo. Prices in USD million, with exchange rate 10.63. N=8,473. Time period: *jul.13 - jun.19*. *Distance to Center* is the Haversine distance to the Oslo Central Station. a.Time on Market is a proxy defined as the time in days from the realtor received the assignment until the house is sold. b.Size is defined in terms of the area of the primary rooms. c.Newly developed units are 4 years or less.

of higher quality. Some attributes, such as requirements for the home's renovation quality, may be easier for buyers to forego, as over time, it is possible to invest in higher renovation quality. In contrast, size is an attribute that is largely fixed.

In this analysis, high quality units are defined as houses that are large (top 15th percentile), newer (4 years or younger), and/or fully renovated[4]. Medium quality units are middle-sized (15-85 percentile), four years or more, and have a neutral renovation status. Low-quality units are small (bottom 15th percentile[5]), more than 4 years old, and/or unmaintained. The segments are mutually exclusive so that no unit is counted twice, which primarily affects the number of units segmented by size in the quality tiers. With this definition, the metropolitan market comprises 29.3% low-quality houses, 47.1% medium-quality houses, and 23.7% high-quality houses (see table 3). Figure 2 provides descriptive evidence of quality ripples in search intensity in these housing markets, where searches for low-quality housing tend to increase during a price boom.

4.2. Spatial and Temporal Aggregation

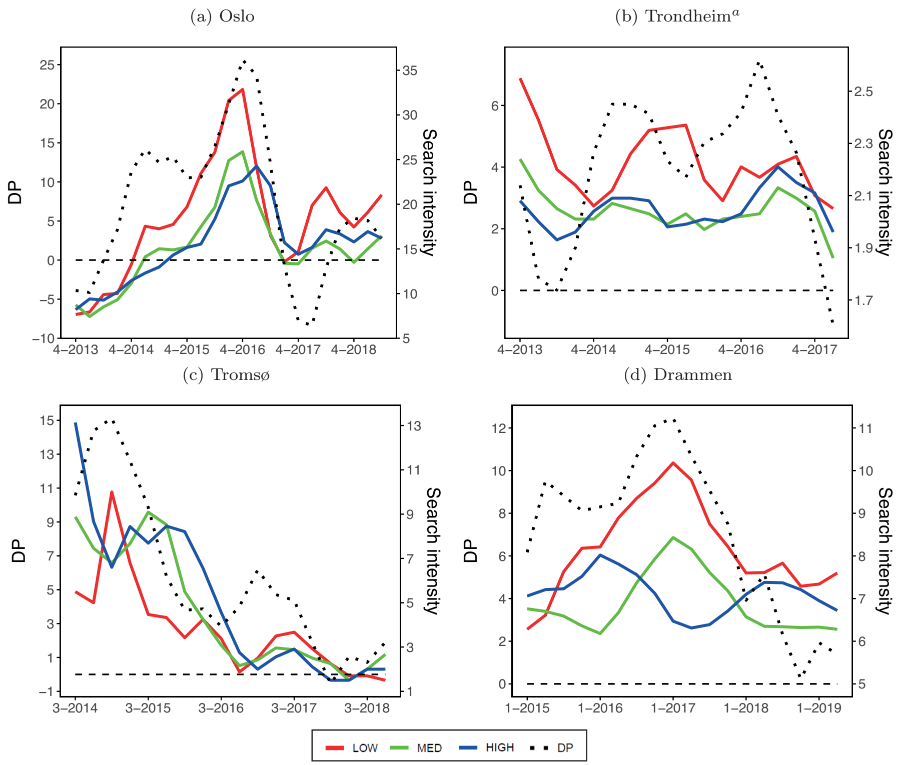
This analysis implements two spatial aggregation definitions: *price zones* and *search zones*. Price zones are spatially non-contiguous and are based on estimates of location premiums for houses of otherwise constant quality[6]. A key advantage of this segmentation is the price information embedded in the zone. Search zones are defined by the average search intensity per city zone (60). As shown in figure 3, location appears to be a decisive

[4] See Mamre and Sommervoll (2022) for details on the renovation criteria.

[5] In the capital, there are many small units compared to the other cities, and thus a larger share (bottom 20th percentile) is included in the low-quality segment. For all cities this results in a threshold value around 50 square meters.

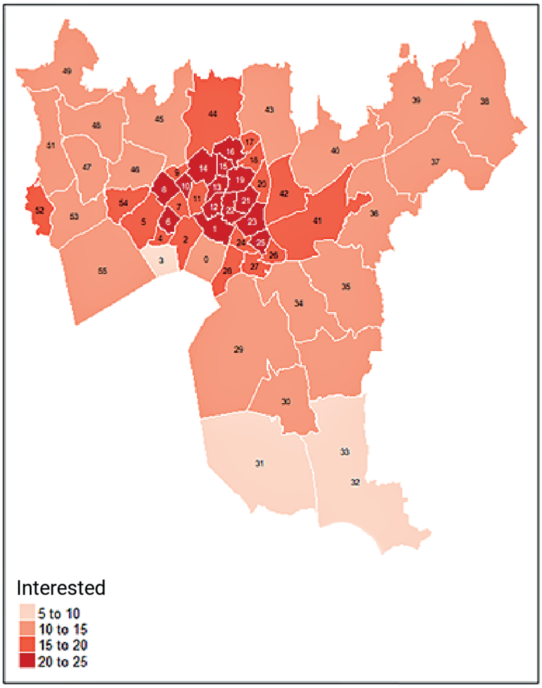
[6] See details in Appendix and in Sommervoll and Sommervoll (2019).

Figure 2: Descriptive Statistics: Search Intensity by Quality tier in four Urban Areas



Notes: The figure shows descriptive results for search intensity by housing quality tier (LOW, MED, HIGH). Search is defined as 4-quarter rolling average of $NrInterested$ per quality class unit. a.Trondheim instead uses $NrBidders$ as search variable. DP is 4-quarter house price growth in the official local price price index, source: Eiendomsverdi ASA.

Figure 3: Search Intensity by Zone



Notes: The figure shows the unweighted average number of interested parties per Oslo zone in the period 2013-2019. We construct the spatial aggregation of 60 zones by combining geometries for basic districts provided by Statistics Norway. A few zones are excluded because they lack the sufficient number of observations, these are not numbered in the figure.

factor for the buyer's search. The search intensity exhibits a clear monocentric pattern in the metropolitan market.

To identify the peaks and troughs in the local house price cycle, we employ the Harding and Pagan (2002) implementation of the Bry and Boschan (1971) algorithm. This algorithm utilizes "soft limits" to determine peaks and troughs, such as a limit of only two months of consecutive increases or decreases to qualify as a phase and only five months to qualify as a full cycle.[7] The price boom and bust episodes are ranked over a twenty-year period according to their *magnitude*, *duration*, and *severity*, following the methodology proposed by Agnello and Schuknecht (2011). These calculations are based on real house prices.[8] The magnitude is measured as the real house price growth from peak to trough and from trough to peak ($\Delta RP_{t,t-j}$), while the duration is measured as the temporal distance

[7]The calculations are based on the SSBQ Stata module (Bracke, 2012).

[8]The nominal price index is deflated by the quarterly consumer price index for Norway that excludes energy prices (CPI-ATE, source: Statistics Norway).

D between the turning points. Severity represents a proxy of the cumulative deviation of house prices from the long-term trend, combining duration and magnitude, and is defined for each episode i as $Severity_i = (\Delta RP_{i,t,t-j} \times D_i) \times 0.5$.

As shown in table 3 in the Appendix, two price booms and two price busts rank among the top three in terms of severity. Moreover, two potential booms rank slightly below the median and two busts rank around the median in terms of severity. With these soft criteria for the price cycles, the housing markets throughout the period are either in a boom or a bust. Additionally, we implement a criterion for the direction of the aggregated search intensity to delineate the market phases. It is plausible to view the average number of searchers per unit as a measure of inventory (im)balance or buyer-seller ratios, where a larger imbalance increases the likelihood of crowding-out effects, in line with the reasoning in Williams (2018). This results in the following temporal aggregation: 1. boom in prices + expanding search intensity (Boom exp); 2. boom in prices + contracting search intensity (Boom con); 3. bust in prices + contracting search intensity (Bust con); 4. Bust in prices + expanding search intensity (Bust exp); 5. otherwise. Table 3 summarizes transactions by quality tier and market phase.

Table 3: Summary Statistics Transaction Volumes

Quality tier	Boom exp	Boom con	Bust con	Bust exp	Total
Shares					
Low	0.287	0.309	0.282	0.298	0.293
Medium	0.472	0.463	0.474	0.468	0.471
High	0.241	0.228	0.244	0.234	0.237
Total	0.395	0.265	0.233	0.107	1
Volumes					
Low	960	692	557	273	2482
Medium	1581	1039	935	432	3987
High	808	511	481	204	2004
Total	3349	2242	1973	909	8473

Notes: The table summarizes the transaction volumes by quality tier and market phase in the metropolitan market (Oslo).

5. Empirical Analysis of Search by Quality Tier

In this section, we empirically investigate whether the search intensity for housing quality varies by market phase. Sellers set an ask price that is posted on the public listing alongside the main characteristics of the unit. We assume that the quality status is common knowledge, as this information is included in the listing text, can be inferred from pictures, and is observable during house visits. Buyers decide which houses to visit and, upon visitation, whether they wish to register interest and place a bid. Our empirical models build on a relationship between the search intensity for each individual house and key determinants such as the ask price, hedonic characteristics, and unobservable factors affecting search intensity. Unobservable factors include information on the extent to which the market is characterized by a buy-first or sell-first market or the share of first-time buyers in the market.

5.1. Benchmark OLS Model

As a benchmark specifications, we estimate a model with interaction terms between quality tiers and market phases as described by (1). This equation is interpreted as a reduced-form relationship:

$$log(Search_{im}) = \alpha_{1m} log(Askprice_{im}) + \alpha_{2m} X_{im} + \alpha_{3m} Q_{im} + \alpha_{4m} D_{\tau m} + \alpha_{5m} Q_{im} \times D_{\tau m} + \varepsilon_{im} \quad (1)$$

Where $Search_{im}$ is an $N \times 1$ vector of dependent observations of the number Interested or the number of Bidders for house i, $i \in (1, ..., N)$ in market m, $m \in (1, ..., M)$. $Askprice_{im}$ is the final ask price of house i in market m. The vector X_{im} contains an intercept and hedonic characteristics, such as the age and size of the home, and the distance to the city center (CBD). It also includes categorical variables (unit type, owner type, transaction season, price zone). Q_{im} represents the home's quality tier, $Q \in$ (low, medium, high). $D_{\tau m}$ includes the four market phases, $D \in$ (boom$_{exp}$, boom$_{con}$, bust$_{con}$, bust$_{exp}$).

Dummies for price zones (12) are constructed as previously outlined, along with the Haversine distance to the city center. The latter is included in the regressions to control for spatial variations in search activity by distance to the CBD (see figure 3). The ask price is annually deflated by the growth in consumer prices, given the length of the study period is up to six years. This specification, which includes interactions between quality tier and cycle phase, allows us to test whether search intensity by housing quality tier varies over the housing cycle.

From this point forward, the market-specific notation is omitted in the discussion. Model (1) is first estimated with $\alpha_3 = \alpha_4 = 0$ and all market phase variables included, except the start of the period. The main coefficients of interest are the *relative coefficients* in the vector α_5. With this semi-log specification we estimate, for instance $\alpha_{5L} - \alpha_{5M}$, which approximates *search dispersion* -the percentage difference in relative search intensity between low and medium-quality tiers.

Potential identification issues include the effect of the ask price on search intensity. In addition to unobserved quality affecting the ask price, it may also indicate the seller's pricing strategy. A low-price strategy may generate more search, thereby creating a simultaneity bias (see discussion in Genesove and Han (2012)). This could pose problems for this paper if such strategies differ in booms and busts, a plausible scenario discussed further in Section 6.1. Another challenge with this non-hierarchical model could be that a generally higher search intensity for low-quality houses may bias interaction effects. Additionally, there is a high correlation between the variables based on estimated variance inflation factors for interaction terms $Q \times D_\tau$ (between 5.4-15.5). However, the non-hierarchical model allows for ease of interpretation and provides separate intercepts for the coefficients of interest.[9]

Table 4 displays results for search intensity, measured by the number of interested parties, with and without price and spatial information. Column (1) provides results without controlling for price and location. Adding spatial information in column (2) changes the interpretations to search for qualities given location. The coefficient estimate on, for instance, low $\times$ boom$_{exp}$ is reduced. Controlling for ask price in column (3), this coefficient increases. The adjusted R squared increases notably when including spatial information, but only slightly when including price. The coefficients are positive in all specifications and significant at a 1 per cent significance level. Note that these are measured relative to the start of the period.

Column (Q/med) displays the estimated search dispersion based on the model in column (3). According to these results, medium-to-low quality dispersion is 19.7 percent when the market is in the boom$_{exp}$ phase and notably lower and less significant in the boom$_{con}$ and bust$_{con}$ phases. Conversely, medium-to-high dispersion is estimated to be -11.6 per cent during boom$_{exp}$ and not significantly different from zero in the remaining market phases. Evaluating instead column (Q/high), high-to-low quality dispersion is even larger, at 31.2 percent in the boom$_{exp}$ phase, then declining and not significantly different from zero during the bust phases.[10]

These results remain consistent when we adjust for differences in the supply composition in each market phase (refer to Table 3). Here, the weight is constructed as the inverse probability weight as compared to the supply share for the total period. Although supply composition varies by quality tier by a few percentages, search intensity rates by quality tier fluctuate to a much larger extent. From this, we deduce that supply composition is not the driving factor behind our main results[11].

[9] Also, since variation occur along two dimensions, both time and quality, simultaneously, this puts strain on interpretations if we include too much information in this single equation model.

[10] All regressions use robust errors (White), which tend to increase the standard error of the estimates in the boom$_{exp}$ phase and decrease them in the bust phases.

[11] These results are not included for brevity, but are available upon request.

Table 4: Results of OLS Search Intensity Regressions

	Dependent variable: log(Nr Interested)				
	(1)	(2)	(3)	(Q/med)	(Q/high)
log(Ask price)			0.158^{***}		
log(distance CBD)		-0.285^{***}	-0.288^{***}		
low × boom_{exp}	1.086^{***}	1.029^{***}	1.072^{***}	0.197^{***}	0.312^{***}
high × boom_{exp}	0.816^{***}	0.787^{***}	0.760^{***}	-0.116^{*}	
low × boom_{con}	0.976^{***}	0.923^{***}	0.955^{***}	0.150^{**}	0.180^{***}
high × boom_{con}	0.834^{***}	0.803^{***}	0.775^{***}	-0.030	
low × bust_{con}	0.760^{***}	0.691^{***}	0.704^{***}	0.075^{*}	-0.027
high × bust_{con}	0.825^{***}	0.790^{***}	0.730^{***}	0.102	
low × bust_{exp}	0.768^{***}	0.694^{***}	0.723^{***}	0.123·	0.122
high × Bust_{exp}	0.675^{***}	0.634^{***}	0.602^{***}	0.002	
Location factors	–	x	x		
Ask price	–	–	x		
med × market phase[a]	x	x	x		
Seasonal dummies	x	x	x		
Structural factors	x	x	x		
Robust errors	x	–	–		
Observations	8,473	8,473	8,473		
Adjusted R^2	0.071	0.134	0.137		
Note:					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Notes: *a*.Not reported for brevity. Columns (1)-(3) displays regression results for estimating OLS model (1) with different sets of control variables and robust standard errors (White). The excluded market phase is the start of the period, which is a period characterized by fairly stable and low search intensity for this metropolitan market. Column (1) shows market phase and quality tier interaction coefficients for a specification without spatial and price information. Column (2) adds spatial information and column (3) adds in addition ask price information. Column (Q/med) shows the estimated search dispersion from quality medium to quality Q, where the specific quality tier and market phase is given by the row label. The same applies for column (Q/high). The significance level in the latter two columns is defined by the confidence interval (CI) for the numeraire coefficient. For instance, a significance level of 0.01 level for the low/med estimate in the boom_{exp} phase indicates that the coefficient of med × boom_{exp} is outside the 99 percent CI of the low *times* boom_{exp} estimate.

5.2. A Negative Binomial Model

The number interested and the number of bidders are count variables, resulting in non-normality in their distributions. These predictors are not only discrete but also overdispersed. To account for these properties, we estimate a zero-truncated[12] negative binomial regression model (NegBin):

$$log(E(Y_{im})) = \alpha'_{1m} Askprice_{im} + \alpha'_{2m} X_{im} + \alpha'_{3m} Q_{im} + \alpha'_{4m} D_{\tau} + \alpha'_{5m} Q_{im} \times D_{\tau m} \quad (2)$$

In this model, the dependent variable is replaced by the mean, $Y_m \sim$ Nr Interested, or Nr Bidders, and the hedonic attributes have the same interpretation as in equation (1). The error term is captured by the log-link parameters. Table 5 shows the regression coefficients for the variables of interest. The dispersion parameter is large in magnitude and significant in all regressions, suggesting that the NegBin model is more appropriate than a Poisson model.[13]

Evaluating the coefficients of interest, for instance the product low $\times$ boom$_{exp}$, this coefficient is statistically significant and estimated at 1.088, similar to the OLS estimate (1.072). However, this is not generally the interaction effects in the NegBin model, rather it contributes to the full interaction effect which can be the discrete double difference (see Norton et al. (2004)). The second column shows the corresponding incidence rate ratios (IRR). These results indicate that the incident rate of low-quality searches in the $boom_{exp}$ phase is 2.970 times the incident rate for the reference period. Moreover, the incidence rate for high-quality searches in the $boom_{exp}$ phase is only 2.216 times the start-of-period incidence rate. Their ratio is calculated in the columns (Q/med) and (Q/high). When the model is specified in this way, this ratio will equal the difference in coefficient estimates $(\hat{\alpha}'_L - \hat{\alpha}'_H)$, and also equal the *prediction of the mean search response*. Overall, results are similar to the previous, with a pro-cyclical movement of search intensity towards low-quality housing and a counter-cyclical movement of search intensity towards high-quality housing.

The estimates considered so far are derived from non-hierarchical models, allowing for straightforward interpretation. However, these models have certain limitations, as previously discussed. In the following analysis, the predictions of the mean response $ln(\hat{Search})$ are compared for models that include the main effects and where the market phase dummies enter the regressions successively.[14] Individual predictions are made for each quality tier in each market phase, while other predictors are set to their mean value. Consequentially, instead of measuring the results relative to the start of period, the reference period is all the remaining market phases.

[12]To be sold, there must be at least one bidder and interested, therefore zero cannot occur.

[13]The variable log(Ask price) has a coefficient of 0.052, which is not statistically significant. The variable log(Distance CBD) has a coefficient of -0.294 which is statistically significant. This means that for each one per cent increase in the distance from CBD, the expected log count of the search intensity decreases by -0.294.

[14]Alternatively to comparing mean responses, we could use mean values by quality tier to test for differences by holding the characteristics constant within segments.

Table 5: Results of NegBin Model. Search Intensity Regressions

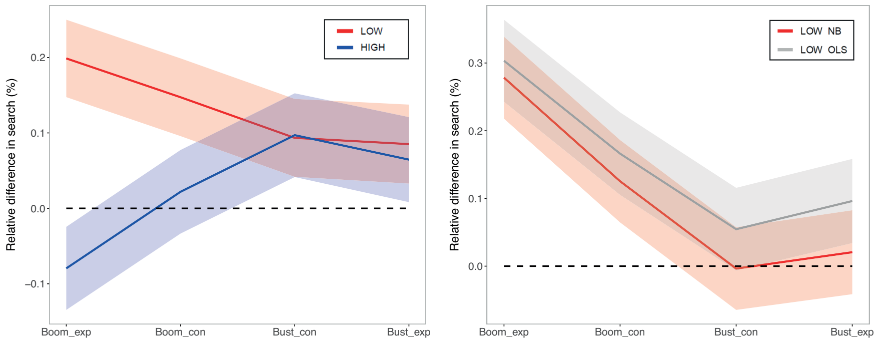
	Dependent variable:			
	Nr Interested			
	(Coeff.)	(IRR)	(Q/med)	(Q/high)
Dispersion	0.770***	2.160		
log(Ask price)	0.052·	1.053		
log(distance CBD)	−0.294***	0.745		
low × boom_{exp}	1.088***	2.970	0.198***	0.293***
high × boom_{exp}	0.796***	2.216	−0.095	
low × boom_{con}	0.940***	2.559	0.154**	0.144**
high × boom_{con}	0.796***	2.216	0.010	
low × bust_{con}	0.649***	1.913	0.079	−0.048
high × bust_{con}	0.697***	2.008	0.127*	
low × bust_{exp}	0.656***	1.926	0.097	0.055
high × bust_{exp}	0.601***	1.824	0.043	
Location factors	x			
Ask Price	x			
med × market phase[a]	x			
Seasonal dummies	x			
Structural factors	x			
Observations	8,473	8,473		
Log Likelihood	-30,956			
θ	2.977*** (0.465)	19.638		
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: *a*.Not reported for brevity. Column (Coeff.) shows regression results for estimation of model (2) and column (IRR) shows incidence rate ratios. Column (Q/med) displays the estimated search intensity ratios for, say, low quality relative to medium quality calculated as α'_L - α'_M for each market phase. Column (Q/high) displays estimated search intensity ratios for low quality relative to high quality. The significance level in these two latter columns is defined by the confidence interval (CI) of the numeraire coefficient. A 0.01 level of significance for, say, low quality in the boom_{exp} phase indicates that the coefficient for Q × boom_{exp} is outside its 99 percent CI, which is now based on z-values.

Figure 4: Results for Search intensity ratios

(a) NegBin: MED to Q quality

(b) NegBin vs. OLS: HIGH to LOW quality



Notes: The figures show ratios of predictions of the mean search response from hierarchical regression models for a metropolitan market. It includes NegBin model results (red, blue) and OLS model results (grey). The 95 % CI's are based on asymptotic standard errors.

Figure (4) displays the results for the estimated dispersion together with the estimated 95 percent confidence intervals. Statistical details of the construction of the confidence intervals are described in the Appendix. Overall, the results are very similar to the estimates from the non-hierarchical model. Comparing the OLS and NegBin models, dispersion into high-quality housing appears to be more counter-cyclical in the NegBin model. The asymptotic standard errors are everywhere smaller for these estimates, suggesting higher precision in this model.

5.3. Other Urban Markets

In this section, results are presented for three additional urban areas, Tromsø, a low-volatility market that experienced mainly a bust during the study period; Drammen, a market that witnessed significant booms and a significant bust; and Trondheim, another low-volatility market during the study period.

The price volatility measure is reported in table 6, along with the share of transactions in each market phase.[15] For both Drammen and Tromsø, the market phases are calculated in the same way as for the metropolitan market (Oslo), based on turning points in the cycle for monthly HPI data and turning points for average search per unit.[16] The quality tiers are also segmented in the same way as before, and the ask price is annually CPI-deflated. All cycle phases are included (soft measure). The regressions control for search zones (6) instead of price zones due to data availability.

Table 6 shows the results of the hierarchical negative binomial models for these urban

[15] Although the bust market (Tromsø) reports a fairly high share of transactions occuring during a "booming market", the boom criteria is very soft, and these episodes are found to be small in both magnitude and persistence (see figure 2).

[16] Turning points are determined by the 6 month rolling average. For Tromsø, we use quarterly HPI and search data to construct the market phases due to thin data.

markets.[17] Specifically, these estimates show that the dispersion in search intensity from medium to low quality housing during the $boom_{exp}$ phase is both important in magnitude and statistically significant for 3 out of 4 cities, ranging from 12 - 21 percent (medium-to-low dispersion), while not significant in one city. High-to-low dispersion ranges from 13 - 32 percent in the same market phase. In the bust phases, medium-to-high dispersion is estimated to be between 6.5 - 13 percent and significant in two markets, while it is insignificant in the other two markets. Due to data availability, we do not perform further analysis for these markets.[18]

Table 6: Results for Search Intensity ratios in Other Urban Markets

Medium to Low Quality	$boom_{exp}$	$boom_{con}$	$bust_{con}$	$bust_{exp}$	Share boom	Share bust
Oslo	0.199***	0.147***	0.093***	0.085***	0.69	0.31
Drammen	0.216***	−0.107	0.119*	0.224***	0.56	0.46
Trondheim	0.123***	0.068	0.140***	−0.102**	0.61	0.39
Tromsø	0.372	−0.608**	−0.270	−0.839**	0.60	0.40
Medium to High Quality	$boom_{exp}$	$boom_{con}$	$bust_{con}$	$bust_{exp}$	Price vol.^{a} (σ)	N
Oslo	−0.080**	0.022	0.097***	0.065**	19.1	8473
Drammen	−0.108*	−0.095	−0.020	0.085	11.4	1600
Trondheim	−0.013	−0.155***	−0.007	0.134***	7.1	5278
Tromsø	−0.026	0.047	0.125	−0.671	7.0	335
High to Low Quality	$boom_{exp}$	$boom_{con}$	$bust_{con}$	$bust_{exp}$		
Oslo	0.278***	0.125***	−0.004	0.021		
Drammen	0.324***	−0.012	0.139*	0.139*		
Trondheim	0.135***	0.223***	0.147***	−0.236***		
Tromsø	0.399	−0.655***	−0.395	−0.168		

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows ratios of predictions of the mean search intensity response from hierarchical regression models (equation 2) for three urban markets. a.Price volatility is estimated as the standard deviation of the local HPI over the period studied, each normalized to 100 at the start of the period.

5.4. Intra-City Submarkets

To assess variations in search by quality and market phase within the city, results for submarkets constructed by *price zones* are included. We distinguish between (1) prime locations, (2) secondary locations and (3) distressed locations. Each submarket comprises 4 out of 12 price zones (e.g. prime locations consists of the top four prize zones). Table 7 shows estimates of search dispersion from non-hierarchical local versions of OLS-model (1). To treat the entire area as a single market and facilitate comparisons of shifts, the submarket estimations use the same city-wide definitions of market phases as previously outlined. As the timing of price and search peaks can vary across submarkets, this has implications for interpretation.

Based on these estimates, there are strong indications of larger high-to-low quality

[17] See regression results in table A3 in the Appendix.

[18] We do not have access to price zones, geographical coordinates are mostly missing for two cities, and data is scarce for two of these urban areas.

dispersion in prime locations in the boom$_{exp}$ phase, where search intensity for low-quality housing is 42.2 per cent higher than for high-quality housing. In comparison, high-to-low dispersion is not significant in distressed locations during this market phase. This is consistent with a tendency to reduce unit quality to maintain "location quality" during the expansionary phase of a boom. Model (1) is also estimated for each submarket using the alternative spatial aggregation *search zones*. We also have more data when using search zones than price zones (see table 7). This definition distinguishes between (1) search 1, (2) search 2 and (3) search 3 locations, where search 1 is the most highly searched.[19] These estimates suggest that results are similar, but that there is a clearer hierarchy of quality dispersion by submarket based on price zones than on search zones, and this result is very similar when adjusting for variations in the sample sizes.[20]

Table 7: Results for Search intensity ratios in Intra-city Submarkets.
High-to-Low quality

	Prime	**Search 1**	**Secondary**	**Search 2**	**Distressed**	**Search 3**
boom$_{exp}$	0.422***	0.398***	0.304***	0.375***	0.166	0.131*
boom$_{con}$	0.219*	0.110	0.185**	0.199	0.183*	0.178**
bust$_{con}$	−0.064	0.124	−0.007	−0.041	0.460	0.086
bust$_{exp}$	0.072*	0.029	0.045	0.125	0.163	−0.114
N	2.305	3.052	4.376	2.356	1.792	5.206

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows estimates of the search ratios between low and high quality during four market phases by price zone and search zone. Price zones: *Prime* is defined as the most expensive locations, *Secondary* medium expensive, and *Distressed* the least expensive locations. Search zones: *Search 1* is defined as the most searched locations, *Search 2* are medium searched, and *Search 3* the least searched locations during the entire period.

6. Implications for Housing Market Outcomes

The theoretical model makes two predictions: (i) higher average search and prices in preferred tiers, and (ii) spatial and qualitative ripples across tiers of search intensity and prices. We have demonstrated that search for low-quality houses in several markets is significantly pro-cyclical, while search for high-quality houses is counter-cyclical. In this section, we relate this to housing market outcomes in two ways. First, we consider housing turnover and the number of bids received at each auction. As discussed by Han and Strange (2015), the housing market clears through both price and time. Therefore, housing liquidity and prices are important parameters for the market outcome. Second, we examine price growth by quality tier and ripple effects. The latter is based on VAR analysis and Granger causality tests.

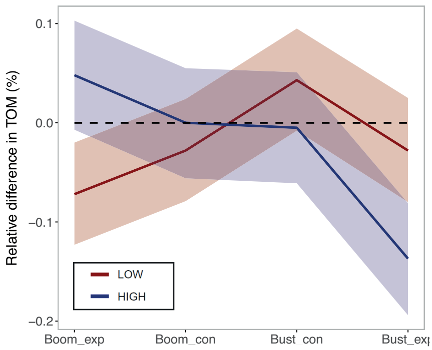
6.1. Turnover and Bids

Figure 5 (a) shows predictions of mean responses when evaluating time on market(TOM) in model (2) as the dependent variable instead of search intensity. Although the standard

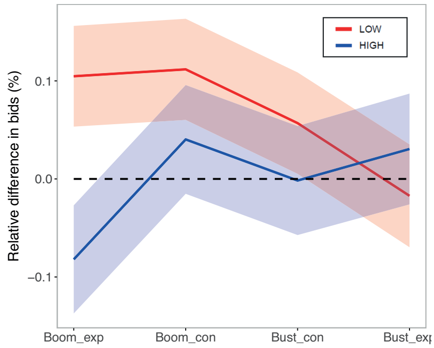
[19] *Search 1* has an average interest of 20-25 parties per unit, *Search 2* range from 15-20, and *Search 3* range from 5-15 (see figure 3).
[20] Not reported for brevity.

Figure 5: Results for Turnover and Bids

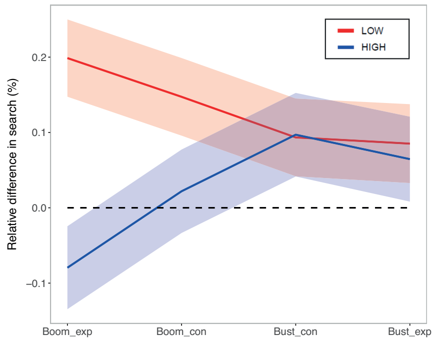
(a) TOM: MED to Q quality



(b) Nr Bids: MED to Q quality



(c) Nr Interested: MED to Q quality



Notes: Figure (a)-(c) compare the predictions from a negative binomial model for different market phases. In the predictions, all other explanatory variables are set to their mean value while market phase and housing quality vary. 95 % CI's are based on asymptotic standard errors.

errors are wide, this evidence supports that dispersion in search is paralleled by dispersion in TOM in the expected way. Similar results hold in (b), which shows predictions of the mean responses when evaluating the number of bids in model (2) as the dependent variable. (c) is the previous result for search intensity based on the number interested, and is included for convenience.

6.2. Aggregate dynamics: Search and Prices

In this section, the relationship between search intensity and aggregate price development by quality tier is examined.A careful inspection of the search intensity data (see figure 2) reveals that the time dimension plays a significant role, as search intensity displays a persistent trend. To some extent, we also test the quality-ripple hypothesis again using this novel data structure.

6.2.1. Hedonic House Price Indexes

To estimate individual house price indexes (HPIs) by quality and spatial segment, we estimate hedonic house price functions. To derive submarket HPIs, the most straightforward method is to construct a separate hedonic model for each submarket. An alternative approach is to include a large set of submarket-specific time dummies in the hedonic model and use the estimated coefficients on these dummies to create local price indexes (Rouwendal and Longhi (2013)). Both methods require each submarket to be large enough to provide sufficient sample sizes and avoid thin market effects. We estimate semi-log specifications with time dummies of the following form:

$$log(P_{iqm}) = \beta'_{1qm} D_t + \beta'_{2qm} X_{iqm} + \epsilon_{iqm}, \tag{3}$$

where P_{iqm} is the log transaction price for unit i in quality tier q sold in market m. D_t contains quarterly time dummies and ε_{iqm} is an error term. Estimating (3) gives an estimate of the HPI using the vector β_{1qm}, for each q and m, conditional on its attributes included in X_{iqm} together with an intercept. This is known as the hedonic time dummy method (see e.g., Xiao and Xiao (2017)). The HPI is given for each t, relative to period 0, by the approximation $100\times\ \exp(\hat{\beta}_{1qm})$.

6.2.2. Search and Price Ripples: A VAR-model and Granger Causality

To further examine the relationship between the house price cycle and search, we test for Granger causality between the house price index and number interested. This is carried out both between these variables for the total market and within and between the different spatial and quality submarkets, enabling us to investigate the spillovers between the house price cycle and search, and spillovers between market subsets.

The VAR model is defined by:

$$Y_{qm,t} = \beta_{0,qm} + \beta_{1,qm} Y_{qm,t-1} + \cdots + \beta_{p,qm} Y_{qm,t-p} + \gamma_{1,qm} X_{qm,t-1} + \cdots + \gamma_{s,qm} S_{qm,t-s} + \varepsilon_{qm,t}$$

where $Y_{qm,t}$ and $X_{qm,t}$ represents the two variables being tested for Granger causality, alternating between house prices and the number interested in all directions, for the metropolitan market in total and within and between each quality and price segment. To ensure stationarity in the series, all variables are measured as first differences of their logarithms, and they are also seasonally adjusted. p and s are the number of lags for each variable, chosen according to the Schwartz's Bayesian information criteria with a maximum lag of four due to the relatively short time series.

We follow the classical literature and first test whether there is evidence of a price ripple across price zones for all quality classes (see Clapp and Tirtiroglu (1994); Pollakowski and Ray (1997)). A Wald test is used to test whether the house price index (HPI) in price zone m Granger causes the HPI in price zone $m+j$. The null hypothesis is that price m does not Granger causes $m+j$, while the alternative hypothesis is that price m Granger causes price $m+j$. The HPI will thus act as a proxy for the house price cycle for each price area.

The results are shown in table 8. The HPI in prime and secondary locations is found to Granger cause HPI in distressed locations, i.e. downwards in the price zone hierarchy. Similarly, the HPI in secondary locations Granger causes the HPI in distressed locations. This is in line with a price ripple effect from more to less preferred locations. However, there is also Granger causality for the HPI from secondary to prime locations, indicating somewhat complex price dynamics in this metropolitan market. This is not surprising since this time period includes both booms and busts, although the market is most often in a boom.

Table 8: Granger Causality Tests I: Price across Price Zones

		HPI Sec →			**→ HPI Sec**		
Price zone	Quality	F	p-value	Lag	F	p-value	Lag
Prime	All	12.854	0.000***	2	0.141	0.869	2
Sec	All	-	-	-	-	-	-
Dist	All	8.731	0.003***	2	0.950	0.408	2
Price zone	Quality	F	p-value	Lag	F	p-value	Lag
		HPI Dist →			**→ HPI Dist**		
Prime	All	2.923	0.077	4	6.502	0.008***	4
Sec	All	0.950	0.408	2	8.731	0.003***	2
Dist	All	-	-	-	-	-	-

Notes: The VAR estimation procedure starts with four potential lags and selects the number of lags for each relationship using the AIC criterion.

We then test whether the house price cycle affects search or the opposite. This is done for each price zone and each quality segment, as well as in total. Table 8 tests Granger causality between the HPI and search intensity. The results of the Granger causality tests indicate that search is only affected by the house price cycle in the low-quality segment in prime locations and for distressed locations when looking at all quality tiers, at a 5 % significance level. However, search Granger causes the price cycle for most quality and submarket segments, with a typical time lag of 1-2 quarters. We conclude that search is an important factor contributing to the house price cycle, but the (lagged) house price cycle only seems to affect the number of interested parties for a few segments of this housing market.[21] This is in line with the prediction of the theoretical model considered.

[21]Simultaneity is detected for low quality and HPI in Prime locations and for all qualities and the HPI in Distressed locations.

Table 9: Granger Causality Tests II: Price and Number Interested

		HPI → Search			**Search → HPI**		
Price zone	Quality	F	p-value	Lag	F	p-value	Lag
Prime	Low	14.673	0.000***	2	8.951	0.002***	2
Sec	Low	1.269	0.274	1	5.727	0.027**	1
Dist	Low	1.458	0.262	2	5.772	0.013**	2
City tot	Low	3.837	0.065	1	1.537	0.230	1
Prime	Medium	0.109	0.745	1	1.921	0.182	1
Sec	Medium	0.453	0.509	1	0.973	0.336	1
Dist	Medium	0.587	0.453	1	8.959	0.008***	1
City tot	Medium	1.415	0.249	1	7.569	0.013**	1
Prime	High	0.016	0.899	1	0.286	0.599	1
Sec	High	0.672	0.524	2	3.182	0.069	2
Dist	High	0.060	0.809	1	5.241	0.034**	1
City tot	High	1.415	0.249	1	0.339	0.567	1
Prime	All	0.176	0.68	1	1.816	0.194	1
Sec	All	2.194	0.155	1	8.927	0.008***	1
Dist	All	4.876	0.040**	1	7.569	0.013**	1
City tot	All	2.181	0.156	1	14.120	0.001***	1

Notes: The VAR estimation procedure starts with four potential lags and selects the number of lags for each relationship using the AIC criterion.

The final table, table10, for the Granger causality tests in this section provides the results for tests of ripples between the number of interested parties per unit across quality segments. These results indicate search ripples *downward* the quality tiers, in line with the predictions of Williams (2018). Specifically, we see that search for high-quality housing Granger causes search for low-quality housing in prime locations, with a level of significance of 1 % and a typical lag of 3 quarters. This is also in line with our previous findings of significantly increased dispersion of search into low quality during the expansionary phase of the boom in prime locations. Likewise, medium-quality Granger cause low-quality housing in distressed locations, and high-quality Granger causes medium-quality housing in distressed locations and for the city total.

However, these results also indicate quality ripples *upward* the quality tiers, but only for prime locations. This is in line with our results for increased dispersion in favor of high quality during busts. Overall, these results point to a complex ripple of search intensity between housing quality tiers within price zones, where the search ripple moves in both directions of the quality tier when testing a period that contains both booms and busts. However, the results are most often significant down the quality hierarchy

Table 10: Granger Causality Tests III: Number Interested across Quality Segments

		Search High →			→ Search High		
Price zone	Quality	F	p-value	Lag	F	p-value	Lag
Prime	Low	8.998	0.002***	3	3.763	0.038**	3
Sec	Low	1.273	0.273	1	0.501	0.488	1
Dist	Low	1.186	0.374	4	0.479	0.751	4
All	Low	2.224	0.134	3	6.967	0.005***	3

		Search Med →			→ Search Med		
Price zone	Quality	F	p-value	Lag	F	p-value	Lag
Prime	Low	0.316	0.580	1	4.420	0.049**	1
Prime	High	0.003	0.957	1	0.004	0.949	1
Sec	Low	0.594	0.450	1	0.007	0.933	1
Sec	High	2.123	0.152	2	2.696	0.098	2
Dist	Low	4.851	0.040**	1	3.831	0.065	1
Dist	High	0.796	0.554	4	5.649	0.012**	4
All	Low	2.363	0.141	1	0.015	0.903	1
All	High	2.395	0.123	2	7.709	0.005***	2

Notes: The VAR estimation procedure starts with four potential lags and selects the number of lags for each relationship using the AIC criterion.

Lastly, table 11 shows the estimated house price growth by quality tier for boom and bust episodes lasting at least half a year. As can be seen, the HPI for low-quality homes increased by 64.4 percent during the major boom (4-2013 - 3-2016), while it increased by 46.3 percent for medium-quality homes and 39.6 percent for high-quality homes, suggesting a clear ranking of price growth by quality tier. During the subsequent boom con episode, the price growth was notably higher for high-quality houses. During the bust episodes, the evidence is mixed.

Table 11: House Price Growth by Boom and Bust Episode

	House price growth			
	Episode	**Low**	**Medium**	**High**
1	4-2013 - 3-2016: Boom exp	0.644	0.463	0.396
2	3-2016 - 1-2017: Boom con	0.082	0.090	0.192
3	1-2017 - 3-2017: Bust con	−0.110	−0.097	−0.090
4	2-2018 - 4-2018: Bust con	−0.029	−0.030	−0.043

Notes: The table shows estimates for house price growth per episode. These are based on quarterly data, as opposed to the previous definition based on monthly data. There is one quarter during the Boom exp episode where aggregate search intensity declines and one quarter where aggregate prices declines. These are included in the episode.

7. Robustness Analysis

This section includes results for various alternative measures of search and aggregations used in the cross-sectional analysis. Figure 6 (a) shows results for an alternative market phase criterion where the smallest boom and bust are omitted. This works to increase the estimated dispersion in the bust phases. Figure 6 (b) shows results for the alternative search variable *Number of Bidders*. The interactions between quality and market phase are even more significant with this alternative search variable, and all with the expected sign (see table A4 in the Appendix)[22]. Using the alternative spatial weights in (c), our main results also hold.

7.1. Threats to Identification and Miscellaneous

A reasonable concern is that there may be biases in the composition of the available inventory over time, such that certain housing qualities are overrepresented in some market phases and underrepresented in others. This can have a direct impact on our response variables, as a lower inventory with certain qualities can lead to intensified search due to supply shortness. As shown in table 3, the low-quality segment is somewhat underrepresented in Boom exp (28.1 percent of the inventory compared to the period's total share of 29.3 percent). However, the difference is small compared to the large dispersion in search intensity. The high quality composition is representative at its period average of 0.237 during Bust con, when the dispersion in favor of high quality tends to peak according to our results.

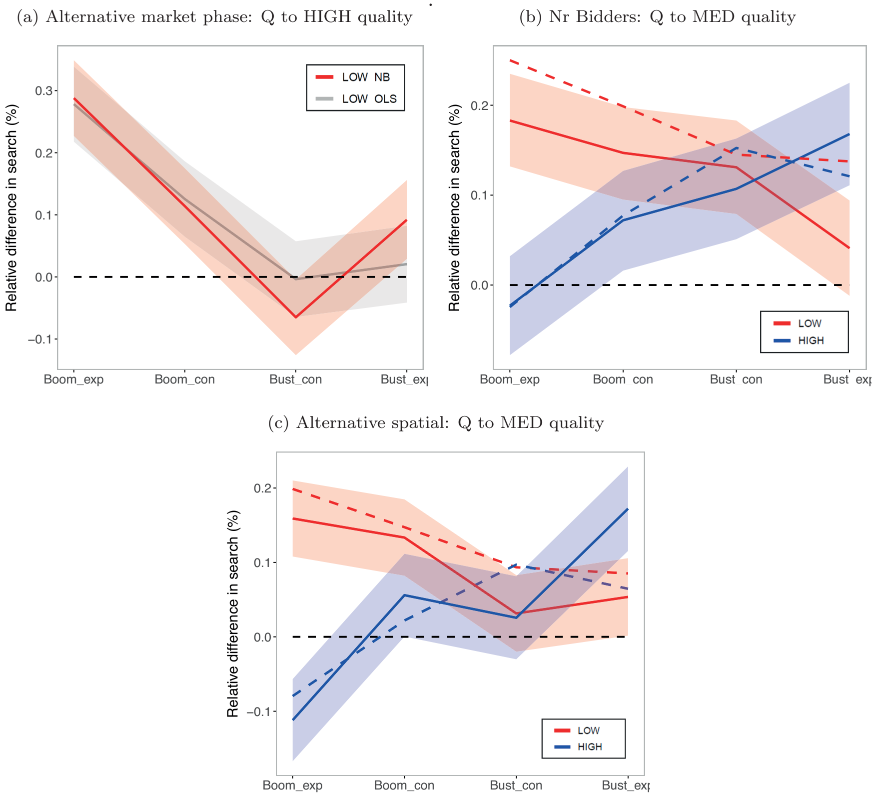
To better account for potential endogeneity in the model due to omitted attribute variables, model (1) is re-estimated including CPI-adjusted price valuations constructed at the time of sale for a sub-sample of the dataset (N=5,920) for which we have access to valuations. The valuations are based on a more comprehensive set of attributes than in our dataset. We first regress $log(Valuation)$ on $log(Askprice)$ in the first stage, and then add the residual from the first stage in the second stage (model 1). As can be seen in table (A5) in the Appendix, this does not affect the results notably. However, the estimated dispersion in favor of high quality during busts increases in magnitude. We may also be concerned about the simultaneity of search and price, for instance that the seller's pricing strategy affects the search intensity. Price and search are interrelated in a complex way, and more complicated models are needed to better account for their relationship.[23]

Figure A1 in the appendix breaks the quality segments down to (most of) their basic attributes in a submarket. Buyers are more likely to search for unmaintained and very small houses during house price booms in prime locations. Note also that the cyclical patterns in this descriptive graph all move in the same direction by quality segment. Finally, we also collect data on online screening from the largest home sale portal Finn.no. Figure A2

[22] The coefficient on the ask price is estimated to -0.467 and is highly significant in this model, quite similar to Han and Strange (2016) which reports an estimate for a large North American metropolitan area of -0.499 in the most similar specification.

[23] Our main issue would be if ask price is correlated with the interactions $Boom \times Quality$ and $Bust \times Quality$, with variations in the correlation among qualities

Figure 6: Results for Search Intensity ratios with Alternative Measures



Notes: The figures show ratios of predictions of the mean search response from hierarchical regression models for a metropolitan market. Figure (a) provides predictions from a negative binomial model for different market phases using a stricter market phase criterion. Figure (b) provides predictions using the alternative search variable Number of Bidders. Figure (c) includes the alternative spatial aggregation *search zones*. In the predictions, all other explanatory variables are set to their mean value while market phase and house quality vary. 95 % CI's are based on asymptotic standard errors.

in the appendix displays the variation in active screenings for renovation quality wordings. Although the time periods and geographical region (mostly) differ due to data availability, there is a clear increase and later decrease in the screening for unmaintained houses that correlates with the house price cycle. Screening for "renovated" wordings is everywhere low, which may indicate that this attribute is not actively screened for by searchers, while "unmaintained" is.

7.2. Additional Note: Policy Changes and Sources of Shocks

During the study period (2013-2019), two important policy changes occurred that affected the housing markets under study. The first was a reduction in the key policy rate in housing markets that were already in a boom in many cases.[24] This can be interpreted as a positive income shock, as many households increased their borrowing capacity. However, due to the sharp rise in house prices that followed this turned out to have a negative net effect for first-time buyers.[25] This is supported by a significant reduction in the volume of first-time purchases during this period of around 20 percent.[26] Evidence also point to an increase in investment purchases in the main Metropolitan city during the booming period, however this appear to be small for the other cities.[27] In response to these effects, the government implemented stricter borrowing constraints, which came into effect in January 2017 with the introduction of a maximum loan-to-income limit. Although beyond the scope of this study, we note that income and credit shocks, as pointed to in the literature (see table 1), may have contributed to these results.

8. Conclusion

In this article, we have presented an empirical study of quality ripples in housing search intensity, utilizing fine-scale data on housing search and transactions. We believe that we make an empirical contribution to the literature by combining micro data on search activity at housing auctions with rich cross-sectional information in our analysis. The spatial segmentation used is based on a carefully estimated price-zone approach. Our key finding is that aggregate search intensity (the ratio of buyers to sellers) by housing quality tier displays clear variations over the housing cycle.

Our key finding is that relative search for lower quality housing is significantly pro-cyclical, while relative search for high quality housing is counter-cyclical, albeit to a lesser

[24] Following the oil price crisis during 2014-2016, the Norwegian policy rate were reduced from its already low level 1.5 in 2013-2014 to 0.50 in the spring of 2016 and remained at this level until autumn 2018. This contributed to fuel many local housing markets whose labor markets were not particularly affected by the oil price crisis.

[25] See e.g. Mamre (2021) who estimate a drop in the purchasing power index of a representative single local first-time-buyer from 16.5 per cent in 2015 to 9.3 per cent in 2016 and down to 1.8 per cent in 2017 in the capital Oslo. The numbers refer to the proportion of transacted homes a representative first-time-buyer could afford and is an aggregate measure/index.

[26] Source: https://nef.no/historisk-boligstatistikk/

[27] The estimated share of buy-to-let as share of the total housing stock decreased from 17.2 per cent in Oslo during 4-13 to 4-15, then increased 16.7 per cent in 4-16 and 17.25 per cent in 2-19. The share of buy-to-let were fairly stable around 9-10 per cent in Drammen during the later period 2019-2023 for which we have data, and similar for Tromsø and Trondheim (NEF, Eiendomsverdi, SØK analyse 2024).

extent. This effect is particularly strong in prime locations. During major booms the dispersion is greater, while during busts this ripple is reversed. The results remain robust if we instead use the number of bidders as a measure of buyer search, or if we instead use an alternative spatial aggregation of search zones. Results are also similar when we include price valuation information based on a richer set of housing characteristic in the estimations and adjust for differences in supply.

We relate this to housing market outcomes in two ways. First, our findings document that search by quality tier is related to housing turnover, the number of bids received and price growth in the expected way. Second, based on VAR analysis and Granger causality tests, our paper demonstrates a positive relationship between search intensity and overall price growth by quality tier, where changes in search tend to precede changes in house prices.

Our results align largely with theoretical predictions and are somewhat consistent with claims often made by realtors; that buyers are more selective in busts, while "anything goes" in booms. The results are also in line with studies such as Landvoigt et al. (2015) and Ho et al. (2008), although there are some important differences in the scope and dynamics considered. The results are also somewhat consistent with what is often claimed by realtors; that buyers are more selective in busts, while "anything goes" in booms. One limitation of our analysis is the lack of identifying information about the searchers across auctions and study volumes. Future work could benefit from studying search at the individual level to disentangle the effects of existing homebuyers and clientele effects. Lastly, we acknowledge that new housing construction can play a significant role in several markets. However, due to the geographical characteristics of the cities studied here and low supply-elasticities, we anticipate that new construction plays a smaller role in counteracting dispersion in these markets.

9. Appendix

9.1. Statistical Detail on Mean Response Predictions and Construction of Confidence Intervals

Model 1 (OLS):

$$Y_1 = ln(S) = x'\beta + e, \quad \text{where} \quad x' = (1, x_1, ..., x_k) \quad \text{and} \quad \beta' = (\beta_0, \beta_1, ..., \beta_k).$$

e is a stochastic error term with expectation 0. The expected response is $\mu_1 = \mu_1(x) = E(ln(S)) = x'\beta$. Parameters of interest, search ratios, labeled θ_1, are determined by comparing the effect on S of two different vectors x, denoted x_A and x_B (in our case they consist of different housing quality and otherwise identical variables). This becomes:

$$\theta_1 = E\left(ln\frac{Y_1(x_A)}{Y_1(x_B)}\right) = \mu_1(x_A) - \mu_1(x_B) = (x_A - x_B)'\beta.$$

Since $ln(1+a) \approx a$,when $|a|$ is small, this becomes $\theta_1 = E\left(ln\left(1 + \frac{Y_1(x_A))}{Y_1(x_B)} - 1\right)\right) \approx E\left(\frac{Y_1(x_A)}{Y_1(x_B)} - 1\right) = E\left(\frac{Y_1(x_A) - Y_1(x_B)}{Y_1(x_B)}\right)$.

Model 2 (NegBin):

Since $S \geq 1$,

$$S = 1 + Y_2, \quad \text{where} \quad Y_2 \quad \text{is negatively binomially distributed over} \quad \{0, 1, 2, ...\}.$$

The expected response is $\mu_2 = E(Y_2) = E(S) - 1$, with linear predictor $\eta = x'\gamma = ln(\mu_2)$,
and link $g(x) = ln(x)$, where $\gamma' = (\gamma_0, \gamma_1, ..., \gamma_k)$. Thus, $\mu_2 = \mu_2(x) = E(Y_2) = e^{x'\gamma}$. Parameters of interest, θ_2, become:

$$\theta_2 = ln\left(\frac{E(Y_2(x_A))}{E(Y_2(x_B))}\right) = ln\left(\frac{E(S(x_A)) - 1}{E(S(x_B)) - 1}\right) = ln\left(\frac{\mu_2(x_A)}{\mu_2(x_B)}\right) = (x_A - x_B)'\gamma.$$

And as before, $\theta_2 \approx \frac{\mu_2(x_A) - \mu_2(x_B)}{\mu_2(x_B)}$.

Confidence intervals (CI):

This shows that both $\theta_1 = (x_A - x_B)'\beta$ and $\theta_2 = (x_A - x_B)'\gamma$ are linear and can be estimated based on maximum likelihood estimators $\hat{\beta}$ and $\hat{\gamma}$. The construction of the CI in both cases is based on the asymptotic covariance matrices, $C_j, j = 1, 2$ for $\hat{\beta}$ and $\hat{\gamma}$, respectively. The standard error for, say, $\hat{\theta}_1$ becomes $SE(\hat{\theta}_1) = \sqrt{(x_A - x_B)'C_1(x_A - x_B)}$ and the asymptotic CI becomes $\hat{\theta}_1 \pm z \times SE(\hat{\theta}_1)$, where z is a quantile in the standard normal distribution. The case of NegBin is exactly identical, based on the covariance C_2.

9.2. Data and Spatial Aggregation Detail

The transaction data only include units sold in free sale, and there are no foreclosures.[28] A few transactions were contracts with a negative dwelling age of -1 to -2 years. These and a few transactions with an erroneously high housing age were removed from the dataset. Units with a very low ask price have been deleted. Subsequently, only residential units were included, and all leisure and commercial properties were removed. Furthermore, only transactions after a certain time period for each city are included as data prior to this time period is very sparse. Some sales lack geographical coordinates (long, lat). For the main market Oslo, these are supplemented from Google Maps (rounded up to 8 decimals). Finally, a set of standard important characteristic variables is selected.

The *price zones* are estimated using the methodology described by Sommervoll and

[28] Poorly maintained units is shown to be overly represented in foreclosures.

Sommervoll (2019).[29] This flexible aggregation method allows us to find areas that are spatially distant that have similar location premiums. The algorithm can be summarized as follows, in our case:

1. Estimate an auxiliary hedonic house price regression.
2. Use a grid to partition Oslo into rectangular cells and restrict the number of submarkets to be fixed at 12.
3. Search for maxima in R^2 for the auxiliary hedonic regression by varying the spatial aggregation of the cells using a genetic algorithm, a variant of gradient ascent.
4. The final result is an aggregation of 373 zip codes to 12 submarkets, represented by a 373-dimensional vector $(7, 2, 7, 1, 12, \dots)$ with cells estimated to have the highest location premium in price zone nr. 12 and the lowest in price zone nr. 1.

[29] The method employed is described in 4.1 Genetic algorithm, p.243-.

9.3. Summary Statistics Other Urban Markets

Table A1: Summary Statistics in three Urban Areas

Trondheim

Time period: jan. 2013 - jan. 2018. N=5,278

Variable	Mean	Median	SD	Min	Max
Interested[a]	7.24	4.0	10.0	1	169
Bidders	2.09	2.0	1.4	1	19
Bids	6.35	5.0	5.6	1	47
Transaction price	0.32	0.28	0.14	0.03	1.55
Ask price	0.31	0.28	0.14	0.04	1.51
Fully renovated	0.13				
Unmaintained	0.03				
Size in m^2	94.6	79.0	53.0	15	481
Dwelling age	43.5	43.0	33.3	1	359

Tromsø

Time period: apr. 2014 - jun.2018. N=335

Variable	Mean	Median	SD	Min	Max
Interested	5.74	4.0	5.7	1	36
Bidders	1.86	2.0	1.1	1	8
Bids	5.41	4.0	4.7	1	35
Transaction price	0.35	0.31	0.14	0.07	1.0
Ask price	0.35	0.31	0.14	0.07	0.85
Fully renovated	0.065				
Unmaintained	0.02				
Size in m^2	98.9	84.0	57.0	24	462
Dwelling age	29.1	21.0	28.2	0	176
Distance CBD[b]	3.61	2.52	3.92	0.07	38

Drammen

Time period: nov. 2014 - may 2019. N=1,600

Variable	Mean	Median	SD	Min	Max
Interested	7.24	5.0	6.0	1	54
Bidders	2.14	2.0	1.3	1	11
Bids	6.44	5.0	5.5	1	39
Transaction price	0.31	0.27	0.13	0.07	1.01
Ask price	0.30	0.27	0.13	0.07	1.03
Fully renovated	0.155				
Unmaintained	0.055				
Size in m^2	99.2	83.0	53.4	14	374
Dwelling age	49.8	45.0	35.1	0	326

Note: The table shows summary statistics for the main variables in the cross-sectional dataset. Prices in USD million, with exchange rate 10.63. a.Summary statistics for *Nr Interested* for Trondheim are for the smaller sub-sample (N=4,402) for which we have access to data. b. *Distance to Center* is the Haversine distance to the Tromsø Central region.

9.4. Results from House Price Cycle Analysis

Table A2: Boom and Bust Episodes in Real House Prices in a Metropolitan Market. Period: 1.2003-4.2023

Booms

	Episode	Magnitude	Duration	Severity
1	jul. 05 - feb. 07	0.312	20	3.123
2	nov. 15 - feb. 17	0.294	16	2.355
3	jan. 14 - jul. 15	0.210	19	1.996
4	jan. 12 - apr. 13	0.120	16	0.963
5	may 20 - feb. 21	0.162	10	0.812
6	jul. 03 - feb. 04	0.187	8	0.747
7	jan. 09 - aug. 09	0.161	8	0.645
8	aug. 10 - may 11	0.117	10	0.583
9	jul. 04 - feb. 05	0.104	8	0.414
10	jan. 18 - jul. 18	0.080	7	0.282
11	jan. 19 - aug. 19	0.054	8	0.215
12	dec. 21 - aug. 22	0.045	9	0.202
13	dec. 09 - may 10	0.042	6	0.126
14	jun. 11 - dec. 11	0.022	7	0.077
15	nov. 19 - feb. 20	0.033	4	0.066
16	jul. 07 - aug. 07	0.017	2	0.017
17	jan. 08 - mar. 08	0.008	3	0.012

Busts

	Episode	Magnitude	Duration	Severity
1	mar. 17 - dec. 17	−0.138	10	−0.690
2	apr. 08 - dec. 08	−0.147	9	−0.661
3	may 13 - dec. 13	−0.088	8	−0.353
4	mar. 21 - nov. 21	−0.047	9	−0.210
5	sep. 07 - dec. 07	−0.066	4	−0.132
6	sep. 22 - nov. 22	−0.079	3	−0.119
7	aug. 18 - dec. 18	−0.036	5	−0.090
8	aug. 15 - oct. 15	−0.038	3	−0.057
9	mar. 04 - jun. 04	−0.028	4	−0.056
10	mar. 05 - jun. 05	−0.047	9	−0.045
11	mar. 07 - jun. 07	−0.018	4	−0.036
12	sep. 09 - nov. 09	−0.024	3	−0.036
13	mar. 20 - apr. 20	−0.035	2	−0.035
14	sep. 19 - oct. 19	−0.024	2	−0.024
15	jun. 10 - jul. 10	−0.013	2	−0.013

Notes: The tables show the boom and bust episodes detected by the Harding and Pagan (2002) algorithm, ranking them according to their magnitude (real price growth), duration (length in months) and severity (a combination of the two). Episodes that fall within the time frame of our dataset are highlighted in red.

9.5. Additional Results 1: Estimation Results in Other Urban Markets

Table A3: Results of NegBin Search Intensity Regressions in three Urban markets

	Dependent variable:					
	Nr Interested/Nr Bidders					
	(Drammen)	(IRR)	(Trondheim)	(IRR)	(Tromso)	(IRR)
Dispersion	0.847^{***}	2.332	1.406^{***}	4.080	0.550^{***}	1.733
	(0.061)		(0.119)		(0.165)	
log(Ask price)^{a}	-0.102	0.903	-0.360^{***}	0.698	-0.001	0.999
	(0.083)		(0.061)		(0.232)	
low × Boom_{exp}	0.325^{**}	1.384	0.592^{***}	1.808	0.302	1.352
	(0.116)		(0.112)		(0.554)	
med × Boom_{exp}	0.115	1.122	0.472^{***}	1.603	0.094	1.098
	(0.090)		(0.103)		(0.454)	
high × Boom_{exp}	0.009	1.009	0.458^{***}	1.581	0.116	1.123
	(0.098)		(0.106)		(0.449)	
low × Boom_{con}	-0.140	0.870	0.591^{***}	1.805	-0.471	0.625
	(0.171)		(0.116)		(0.450)	
med × Boom_{con}	-0.046	0.955	0.538^{***}	1.713	0.047	1.048
	(0.122)		(0.103)		(0.381)	
high × Boom_{con}	-0.148	0.862	0.393^{***}	1.481	0.146	1.158
	(0.143)		(0.109)		(0.391)	
low × Bust_{con}	0.123	1.131	0.428^{***}	1.534	-1.002^{*}	0.367
	(0.115)		(0.116)		(0.503)	
med × Bust_{con}	-0.000	1.000	0.297^{**}	1.346	-0.783^{*}	0.457
	(0.097)		(0.104)		(0.388)	
high × Bust_{con}	-0.033	0.967	0.283^{**}	1.327	$-0.652^{\cdot}$	0.521
	(0.108)		(0.109)		(0.396)	
low × Bust_{exp}	0.203	1.225	$0.407^{\cdot}$	1.502	-0.186	0.830
	(0.128)		(0.211)		(0.733)	
med × Bust_{exp}	-0.026	0.974	0.509^{***}	1.663	0.614	1.847
	(0.100)		(0.129)		(0.408)	
high × Bust_{exp}	0.052	1.053	0.645^{***}	1.906		
	(0.110)		(0.132)		–	–
Search zones	x		x		x	
Nr Bidders	–		x		–	
Seasonal dummies	x		x		x	
Structural factors	x		x		x	
Observations	1,600		5,299		335	
Log Likelihood	-4,499		-7,330		-765	
θ	3.291^{**} (1.270)		5.134^{***} (0.914)		0.375 (3.688)	

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: The table shows regression results for three urban markets. Columns (Coeff.) display regression results for estimation of model (2) and column (IRR) shows incidence rate ratios. Note that these interaction coefficients are measured relative to a reference period and our scope is the relative differences of coefficients. a.A Hauck-Donner effect is detected in the Ask price variable in the Trondheim regression.

9.6. Additional Results 2: Number of Bidders

Table A4: Results of NegBin Search intensity regressions. Alternative Search Variable

	Dependent variable:		
	Nr Bidders		
	(Coeff.)	(IRR)	(Q/med)
Dispersion	1.390***	4.016	
	(0.058)		
log(Ask price)	−0.467***	0.627	
	(0.036)		
log(Distance CBD)	−0.154***	0.857	
	(0.018)		
low × $Boom_{exp}$	0.592***	1.808	0.194***
	(0.074)		
high × $Boom_{exp}$	0.366***	1.442	−0.032
	(0.075)		
low × $Boom_{con}$	0.479***	1.614	0.161**
	(0.075)		
high × $Boom_{con}$	0.382***	1.465	0.064
	(0.079)		
low × $Bust_{con}$	0.112	1.119	0.124
	(0.079)		
high × $Bust_{con}$	0.108***	1.114	0.120
	(0.084)		
low × $Bust_{exp}$	0.083	1.087	0.068
	(0.086)		
high × $Bust_{exp}$	0.169***	1.184	0.153*
	(0.092)		
Location factors	x		
med × market phase[a]	x		
Seasonal dummies	x		
Structural factors	x		
Observations	8,473		
Log Likelihood	-15,443		
θ	8.526*** (0.559)		

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: *a*.Not reported for brevity. Column (Coeff.) shows regression results for estimation of model (2) with the number of bidders as the explanatory variable and column (IRR) shows incidence rate ratios. Column (Q/med) displays the estimated search intensity ratios. The significance levels for the estimates in this column is defined by the confidence interval (CI) of the numeraire coefficient. A 0.01 level of significance for, say, low quality in the $boom_{exp}$ phase indicates that the coefficient for Q × $boom_{exp}$ is outside its 99 percent CI.

9.7. Additional Results 3: Price Valuations

Table A5: Results of OLS Search intensity regressions. With and without Price valuation

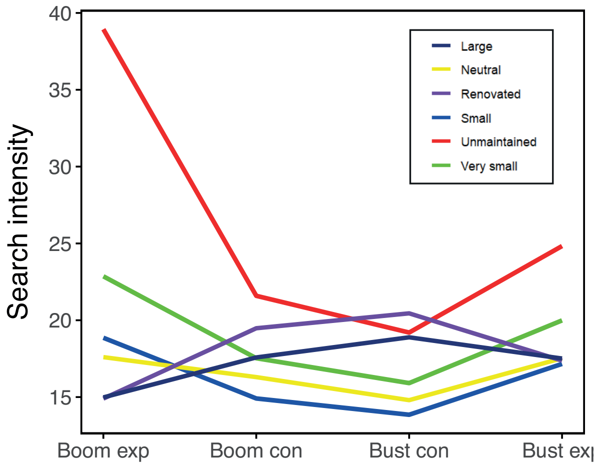
	Dependent variable:			
	log(Nr Interested)			
	(1)	(2)	(Q/med 1)	(Q/med 2)
log(Ask price)	0.170***	0.194***		
	(0.037)	(0.036)		
log(Distance CBD)	−0.275***	−0.262***		
	(0.019)	(0.019)		
low × $Boom_{exp}$	1.047***	0.928***	0.201***	0.205***
	(0.073)	(0.072)		
high × $Boom_{exp}$	0.742***	0.682***	−0.103	−0.041
	(0.072)	(0.070)		
low × $Boom_{con}$	0.994***	0.856***	0.189**	0.185**
	(0.076)	(0.074)		
high × $Boom_{con}$	0.774***	0.703***	−0.031	−0.058
	(0.076)	(0.075)		
low × $Bust_{con}$	0.730***	0.641***	0.129*	0.123
	(0.078)	(0.076)		
high × $Bust_{con}$	0.714***	0.698***	0.113	0.180**
	(0.078)	(0.076)		
low × $Bust_{exp}$	0.789***	0.704***	0.235***	0.240***
	(0.085)	(0.084)		
high × $Bust_{exp}$	0.511***	0.486***	−0.043	0.022
	(0.087)	(0.085)		
Location factors	x	x		
Valuation	–	x		
med × market phase[a]	x	x		
Seasonal dummies	x	x		
Structural factors	x	x		
Robust errors	x	x		
Observations	5,920	5,920		
Adjusted R^2	0.137	0.173		

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: a.Not reported for brevity. Column (Coeff.) shows regression results for an estimation of model (1) and column (2) shows regression results for an estimation of model (1) including price valuation information. Columns (Q/med) and (Q/high) displays the estimated search intensity ratios. The significance levels for the estimates in these two latter columns is defined by the CI of the numeraire coefficient. A 0.01 level of significance for, say, low quality in the $boom_{exp}$ phase indicates that the coefficient for Q × $boom_{exp}$ is outside its 99 percent CI.

9.8. Additional Figures I: Summary statistics by Quality Component

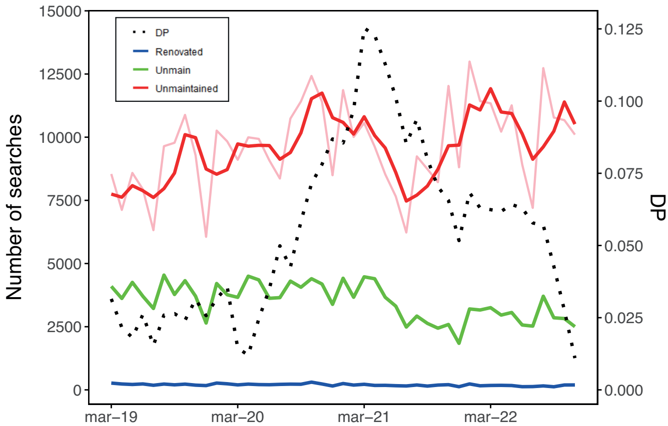
Figure A1: Housing Search by Phase and Quality Component in Prime Locations



Notes: The figure shows the average search intensity in Prime locations decomposed by house quality measures. A unit is *renovated* or *unmaintained* if it is listed as fully renovated or unmaintained. A *neutral* unit contains no such information in the listing. House sizes are defined as size sixtiles or quintiles, depending on the size distribution in the city.

9.9. Additional Figures II: Online Screening for Renovation Wordings

Figure A2: Online Screening for Renovation Wordings



Notes: Data is compiled by Finn.no and counts screening (online search) for various wordings on the Norwegian real estate portal, which distributes more than 80 percent of sales in the Norwegian housing market, for the time period january 2019 - jan 2023. *DP* is calculated as 4-quarter house price growth based on HPI data from Eiendomsverdi ASA.

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5 Paper III

We present an amenity-based theory of location by income. The theory shows that the relative location of different income groups depends on the spatial pattern of amenities in a city. When the center has a strong amenity advantage over the suburbs, the rich are likely to live at central locations. When the center's amenity advantage is weak or negative, the rich are likely to live in the suburbs.

Brueckner, Thisse & Zenou, 1999

Income and Household Location Choice in Amenity-rich and Amenity-poor Cities*

Zeno Adams†, Luca Liebi‡, Mari O. Mamre§

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ABSTRACT

This paper investigates household location choices by income within city regions, noting that the existing empirical studies typically report mixed results for the income - distance gradient across cities. Our approach emphasize the importance of idiosyncratic city characteristics and amenity concentration for hypotheses about the income-distance gradient. By extracting data from a geographic database, we distinguish between amenity-rich and amenity-poor city centers relative to the larger urban area in eight Swiss cities. Although their concentration may be related in a complex way to other fundamental drivers, our findings reinforce the importance of amenities for household location choice. In line with theory, we estimate an inverse relationship between the degree of amenity-superiority of the city center and the income - distance gradient. Finally, the study examines how households respond to increased access to amenities such as public transportation at the city edge, as well as local variations in taxes.

Keywords: Household location choice, income gradient, amenities, spatial sorting

JEL Classifications: R20, R23, R30

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†University of St. Gallen, Swiss Institute of Banking and Finance, Unterer Graben 21, CH-9000 St. Gallen, Switzerland; Tel.: +41 71 224 7014; E-mail address: zeno.adams@unisg.ch.

‡University of St. Gallen, Swiss Institute of Banking and Finance, Unterer Graben 21, CH-9000 St. Gallen, Switzerland; Tel.: +41 71 224 7004; E-mail address: luca.liebi@unisg.ch.

§Oslo Metropolitan University, Institute for Urban and Regional Research, Oslo; Tel.: +47 90787163; E-mail address: mari.mamre@oslomet.no.

I. Introduction

The spatial sorting of households in city regions has gained considerable attention in recent decades. Following the seminal work of Alonso (1964), Mills (1967), and Muth (1968), urban economists have identified commuting costs as a key determinant of household location choice. The traditional urban model posits that, under specific conditions, high-income households choose to reside near the Central Business District (CBD). However, subsequent research have explored other determinants of location choice, with one noted limitation of the classical model being the absence of spatial differences in access to transportation and amenities. When expanding the analysis to account for amenities, Brueckner, Thisse, and Zenou (1999) suggest that high-income households may reside closer to the CBD if the amenity advantage of the CBD is large, or reside near the city's edge if the amenity advantage of the CBD is marginal. Other studies put emphasis on the enduring value of natural amenities for cities (Albouy (2016)) and their impact on the income distribution within cities over time (Lee and Lin, 2018). Consequentially, idiosyncratic city characteristics and amenity concentration may be influential for hypotheses about the income-distance gradients across cities.

The empirical studies on household location choice often report mixed results for the income - distance gradient, with income estimated to both increase and decrease with distance to the work center(s) (see e.g., Cuberes, Roberts, and Sechel (2019)), Axisa, Scott, and Bruce Newbold (2012)), Rosenthal and Ross (2015)). These mixed results are observed across different countries, urban settings, and time periods, with some geographical variation. Importantly, despite growing evidence highlighting the significance of relative amenity values of locations, this is typically not addressed in this empirical literature, largely due to the difficulties involved in measuring amenities and the large number of inter-related variables involved. Further, the recreational value of nature amenities found at the city's edge and the value attributed by households to a larger proportion of villas are not usually accounted for.

In this paper, we examine household location choice in Switzerland. Our study contributes to the current income and amenity-based sorting literature, primarily focused on the United States. The advantage of studying smaller cities is that the monocentric city assumption is more likely to hold, given that these cities generally have one well-defined center of commercial and social activity. The Swiss cities studied also share similar institutional settings. We use a representative survey of households (Swiss Household Panel) in eight cities from 1999-2014 to explore how household income, amenities, transportation, and local variations in taxes influence household location choice. Information from the geographical database Open Street Map is retrieved for six categories of amenities. The analysis differentiates between *urban amenities* such as restaurants and theatres and *natural amenities* such as recreational areas, lakes, and national borders. Lakes and lake views constitute important natural amenities, while national borders offer access to foreign amenities and limit the extent to which a city can expand its territory.

We document that the number of urban amenities is spatially patterned and decreases quickly with distance to the city centers in these urban areas. However, the degree of concentration varies significantly across cities. We distinguish between amenity-rich and amenity-poor city centers relative to the larger urban area. Our findings reinforce the importance of amenities' pull factor. Although their concentration may also be related in complex ways to unobserved effects such as agglomeration benefits (Rosenthal and Strange (2004)), peer effects ((Schmidheiny, 2006)), or "superstar dynamics" ((Gyourko, Mayer, and Sinai, 2013))[1], our results suggests that amenities and amenity value are influential for location choice.[2]

The key finding is an inverse relationship between the level of intra-city amenity concentration and the income-distance gradient. This pattern is even more pronounced when we relax simplifying assumptions, and it aligns with predictions from an extended canonical urban model (Brueckner et al., 1999). These predictions serve as long-term insights, in contrast to short-term responses to various shocks. We address the endogeneity of amenities and household location choices by considering alternative specifications with more exogenous amenities such as natural amenities and the level of taxes, and by using a supply elasticity instrument. To relax the assumption of full household mobility, separate results are estimated for the subset of households who recently moved. These findings have significant implications for the amenity-based sorting literature and local urban planning.

Additionally, we examine household responses to increases in transportation. Our findings indicate that enhanced transportation access outside the CBD is associated with households locating further from the CBD across all cities. For instance, a one standard deviation increase in transportation access outside the CBD, equivalent to the addition of 50 platforms, is estimated to increase households distance to CBD by as much as 50 per cent in the transportation-rich canton of Basel. Insights are further enriched when we consider household characteristics and fiscal differentials. Certain factors, such as age and type of household, may influence how households value amenities. The significant variation in income taxes within these city regions may serve as a considerable pull factor, influencing

[1]High house prices and price-to-rent ratios in "superstar" areas characterised by low housing supply and high demand may crowd out lower-income households. In the city Zürich this is a plausible theoretical channel.

[2]For instance, the level of amenities can affect the quality of living but also attract production and jobs or more attractive peers (neighbors).

household location decisions (Schmidheiny (2006)). Finally, an illustrative empirical analysis involving spatial non-linearities is provided. A triple interaction partial model suggests that there may be important dependencies between the spatial patterning of dwelling types and nature amenities that, when taken into account, works to invert the income gradients. However, more work remains to incorporate such spatial non-linearities in fully specified models of household location choice.

The remainder of the paper is structured as follows. In section II, we present a brief overview of the literature. In section III, inference for the income gradient of amenity concentration is discussed based on a canonical theoretical model of household location choice. In section IV, background and descriptive statistics for the data is provided. The empirical results are discussed in section V and simplifying assumptions along several dimensions are relaxed in section V.B. Section VI concludes our findings.

II. Related Literature

The topics of local income concentration, amenities, and spatial patterns have remained at the forefront of urban economics literature. The significant impact of amenities (and disamenities) on the urban distribution of population and housing rents has been widely recognized, following the seminal works of Rosen (1979) and Roback (1982), and more recently, Ng (2008). The majority of studies have primarily investigated the extent to which individual amenities are valued by households. The positive effects of specific amenities, like forests (Hand, Thacher, McCollum, and Berrens, 2008), climate amenities (Lu, 2020), waterfront access (Lee and Lin, 2018), and ocean views (Rappaport and Sachs, 2003) have been documented. However, few studies have incorporated a broad range of amenities and household characteristics into their analyses.

The spatial income pattern in many U.S. metropolitan areas, where median income increases with distance from city centers, is a well-documented phenomenon (Rosenthal and Ross, 2015). This pattern is so prevalent in the U.S. that it has informed the concept of poor cities and affluent suburbs (Jargowsky, 1997; Glaeser, Kahn, and Rappaport, 2008; Brueckner and Rosenthal, 2009). However, after controlling for amenities and other factors influencing household location choice, this salient income pattern appears to be less pronounced, and recent literature points to disparities in location choices between amenity-rich and amenity-poor cities Letdin and Shim (2019)[3].

[3]The study confirm the overall negative income gradient for U.S. cities but does not control for differences in access to natural amenities or consider intra-city differences in amenity concentration.

In contrast, studies focusing on European cities have reported mixed results, with significant variations in the direction of the spatial income coefficient. For instance, Brueckner et al. (1999) demonstrate that in French cities, such as Paris and Lyon, income is typically higher in the center. Similar patterns are observed in other European and Latin American cities (Hohenberg and Lees, 1995; Ingram and Carroll, 1981). Examining U.K. cities, Cuberes et al. (2019) investigate the income gradient while controlling for a large set of amenities and heterogeneous households. They found no significant relationship between income and distance to the CBD for five of the eight cities investigated, with mixed results for the remaining three.

Our study contributes to the existing literature by examining household location choices by income within an urban geography characterized by short internal distances and comparable institutional settings. We estimate intra-city amenity concentration directly from geographical data, distinguishing between natural and urban amenities, as well as fiscal differences. Our study is closely related to the canonical theoretical model proposed by Brueckner et al. (1999). They argue that exogenous amenities can lead to a variety of household location choice patterns across cities. For instance, the historical amenities in the city center of Paris are expected to attract affluent households. More recently, Lee and Lin (2018) extended this notion to a dynamic setting, positing that persistent natural amenities can anchor neighborhoods to high-income households. Their findings for Danish cities suggest that in cities with lower natural amenity heterogeneity, the spatial income distributions are more likely to shift among neighborhoods. Comparing different geographies, such as the U.K., U.S., and Switzerland, likely involves a broad spectrum of differences. However, the amenity and workplace-based theory offers a plausible explanation for variations in location choices and commuting patterns across diverse urban settings.

A third strand of academic literature examines the influence of tax rates on household location choice, particularly in the U.S. Studies have demonstrated that retirees tend to avoid areas with high property taxes (Cebula, 1974; Duncombe, Robbins, and Wolf, 2001) and inheritance taxes (Dresher, 1993; Voss, Gunderson, and Manchin, 1988). A study by Duncombe, Robbins, and Wolf (2003), which analyzed county-to-county migration, found that among all investigated fiscal variables, income taxes had the most significant impact on the migration decisions of retirees. In the context of Switzerland, Schmidheiny (2006) examined the effect of income tax differentials across municipalities in the Swiss canton of Basel. Their findings suggest that wealthier households are substantially more likely to move to low-tax municipalities than their less affluent counterparts. Other major factors for income segregation included social interactions (peer effects) and distance from the Central Business District (CBD). The next section outline a canonical model of location choice.

III. Theoretical foundations

The following stylized model emphasizes the role of disposable income and the spatial distribution of amenities in residential choice. To illustrate our key economic variables and their implications, we consider the monocentric city model of household location choice with amenities presented in Brueckner et al. (1999). Our model diverges from theirs by incorporating taxes, which demonstrate significant spatial variation in this area, as well as two types of amenities, *natural amenities* and *urban amenities*. The objective is to explore how the introduction of these features is expected to influence household location choice by income level within an urban area. While we focus on these specific factors, we acknowledge that other elements, such as wages, moving frictions, and production, may also play crucial roles in the joint decisions of household location and production. These factors are often highlighted in the quantitative spatial literature (see Redding and Rossi-Hansberg (2017) for a review).

A. A Canonical model of Household Location Choice

Households are perfectly mobile and choose where to locate in an urban area to maximize utility. Let x be the distance to the Central Business District (CBD), and $a_N(x)$ be the level of *natural amenities* and $a_U(x)$ the level of *urban and transport amenities* at that distance. Natural amenities might include recreational lakes or green spaces. Urban and transport amenities could encompass restaurants and transportation access. For simplicity, we assume that the amenity levels are exogenous[4] and costless for consumers to use[5]. We also assume that the aggregate amenity level in each group is net positive, i.e., they are goods and not bads. c represents a composite non-housing good with a price of unity, and $h(x)$ is housing services that also depend on location x. Household preferences are given by:

$$u(c, h, a_U, a_N) \quad (1)$$

Assume that preferences are strictly convex over the consumption bundle and the utility function is continuous. Initially, assume income y is identical for all households. Let t represent a fixed commuting cost per distance unit. The urban area is populated with various local governments financed by a local income tax, which varies by location, $\tau(x)$. The household disposable income at distance x is $y(1 - \tau(x)) - tx$. The price per unit of

[4]This assumption is maintained only for urban amenities for simplicity of exposition. The empirical analysis aims to relax this unrealistic assumption.

[5]For instance, Diamond Jr (1980) introduces separate prices for amenities.

housing is given by p. The household's budget constraint is then given by:

$$c + ph = y(1-\tau) - tx \quad (2)$$

Households maximize equation (1) wrt. h and c. Substituting c from (1) by incorporating equation (2), the households' optimization problem becomes:

$$\max_h u(y(1-\tau) - tx - ph, h, a_U, a_N) \quad (4)$$

The first-order condition for this problem is given by:

$$u'_h = pu'_c \quad (5)$$

Under the assumption of perfect mobility, a key equilibrium condition in the canonical model stipulates that all identical households attain the same utility, denoted here as u^0. This implies that, in a spatial equilibrium, house prices p must vary with distance x to ensure every identical household achieves the same utility.

$$u(y(1-\tau) - tx - ph^*, h^*, a_U, a_N) = u^0, \quad (6)$$

where * denotes the optimal level of housing consumption. The simultaneous system of equations (5)-(6) determines the solution for p. This solution depends on all the parameters and exogenous variables of the system: x, y, τ, t, a_U, a_N and u^0. For our purposes, we are particularly interested in x. Totally differentiating (6) wrt. x, where subscripts denotes partial derivatives, we get:

$$u'_c(-y\tau'(x) - t - p'(x)h(x) - p(x)h'(x)) + u'_h h'(x) + u'_{a_U} a'_U(x) + u'_{a_N} a'_N(x)$$

Using the first-order condition in (5) and solving for $p'(x)$, this becomes:

$$\begin{aligned} p'(x) &= \frac{-\tau'(x)y}{h(x)} - \frac{t}{h(x)} + \frac{u'_{a_U} a'_U(x)}{u'_c h(x)} + \frac{u'_{a_N} a'_N(x)}{u'_c h(x)} \\ &= \frac{-\tau'(x)y}{h(x)} - \frac{t}{h(x)} + \frac{v'_{a_U}}{h(x)} a'_U(x) + \frac{v'_{a_N}}{h(x)} a'_N(x) \quad (7) \end{aligned}$$

Equation (7) gives the slope of the bid-price function for housing. In the second line of (7), the marginal rate of substitution u'_{a_i}/u'_c is rewritten as the amenity derivatives of the corresponding indirect utility functions, $v_i[y(1-\tau) - tx, p(x), a_U(x), a_N(x)]$, where $i = U, N$. Note that v'_{a_i} represents the marginal valuation of amenity levels after optimal choice of housing services has been made.

To discuss the contributions of the various elements in equation (7) to the overall sign of $p'(x)$, note that when $\tau'(x) = v'_{a_U} = v'_{a_N} = 0$, we arrive at Muth's classical result $p'(x) = -\frac{t}{h(x)}$. In this case, the housing price is a decreasing function of distance to the CBD. This reflects the need for households that move further away to be compensated for their higher commuting costs through lower housing prices. If $\tau'(x) < 0$, this counteracts this effect since households will benefit from lower taxes at the city's edge. The same reasoning applies to the third and fourth terms in equation (7). If $a'_U(x) < 0$, prices fall more with distance as households must be compensated for lower amenity levels. However, if $a'_N(x) > 0$,indicating that natural amenities are more abundant at the city's edge, this effect is counteracted.

B. The income gradient

To discuss the income gradient, now assume that there are two income groups in this market, High and Low income: y_H, y_L. This results in two bid-price functions, $p_H(x), p_L(x)$, where the highest bidder get any given house in the market. Let $\hat{x}$ represent the threshold location where the bid-prices of the two groups are equal, i.e., $p_H(\hat{x}) = p_L(\hat{x})$. The relative slopes of the bid-price curves at the threshold location determine which income groups' bid is higher. If $p'_H(\hat{x}) > p'_L(\hat{x})$, the Low-income group's curve is more negatively sloped at $\hat{x}$, and they outbid the High-income group for central locations, and vice versa. By incorporating equation (7), we get:

$$\nabla = p'_H(\hat{x}) - p'_L(\hat{x}) = \frac{\tau'(\hat{x})y_L}{h_L(\hat{x})} - \frac{\tau'(\hat{x})y_H}{h_H(\hat{x})} + \frac{t}{h_L(\hat{x})} - \frac{t}{h_H(\hat{x})}$$
$$+ a'_U(\hat{x})\left(\frac{v^{H'}_{a_U}}{h_H(\hat{x})} - \frac{v^{L'}_{a_U}}{h_L(\hat{x})}\right) + a'_N(\hat{x})\left(\frac{v^{H'}_{a_N}}{h_H(\hat{x})} - \frac{v^{L'}_{a_N}}{h_L(\hat{x})}\right) \quad (8),$$

where $v^H_i[y_H(1-\tau) - t\hat{x}, p_H(\hat{x}), a_U(\hat{x}), a_N(\hat{x})]$ and similarly for v^L_i, for $i = U, N$. $h_H(x)$ and $h_L(x)$ represents the level of housing services for the two groups. Consider the first two terms in equation (8) in isolation. Since the price of housing is the same for both groups at $\hat{x}$, $h_H(\hat{x}) > h_L(\hat{x})$, because $y_H(1-\tau(\hat{x})) > y_L(1-\tau(\hat{x}))$. Then, the overall sign is ambiguous. If income differences are larger, then high-income households will live at the city's edge, given $\tau'(x) < 0$. For the next two terms, the overall sign is positive. Thus, when commuting costs are identical, the higher housing service level demanded by the high-income group implies that high-income households will live at the city's edge.[6] The overall sign of (8) also depends on the differentials in amenity effects. If v'_{a_i} rises with income and its rise is more

[6] In the classical model, it is common to use different commuting costs which could change this result.

rapid than the increase of housing consumption, the net effect of the forth and fifth term is negative, given that $a'_U(x) < 0$. Thus the higher valuation of urban amenities by high-income households contributes to these households living closer to the city center. The same line of reasoning will give the opposite result for the last two terms, given that $a'_N(x) > 0$. This discussion is summarized in the following ceteris paribus predictions:

Prediction 1: $\frac{\partial \nabla}{\partial a'_i(\hat{x})} < 0, \quad i = U, N$: If the amenity advantage of the CBD is lower, this contributes to a negative income gradient. If the amenity advantage of the work center is large, we might expect a negative income gradient.

Prediction 2: $\frac{\partial \nabla}{\partial \tau'(x)} > 0$: If the tax advantage of the city's edge is high, this contributes to a positive income gradient. Conversely, if the tax advantage of the city's edge is low.

Prediction 3: $\frac{\partial \nabla}{\partial h_H(x)} > 0$: If the housing consumption of high-income households is larger, this contributes to a positive income gradient if such units are more numerous and affordable at the city's edge.

The possible solutions to this model include both perfect sorting and multiple equilibria. These predictions serve as long-term insights, in contrast to short-term responses to various shocks. The following sections describe the data, analyze the spatial sorting of key variables in these urban areas, and test these predictions. We also analyze the effects of relaxing assumptions of the stylized model along several dimensions.

IV. Data and Descriptive Statistics

We obtain data from three primary sources: (1) OpenStreetMap for local amenities, (2) The Swiss Household Panel for household characteristics, and (3) Fahrländer Partner Raumentwicklung for house prices. Information from municipalities is combined with data on individual households. Section IV.A defines the distance measures used, followed by a description of all explanatory variables.

A. Distance to CBD and Regional Detail

The dependent variable measures the straight-line kilometer distance of each household to the CBD. For anonymity reasons, household location is only known at the municipality level. The distance is measured from the centroid of each municipality where the household is located.

The empirical literature proposes numerous landmarks to represent a city's employment center. Cheshire, Hilber, Montebruno, and Sanchis-Guarner (2018) discuss the ambiguities in defining the CBD. Following recent literature, we define the CBD as the coordinates of the main railway station (Cuberes et al., 2019; Nathan and Urwin, 2005). In many U.K. cities, railway stations are located in commercial activity clusters[7]. An alternative CBD identification is based on the city hall coordinates (Atack and Margo, 1998; Paul, Research, and 1991, 1991; Schuetz, Larrimore, Merry, Robles, Tranfaglia, and Gonzalez, 2018). In Switzerland, the city hall is often located close to the main train station. For instance, the city hall in St. Gallen is within 100 meters of the main train station. In Zürich, the distance between the main railway station and the city hall is 800 meters. For Lausanne, it is 400 meters. Thus, choosing between the main railway station or the city hall will yield very similar results.

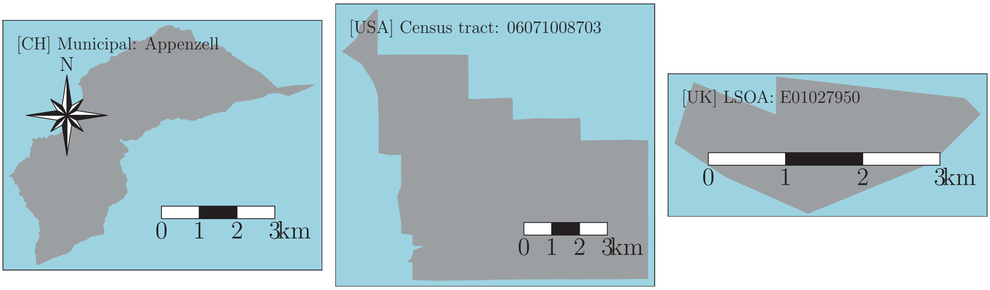
Although our empirical results are based on the haversine distance, we also provide evidence of the robustness of our findings with respect to travel distance by car or public transportation. Differences between these three types of distance measures typically occur due to city topography. For instance, the city of Zürich spans around the lake of Zürich and the city of Lausanne is built on a steep mountain slope, making navigation by car challenging. In both cases, travel distance is likely to be larger than the straight-line distance. However, the correlation between the three types of distance measures is close to 95%. Finally, it is worth noting the typical size of a Swiss municipality. The empirical literature on U.S. cities often examines census tracts, while the U.K. literature studies lower spatial output areas (LSOAs). Figure 1 compares three spatial units that are typical in terms of surface area and population. Judging from the mean area size, Swiss municipalities are somewhat smaller than U.S. census tracts but larger than U.K. LSOAs. In total, Switzerland comprises 2,202 municipalities, each of which belongs to one of 26 cantons.

B. Amenity and household data

This section describes the main variables consisting of amenities and household characteristics, and discusses the unique role of taxes in Switzerland.

[7] For instance, King's Cross Station in London introduced its own postal code for all the buildings around the main station (The Economist (2014)). A similar situation holds for Switzerland: Zurich city is organized into 12 circles or "Kreise". "Kreis 1" covers a broader definition of the CBD. The Bahnhofstrasse ("Railway Station Street") in Zürich is an iconic Swiss commercial activity landmark featuring numerous shops and restaurants (Swissinfo.ch (2016)). As the name suggests, the Bahnhofstrasse starts right next to the main train station.

Figure 1. Average size of a municipal, census tract, and LSOA
This figure compares the area in square kilometres of a typical municipality in Switzerland, with a census tract in California and a lower spatial output area in the United Kindom. From left to right the figure visualizes the municipality Appenzell in Switzerland with an area of 16.88 km^2 and a population of 5,728. The depicted census tract in California has a size of 60.14 km^2 and a population of 6,496. The LSOA in the U.K. covers an area of 4.35 km^2, with a population of 1,907. Each of the three spatial units represents the average size of the corresponding spatial unit.



	[CH] Municipal	[USA] Census tract	[UK] LSOA
Mean Surface Area	17.35	50.97	4.35
Median Surface Area	7.93	1.91	0.47

B.1. Amenities

Coordinates for a broad set of amenities in Switzerland were sourced from OpenStreetMap (OSM). Launched in 2004 at the University of London, OSM adopted the peer production model, also utilized by Wikipedia. However, unlike Wikipedia, only registered users can contribute to the OSM database (Haklay and Weber, 2008)[8]. Given that OSM data is user-generated, concerns about data quality and geographical accuracy have been raised. Several academic studies have investigated OSM data quality by comparing OSM data to a reference dataset. ISO 1915 defines six categories for evaluating the internal quality of a spatial dataset, including positional accuracy, thematic accuracy, completeness, temporal quality, logical consistency, and usability. Ciepłuch, Jacob, Mooney, and Winstanley (2010) found that positional differences between OSM and Google Maps data for some sites in Ireland can be up to 10 meters. Completeness, as defined by ISO 1915, refers to the presence of features in the spatial data set. Haklay (2010) identified a bias in the U.K.'s OSM data

[8]As of today, OSM comprises over 7 million registered users. The crowdsourced spatial database has a current uncompressed size of over 1,323 GB and contains information on various amenities. A list of all types of amenities can be found online on the official OSM Wikiwebpage (OpenStreetMap, 2020).

coverage towards more affluent areas[9] Despite these shortcomings, the OSM data is sufficient for our purposes since we are interested only in the number of amenities at the aggregate municipality level. Moreover, the OSM dataset provides a powerful API that allows users to write OSM QL queries to collect the id, name, and coordinates for each amenity in Switzerland.

Information from OSM is retrieved for six categories of amenities: (i) Entertainment facilities, such as art centers, casinos, cinemas, nightclubs, and theatres. (ii) Eating-out facilities, including restaurants, pubs, bars, biergarten, and cafés. (iii) Outdoor recreation, such as parks, playgrounds, firepits, and gardens. (iv) Public services, such as schools, kindergardens, clinics, dentists, doctors, and hospitals. (v) Transportation points, including all platforms where passengers are waiting for public transport vehicles; and (vi) Sport facilities, such as fitness centers, sport centers, and swimming pools. The number of amenities in each category is aggregated at the municipality level as of 2020. Additionally, we retrieved information on further geographical features of interest ,such as lakes and national borders. Lakes and lake views fulfill important recreational functions, while national borders limit the extent to which a city can expand its territory.[10]

Figure 2 illustrates the number and density of urban and transport amenities, as well as outdoor amenities, as a function of distance to the CBD. Panel A shows the number of amenities aggregated across all eight cities. The city centers appear to be not only centers of commercial and social activity but also amenity clusters.[11] Panel B of Figure 2 disaggregates Panel A to show the number of amenities for each city. This view emphasizes the large proportion of eating-out facilities in the total number of amenities and confirms that all amenities' presence diminishes with increasing distance from the city center. Overall, we conclude that the number of urban and transport amenities is clearly spatially patterned and decreases quickly with distance from the city centers.

Table I presents our ranking of cities into three levels of amenity concentration, along with a measurement of the amenity advantages of the CBD areas by category. It also includes the corresponding relative tax rates, house prices, and housing sizes in each area. The ranking is based on a weighted combination of the amenity concentration levels of the

[9]see Costa Fonte, Antoniou, Bastin, Estima, Jokar Arsanjani, Laso Bayas, See, and Vatseva (2017) for a comprehensive review on OSM data quality.

[10]The city of Geneva is spatially constrained by the national border with France and Lake Geneva. Zürich, Lausanne and Luzern are built around lakes. Basel is located at the border with Germany.

[11]Note that the number of outdoor/recreation amenities may be a bit misleading because the natural amenities are not included. In fact, it is the lack of nature in the city center that requires the city to provide these amenities in the form of city parks and playgrounds.

'Eating out', 'Public services', and 'Entertainment' categories. Applying different weights produces very similar results for the overall ranking. Notably, Zürich stands out due to its high amenity superiority in the city center. For instance, there are, on average, 136.1 times more restaurants and cafes in Zürich's city center than in the average surrounding municipality. Additionally, taxes are 9 % higher and house prices are 35 % higher on average than in the surrounding municipality. Following Zürich are medium-concentrated cities such as Genf and Basel, and finally low-concentration cantons such as Luzern and Aarau. Some cities display unique combinations of amenities and transportation access. For instance, Basel has a high concentration of 'Entertainment' amenities in the city center and a well-developed transportation system in the larger area. In the empirical analysis, we differentiate between the degree of amenity concentration of the city in the interpretation of results.

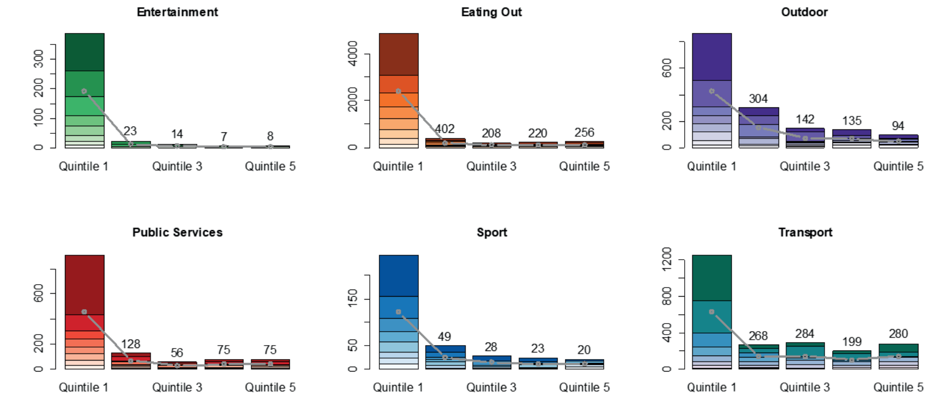
Table I Amenity concentration ranking

City	Rank	Eating out	Public Serv.	Entertain.	Transport.	Tax	Price	Size[a]
Zürich	1	136.1	120.6	213.9	28.3	1.09	1.35	0.85
Genf	2	63.0	26.4	66.1	3.9	1.02	1.24	0.74
Bern	2	53.7	25.3	120.3	13.8	1.01	1.31	0.80
Basel	2	58.6	19.1	138.6	2.0	1.08	1.18	0.85
Lausanne	2	52.6	16.4	87.8	14.3	1.05	1.06	0.79
St. Gallen	3	33.5	16.8	41.4	21.3	1.04	0.95	0.92
Luzern	3	32.5	14.5	46.1	1.9	1.03	1.10	0.78
Aarau	3	20.4	25.7	51.4	4.9	0.89	1.13	0.79

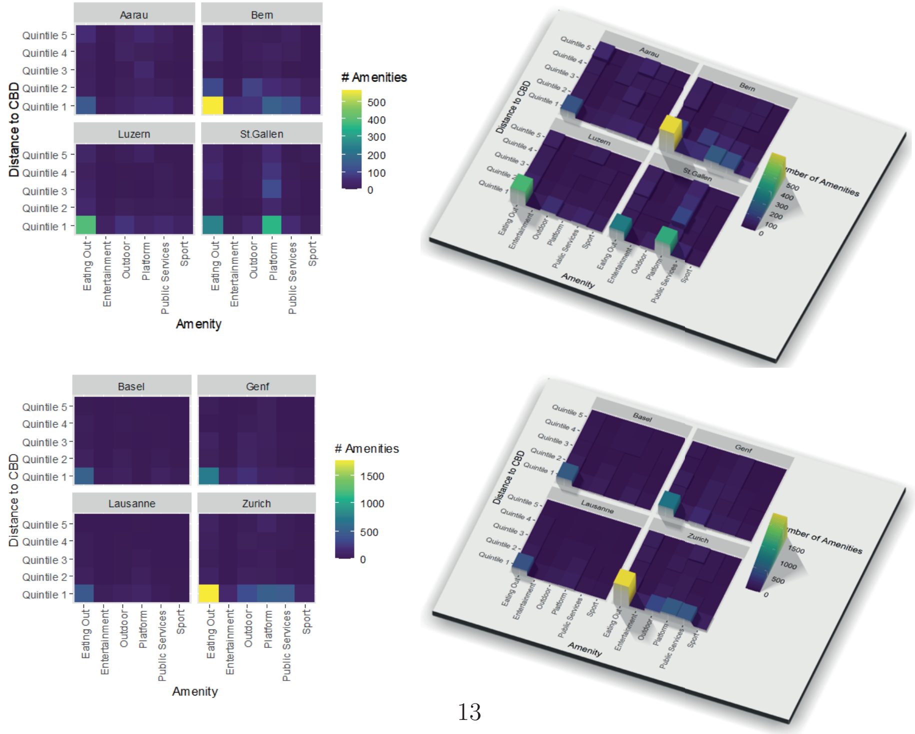
Notes: The table shows the ratio of the amenity level of the CBD municipality to the non-CBD municipalities. It gives the ranking from 1-3 and the ratio of amenities in the CBD municipality to the non-CBD municipality average, as well as the corresponding ratios of the income tax, average house prices, and house sizes. The amenities in column 3-6 is based on data from 2020, while taxes, house prices and house size are from 2014. *a*.Size is defined as the number of rooms of the housing units inhabited by households in our panel.

Figure 2. Number of Amenities and Distance to CBD
This figure shows the distribution of amenities as a function of distance to the employment center for eight Swiss cities. Panel A aggregates over all cities, highlighting that some amenities such as restaurants and transportation are more frequent than others. Panel B further decomposes the amenities to the individual city level. Berne is the government center of Switzerland (federal city or de facto capital) which is reflected in the higher number of public services. While transportation and other amenities also occur outside the city center, urban amenities such as entertainment and restaurants are strongly concentrated in the CBD.

Panel A: Amenities and distance quantile



Panel B: Amenities and distance quantile per city



B.2. Household Characteristics

We obtain detailed household characteristics from 1999 to 2014 for 16,940 households from the Swiss Household Panel (SHP). The SHP is an annual panel survey of households from all regions and across all population groups in Switzerland (Voorpostel, Tillmann, Lebert, Kuhn, Lipps, Ryser, Antal, Monsch, Dasoki, and Wernli, 2019). The survey covers a broad range of more than 100 quantitative and qualitative household attributes. The data contained in the SHP range from socio-demographic, financial, health, and educational household information to qualitative interview responses such as the importance of air quality, and potential issues with noise in the neighbourhood. Due to the broad coverage of the SHP data, it has been used in a number of previous studies, including the effect of employment uncertainty on fertility (Hanappi, Ryser, Bernardi, and Le Goff, 2017), the effect of immigration on household dislocation (Adams and Blickle, 2018), and the effect of attending cultural events on personal well-being (Węziak-Białowolska, 2016). The SHP data is representative of the Swiss population and exhibits a high retention rate. On average, each household appears in the survey for more than six years. For the empirical part of this paper, we can therefore observe the cross-sectional variation of relevant household characteristics over time.

To obtain a first impression of the income gradient, Figure 3 shows the relationship between annual gross income and distance to CBD for each city. Although these simple scatter plots do not control for amenities and household characteristics, we note that the majority of our cities show an increasing income - distance relationship where only Bern and St. Gallen show a clear negative relationship. There also appear to be important non-linearities in these relationships. Figure A1 in the Appendix highlight the extent of spatial variation in average income. Although the CBD is characterized by households with relatively high income in several cities, some of the highest income municipalities are found towards the city edge and along the lakes. In the empirical part below, we will control for municipalities that border to a lake to account for this effect.

B.3. Taxes

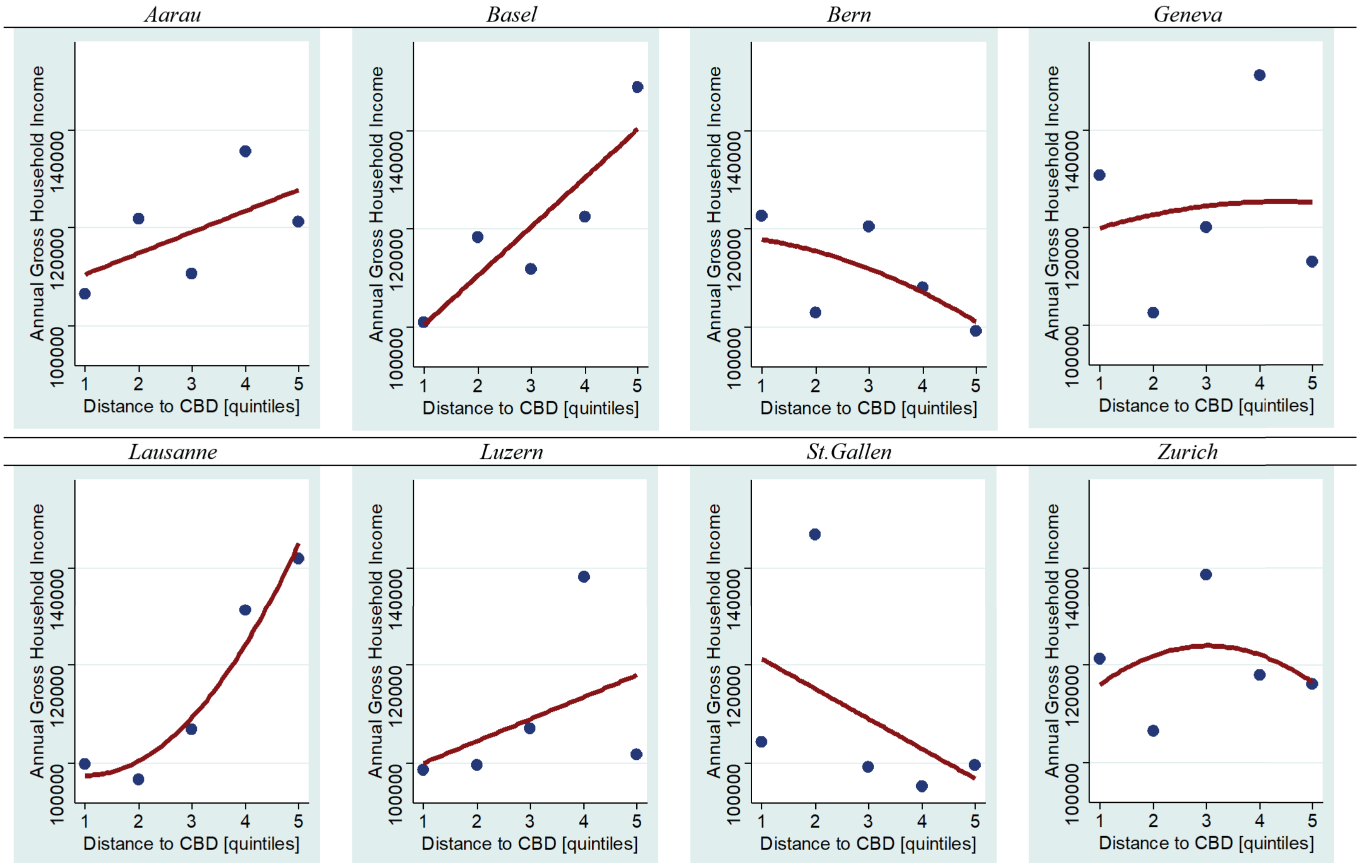
Switzerland's federalism has led to a unique feature in its tax system. Switzerland is divided into 26 cantons. Each canton has a supplementary taxation right and can raise any taxes that are not explicitly under the jurisdiction of the federation. This leads to significant tax differences between cantons where each canton sets a level of income tax and decides on the tax progression autonomously. The 26 cantons are further subdivided into 2,202 municipalities. Each municipality sets a so-called income tax shifter. Multiplying the municipal tax shifter with the cantonal tax rate determines the municipal tax burden. For instance, consider two identical single household with an annual taxable income of CHF 85,000 (about $\$100,000$) living in the canton of Zurich. One household lives in the municipality of Zürich and the other in Uitikon. Uitikon is a direct neighbor of the municipality of Zürich and lies only 7.5km to the west. Table II shows the difference in yearly tax burden for the households. Both households pay the same amount of federal and cantonal taxes of CHF 1,884 and CHF 4,945, respectively. However, the annual tax burden differs by 1,929 CHF (about $\$2,275$). This stylized example illustrates tax differences across municipalities within a city. Figure A2 in the Appendix generalizes this example to all cantons in Switzerland, documenting that there exists a considerable variation of income tax burdens across municipalities within the same canton.

Table II Stylized Tax Burden Example

This table provides a stylized example of tax burdens within the same canton, but different municipalities. We assume a single household with an annual taxable income of 85,000 CHF. This is equal to the mean annual taxable income of a single household living in Zürich as of 2020.

	Zürich (canton: Zürich)	Uitikon (canton: Zürich)
Taxable income	85,000 CHF	85,000 CHF
Federal tax	1,884 CHF	1,884 CHF
Cantonal tax	4,945 CHF	4,945 CHF
Municipal tax	5,885 CHF	3,956 CHF
Total tax	12,738 CHF	10,809 CHF

Figure 3. Income by Distance Quintiles
The figure shows the income of eight Swiss urban areas and distance to the city center. We measure distance with quintiles with the 5^{th} quintile located 10 kilometers from the CBD.



V. Empirical Models and Results

A. Benchmark Regressions

In this section, we build on the discussion of the income gradient in section III, and consider a reduced-form specification. Household characteristics may provide information on differences in valuation of amenities and housing services. In this model, distance serves as the dependent variable, while income, amenities, tax rates, and household characteristics are explanatory variables. In order to test the predictions of the importance of the relative spatial distribution of amenities and tax differentials, both amenities, prices, and the tax rate are weighted by distance prior to entering them into the regression model. Household characteristics can provide valuable information on differences in valuation of amenities and housing services. To test the predictions on the importance of the relative spatial distribution of amenities and tax differentials, we weight both amenities, prices, and the tax rate by distance before incorporating them into the regression model. Amenities are measured as a fraction of the level of amenities in the CBD. This approach aims to capture the relative evaluation of amenity levels and prices at the city edge compared to those in the CBD.

While we have collected data on other urban amenities, including public services, sport, and entertainment amenities, these tend to exhibit high correlation with each other. This is due to the availability of amenities data only on the municipality level for the most recent year, which introduces multicollinearity into our model. Consequently, our initial focus is directed towards "eating out" and "transportation amenities", as well as natural amenities such as lakes and borders, where applicable. The benchmark regression specification of household location choice is defined by equation 1:

$$log(D_{i,j,k,t}) = \alpha + \beta \cdot log(I_{i,j,k,t}) + \gamma_1 A_{j,k} + \gamma_2 H_{i,j,k,t} + \gamma_3 T_{j,k} + \epsilon_{i,j,k,t} \tag{1}$$

where $D_{i,j,k,t}$ is the kilometer distance of household i, in city j, located in municipality k, in year t. We locate the employment center in the vicinity of the main railway station. Annual gross income is denoted by I and is measured on the individual household level. The regressor matrix A contains two urban amenities, eating out and transportation, as well as house prices, all measured on the municipality level. Since house prices is aggregated at the municipality level and not at the individual household level, we consider it to be an aggregate measure of residential/neighborhood valuation and include it in the amenity matrix. H is a set of household characteristics and includes age, number of children, years of education, marital status, and other indicator variables denoting whether a household is a homeowner, is unemployed, or native Swiss. We treat the municipality level tax rate T as a separate variable although it may be related to the level of income, cf. our discussion in section III.

Equation 1 is estimated using pooled Ordinary Least Squares (OLS). Some variables, such as gender, are time-invariant, while others, such as age, change similarly over time for all households. This prevents us from using household or year fixed effects.[12] We also recognize potential endogeneity concerns with variables, such as urban amenities and house prices. Furthermore, there may be unobserved municipality or household factors, which could either be time-varying or time-invariant, that could influence the results. To address these concerns, we consider alternative specifications with amenities that are more likely to satisfy the exogeneity assumption in section V.B, where we also estimate a 2SLS model with a municipality level housing supply instrument. Moreover, our approach of distance-weighting and the inclusion of area-level prices are expected to mitigate the endogeneity problem in the benchmark regressions as well. In section V.B.3, we provide a more detailed discussion on this issue and present a sensitivity analysis. The analysis suggests that the bias in the income estimate is moderate.

Table III presents the regression estimates for the benchmark specification in Equation 1. The results reveal significant variations across cities with different levels of amenity concentration. In Zürich, a highly amenity-concentrated city, the income coefficient is found to be significantly negative. This indicates that as income increases, the distance to the Central Business District (CBD) decreases. In medium amenity-concentrated cities, the income gradient is about zero in three out of four cities and positive in one. Notably, in Basel, a 1 % increase in household income is expected to increase the distance to the CBD on average by 0.084 %. To put this into context, a household living 5km away from the CBD that experiences a 50 % increase in gross income would move 420 meters further away from the CBD. In low amenity-concentrated cities, the income gradient is found to be around zero or significantly positive. Evaluating household characteristics, being native Swiss households, families, homeowners, or being an older household is associated with living further away from the city center. In contrast, higher education is associated with living closer to the CBD.

[12] An alternative is to estimate a random effects model. However, this will build on the very strict assumption that any unobserved household heterogeneity is distributed independently of the explanatory variables, which is unlikely in this model.

Table III Household Location Choice Regression

The table shows individual city regressions of log(distance to CBD) on log(income), a set of household characteristics, and selected amenities. The number of households Ni varies by city and are observed over 16 years from 1999 to 2014. The coefficients are estimated with pooled OLS. Standard errors are robust to unknown forms of heteroscedasticity (Long and Ervin, 2000).

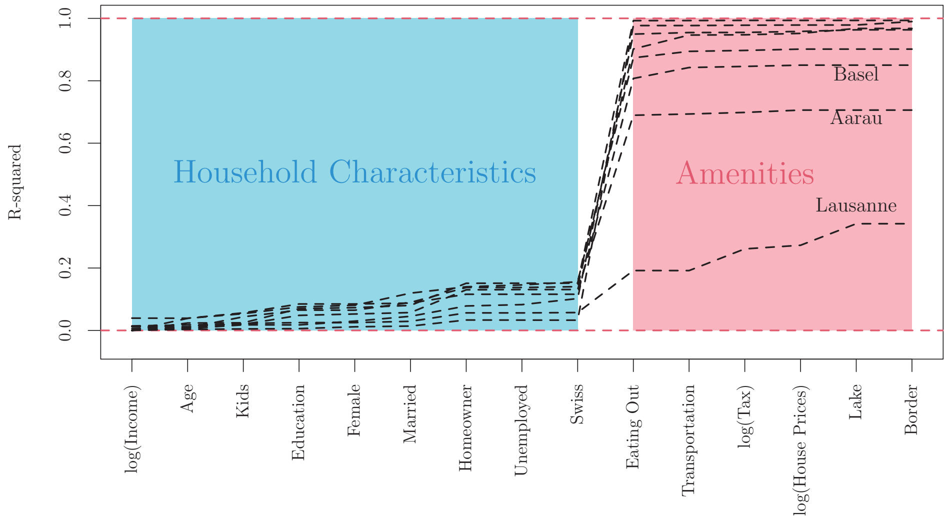
	Dependent variable:							
	log(distance to CBD)							
	Zürich (1)	Genf (2)	Bern (2)	Basel (2)	Lausanne (2)	St. Gallen (3)	Luzern (3)	Aarau (3)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Income)	−0.008**	−0.005	0.005	0.084***	0.004	0.051	0.069***	0.133***
Age	−0.0004**	0.002**	0.004***	0.001	−0.0005***	−0.003*	−0.002*	−0.001
Kids	0.022***	0.077***	0.021	0.079***	0.010*	0.358***	0.066**	0.065*
Education [Years]	−0.003***	0.005	−0.012***	−0.007***	−0.002***	−0.021*	0.002	−0.018**
Female	−0.009**	0.015	−0.036**	−0.034**	−0.010**	−0.207***	0.065***	0.118***
Married	−0.013**	−0.036	0.083***	−0.036**	0.026***	0.150***	0.143***	−0.023
Homeowner	0.003	0.232***	0.041**	−0.047**	0.025***	0.293***	0.297***	0.261***
Unemployed	0.004	0.030	−0.036*	0.045**	0.006	−0.114*	0.033	−0.051
Swiss	0.010	−0.036	0.155***	−0.034	0.024***	0.588***	0.069	0.132***
Eating Out	-0.149***	0.003	0.015***	0.303***	0.010***	0.436***	0.307***	0.194***
Transportation	0.090***	0.382***	0.075***	0.498***	0.003	0.018**	0.114***	0.071***
log(Tax)	1.730***	−15.318***	-6.715***	−7.422***	−5.519***	−4.330***	−2.571***	1.657***
log(Area House Prices)	−0.041***	−0.103***	−1.275***	−0.390***	−0.019***	−2.309***	−0.492***	−1.041***
Lake	−0.137***	−2.275***			−0.314***	0.330***	0.182***	
Border		0.150***		−0.121***				
(Intercept)	-13.403***	151.294***	84.924***	78.238***	56.516***	73.251***	31.259***	−2.193
Observations	4,571	2,511	1,752	2,556	5,175	1,989	1,830	1,681
Adjusted R^2	0.986	0.869	0.617	0.761	0.351	0.576	0.549	0.368
Note:								*p<0.1; **p<0.05; ***p<0.01

We next examine the impact of distance-weighted amenities on household location choices. Our results show that improvements in transportation access outside the Central Business District (CBD) can influence household relocation, as it provides a better connection to the center. Increases in transportation access outside the CBD are associated with households locating further from the CBD in all cities. For instance, a one standard deviation increase in transportation access outside the CBD, equivalent to 50 additional platforms, is estimated to increase households' distance to the CBD by about 7.5 % in Bern and by 11.4 % in Luzern. In Basel, a city with significant transportation access, the coefficient is found to be highly positive, at 50 %.

The impact of area house prices and taxes is also tested for. While house prices capture a variety of latent local factors, taxes play a special role in this study due to their regional variation. Our results imply a strongly negative coefficient in the distance-weighted tax rate for 6 out of 8 cities, indicating that lower taxes outside the city center often lead to relocation towards low tax municipalities at the city's edge. For instance, a 1% decrease in taxes outside the CBD is associated with increases in the location of households by distance to the city center of 7.4% in Basel, and 15.3% in Genf, the most tax sensitive cities according to these results. This result is consistent with the findings in Schmidheiny (2006). Lastly, a negative house price shock at the city edge is related to distance to center in the expected way in all cities.

Figure 4 illustrates the level of R-squared when variables are sequentially added to the regression. Sequentially adding variables has the disadvantage that the ordering of the variables is not taken into account. This approach has the disadvantage that the ordering of the variables is not taken into account. For instance, if we switch the position of 'eating out' with 'log(taxes)', the increase in R-squared is quite similar. However, the improvement of R-squared is fairly robust across different orderings. As can be seen, 'log(income)' alone has little explanatory power. Adding household characteristics only moderately improves the R-squared. A regression model with all nine household characteristics explains less than 20% of the variation of household's distance to the CBD. In contrast, adding amenities to the regression significantly improves the R-squared, particularly for amenity-concentrated cities. While gains are substantial for less concentrated cities such as Aarau, amenities appear to explain less of the variation in household distances.

Figure 4. R-Squared Response to Sequentially Adding Variables
This figure plots the level of R-squared when the variables labelled on the x-axis are sequentially added to the regression. The regression specification is according to Equation 1.



In line with the discussion in section III, higher access to certain amenities, such as transportation or recreational areas, may compensate households for lower access to others, such as restaurants and theatres. To aggregate across amenities, we next construct a distance-weighted amenity index. This allows us to compare the relative aggregate amenity value across locations. We also include interaction terms between household characteristics and the amenity level, recognizing that different households may value the neighborhood amenity level differently. The amenity index $A_{j,k}$ is computed as the first principal components from the following five amenities: “Entertainment”, “Eating Out”, “Outdoor/Recreation”, “Public Services”, and “Transportation”. On average, these principal components explain about 74 percent of the variance for the eight cities. This suggests that the amenity index can serve as a reasonably representative amenity variable. The interaction regression specification of household location choice is given by equation 2:

$$log(D_{i,j,k,t}) = \alpha + \beta \cdot log(I_{i,j,k,t}) + \gamma_1 \tilde{A}_{j,k} + \gamma_2 H_{i,j,k,t} + \gamma_1 \tilde{A}_{j,k} \cdot \gamma_2 H_{i,j,k,t} + \gamma_3 T_{j,k} + \epsilon_{i,j,t} \quad (2)$$

Table IV presents the results for the interaction model. Notably, the income elasticity becomes more negative in Zürich and more positive in Aarau and Luzern. Moreover, several significant interaction terms indicate that households' valuation of amenity levels varies with household characteristics. Figure 5 further illustrates this, comparing the economic size of interaction effects. Panel A shows the dislocation response from a one standard deviation increase in amenities outside the CBD for various households. In most cases, households respond by increasing their distance to the city center. The response is particularly large in Basel and Luzern. For instance, a one standard deviation increase in amenities outside the CBD in St. Gallen, is expected to increase the distance to the city center by around 20%. However, females responds more strongly than highly educated households.

While Panel A shows the variation across cities, Panel B emphasizes the differences among household.[13] For instance, homeowners and married households typically show a stronger dislocation response to amenities outside the CBD than others. Possible explanations for this finding is that these types of households may have higher housing services demand or be more price sensitive. Thus, they may be more inclined to choose a less central location than other households if amenity levels further out increase.

Overall, the empirical findings in this section suggests that income gradients are inversely related to the urban amenity-superiority of the city and natural amenities are everywhere significant. The next section relaxes some of the strict assumptions imposed so far.

[13]Note that a one-unit increase in age and education is measured in years.

Table IV Household Location Choice Regression with Interaction Terms

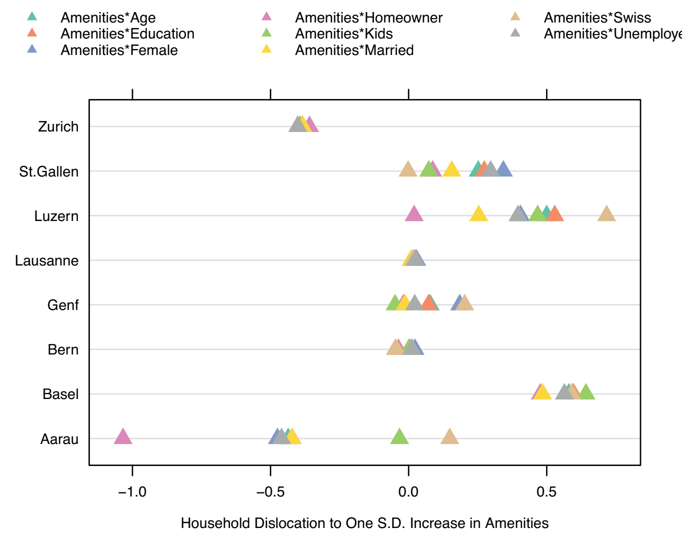
The table shows individual city regressions of log(distance to CBD) on log(income), a set of household characteristics, and an amenity variable that is estimated from the first principal component of the individual amenities "Entertainment", "Eating Out", "Outdoor/Recreation", "Public Services", and "Transportation". The proportion of the variance that is explained by the principal component is shown in the lower part of the table. The number of households Ni varies by city and are observed over 16 years from 1999 to 2014. The coefficients are estimated with pooled OLS and standard errors are robust to unknown forms of heteroscedasticity (Long and Ervin (2000)).

	Dependent variable:							
	log(distance to CBD)							
	Zürich (1)	Genf (2)	Bern (2)	Basel (2)	Lausanne (2)	St. Gallen (3)	Luzern (3)	Aarau (3)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Income)	−0.021**	−0.006	0.020	0.087***	0.005	0.039	0.077***	0.147***
Age	−0.001	0.001	0.003**	−0.001	−0.001	−0.006**	−0.003**	−0.002
Amenities	−0.393***	0.077	0.005	0.574***	0.023*	0.249**	0.497**	−0.444
Kids	0.033	0.169***	0.005	0.060*	0.050*	0.424***	0.074	−0.093
Education [Years]	−0.007	0.006	−0.029***	−0.014***	−0.010**	−0.039***	−0.014*	−0.034***
Female	−0.113***	−0.074*	−0.067*	−0.045*	−0.054*	−0.309***	0.112***	0.119
Married	−0.066**	0.015	0.191***	−0.017	0.123***	0.170**	0.222***	−0.041
Homeowner	−0.076***	0.322***	0.142***	−0.0002	0.062**	0.431***	0.512***	0.439***
Unemployed	0.039	0.033	−0.036	0.041	−0.014	−0.199**	0.100**	−0.042
Swiss	0.109***	−0.067*	0.234***	−0.038*	0.050	0.801***	−0.147	−0.023
log(Tax)	0.566***	−17.199***	−6.646***	−5.823***	−5.232***	−6.683***	−2.371***	2.006***
log(Area House Prices)	−0.278***	−0.129***	−1.224***	−0.411***	−0.016*	−2.362***	−0.560***	−1.183***
Lake	−0.201***	−2.326***			−0.270***	0.109	0.175***	
Border		0.146***		−0.181***				
Amenities*Age	0.0003**	0.001	−0.0001	0.006***	0.0001	0.003***	0.003*	0.008**
Amenities*Kids	−0.0005	−0.126***	−0.004	0.068	−0.006*	−0.176***	−0.030	0.411
Amenities*Education	0.0000	−0.005	0.008***	0.023***	0.001**	0.025***	0.032***	0.022
Amenities*Female	0.009***	0.108***	0.018*	0.017	0.006*	0.094***	−0.092*	−0.031
Amenities*Married	0.010***	−0.090**	−0.051***	−0.089*	−0.014***	−0.093***	−0.243***	0.021
Amenities*Homeowner	0.034***	−0.096*	−0.042***	−0.097**	−0.007**	−0.162***	−0.477***	−0.590***
Amenities*Unemployed	−0.008**	−0.055	0.007	0.010	0.002	0.048	−0.101*	−0.016
Amenities*Swiss	−0.009**	0.126***	−0.053***	0.017	−0.006	−0.251***	0.220*	0.593
(Intercept)	1.440	170.058***	83.566***	62.984***	53.710***	97.363***	30.532***	−3.486
Observations	4,571	2,511	1,752	2,556	5,175	1,989	1,830	1,681
Adjusted R^2	0.945	0.855	0.629	0.757	0.395	0.563	0.601	0.445
Variance of Princ. Comp.	85%	66%	83%	70%	98%	83%	55%	55%
Note:								*p<0.1; **p<0.05; ***p<0.01

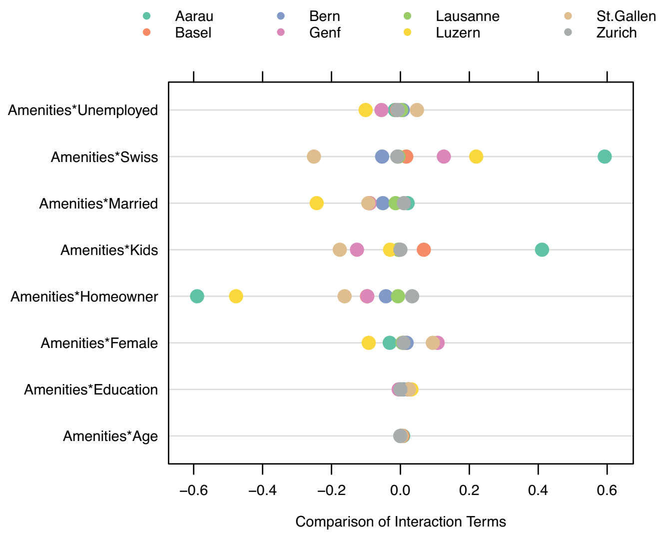
Figure 5. Visual Comparison of Amenity Interaction Terms

This graph visualizes the amenity-household interactions from Table IV. The upper graph shows the dislocation response from a one standard deviation increase in amenities. The lower graph compares the interaction terms for different household characteristics.

(a) City Variation in Amenity Interactions Terms



(b) Comparing the Size of Interaction Terms



B. Relaxing Simplifying Assumptions

B.1. The Assumptions of Exogenous Urban Amenities and Full Mobility of Households

Urban amenities such as restaurants and coffee shops are not exogenous. While amenities contribute to the attractiveness of a location and influence households' location decision, they are simultaneously strategically located in high population density areas, a phenomenon often referred to as the endogeneity problem of urban amenity models. Although we lack instruments to fully account for this issue, we address it using a pooled two-stage least squares (2SLS) regression of equation 1.

In our specification, 'Eating Out' amenities are instrumented with the municipality-level housing supply elasticity estimates (new construction) described in Büchler, Ehrlich, and Schöni (2021).[14] The supply elasticity estimates exhibit considerable variation between city centers and nearby municipalities, as well as among city centers themselves. For instance, it is estimated at 0.251 in the city center of Zürich, 0.348 in Genéve, and 0.494 in the city center of Aarau. The choice of instrument is motivated by the mechanisms described in Gyourko et al. (2013). The authors document that inelastic housing supply in unique locations, combined with national income growth, tends to be phased into the housing prices in such "Superstar City locations". This is expected to increase the level of urban amenities.[15] Thus, the instrument relevance can be illustrated by the following relationship:

$$\text{Low SupplyEl} \Rightarrow P \uparrow \& Y \uparrow \Rightarrow \text{'Eating out' amenities} \uparrow$$

Where P is the level of housing prices and Y denotes the level of household income. In the 2SLS regressions, the area house price is excluded. Table A2 presents the results for the income-distance gradients. The first stage regression, which also includes household incomes and the other explanatory variables, reveals that *SupplyEl* is highly related to 'Eating out' amenity levels (the test statistic is reported in table A2). Importantly, the pattern of an inverse relationship between the income gradient and amenity concentration is maintained.

Another strategy is to re-estimate Equation 2 with amenities that are more likely to satisfy the exogeneity assumption, such as natural amenities, taxes and transportation access. Although the latter could also be influenced by population growth, the public transportation network operates independently of market forces and transportation investments depend on the priorities of both local and central governments. Similarly for the level of the municipality

[14] This analysis uses the supply responsiveness with respect to house price changes. We obtained these estimates for this analysis with the explicit consent of the original authors.

[15] Since house prices vary annually while the supply elasticity estimates are fixed, this is not a suitable instrument for these house price data.

income tax.[16] The urban model presented also assumes that all households are willing and able to move to their most optimal location, a supposition underlying the spatial equilibrium hypothesis. However, various factors such as moving costs or proximity to friends and family challenge this assumption. To account for this, we estimate our model for the subset of households that recently moved, which makes the full mobility assumption more plausible.[17] As can be seen in Table V, which reports results from estimating equation (2), the pattern of an inverse relationship between the income gradient and amenity concentration is reinforced.

B.2. Housing demand, natural amenities and the linearity assumption

In the main specification, we include household characteristics, which may indicate differences in location preferences and amenities but may also signal variations in housing demand. As housing sizes are often spatially patterned, we introduce size into the model with exogenous amenities. Table Vc) shows that the results for the income gradients are largely consistent with previous findings. These findings suggest that access to larger houses may be an important factor for relocating towards the city's edge. Additionally, the effects of increased transportation access at the city edge remain similar to previous findings. Additionally, we extend our investigation using a different methodology. The urban model, while insightful, does not provide clear guidance on the functional form of the true relationship between location choice, income, and amenities. The regression models specified so far follow the classical approach often used in economics, providing an intuitive economic interpretation. While this approach has clear advantages, it may also mask non-linearities between variables. To address this, we test an alternative partial model that considers complex interactions between three variables: (1) distance to the Central Business District (CBD), (2) access to nature, and (3) a preference for large single-family homes. The city center is characterized by apartments and densely populated areas, while access to nature and spacious homes are often found at the city's edge.

We estimate a regression with a triple interaction term consisting of distance to the CBD, the presence of nearby nature/recreation amenities, and the number of rooms of the house occupied by a household. For examining the income gradient in this model, we place income on the left-hand-side of the equation and distance on the right, which is another interpretation of the urban model (see e.g. Gaigné, Koster, Moizeau, and Thisse (2022)). The specification proposed here is partial and lacks causal interpretation as it neglects to

[16] The fact that the estimated correlation between "Transportation" or "Tax" and "Eating out" amenities is fairly low, reinforces this impression.

[17] Ideally, we would estimate the income gradient and response to amenities based on the place they move from and to, but this is not possible with the available data since the exact timing of the relocation is not clearly defined.

control for other important drivers of location choice.

$$Income_{i,t} = \alpha + \beta' \cdot distance_{i,t} \times rooms_{i,t} \times outdoor_{i,t} + \epsilon_{i,t} \tag{3}$$

which can be expanded to

$$\begin{aligned} Income_{i,t} = \alpha &+ \beta_1 \cdot distance_{i,t} + \beta_2 \cdot rooms_{i,t} + \beta_3 \cdot outdoor_{i,t} + \\ &\gamma_1 \cdot distance_{i,t} \cdot rooms_{i,t} + \gamma_2 \cdot distance_{i,t} \cdot outdoor_{i,t} + \gamma_3 \cdot rooms_{i,t} \cdot outdoor_{i,t} + \\ &\delta_1 \cdot distance_{i,t} \cdot rooms_{i,t} \cdot outdoor_{i,t} + \epsilon_{i,t} \end{aligned} \tag{4}$$

The multiplicative specification in this equation prevents an intuitive interpretation of the marginal effects of the regressors. However, a visualization of the predicted nature between income and distance is instructive. To obtain predicted values of income for increasing levels of distance, we employ the following approach:

1. Estimate the triple interaction Equation (4).

2. Fit the number of rooms on distance to CBD using second or third order polynomials when statistically significant:

$$Rooms_{i,t} = f(distance_{i,t}) + \epsilon_{i,t} \tag{5}$$

3. Based on the results from the regression in equation (5), predict the number of rooms with increasing distance.

4. Estimate a regression of outdoor amenities on distance using higher order polynomials when necessary as before:

$$Outdoor_{i,t} = f(distance_{i,t}) + \epsilon_{i,t} \tag{6}$$

5. Based on the results from the regression in equation (6), predict the number of outdoor amenities with increasing distance.

6. Predict the relationship between income and distance based on equation (4) and taking the predicted behavior of the number of rooms (equation (5)) and the presence of outdoor amenities (equation (6)) into account.

Figure 6 displays the estimated income - distance relationship for all eight cities based on the multiplicative interaction specification of Equation (4). For comparison, the black line shows the same relationship when income is regressed on distance alone. The findings in figure 6 suggest that the relationship between distance, outdoor amenities, and more spacious homes is highly non-linear. Moreover, we observe that the steepness of the income - distance relationship is greatest for the highly amenity-superior city of Zürich, while it is more flat for cities at the opposite end, such as St. Gallen. Future research could benefit from incorporating such spatial non-linearities in fully specified models of household location choice.

Table V Regressions with a) "Endogenous amenities", b) "Exogenous amenities" and c) "Exogenous amenities", and Housing size. Recent movers

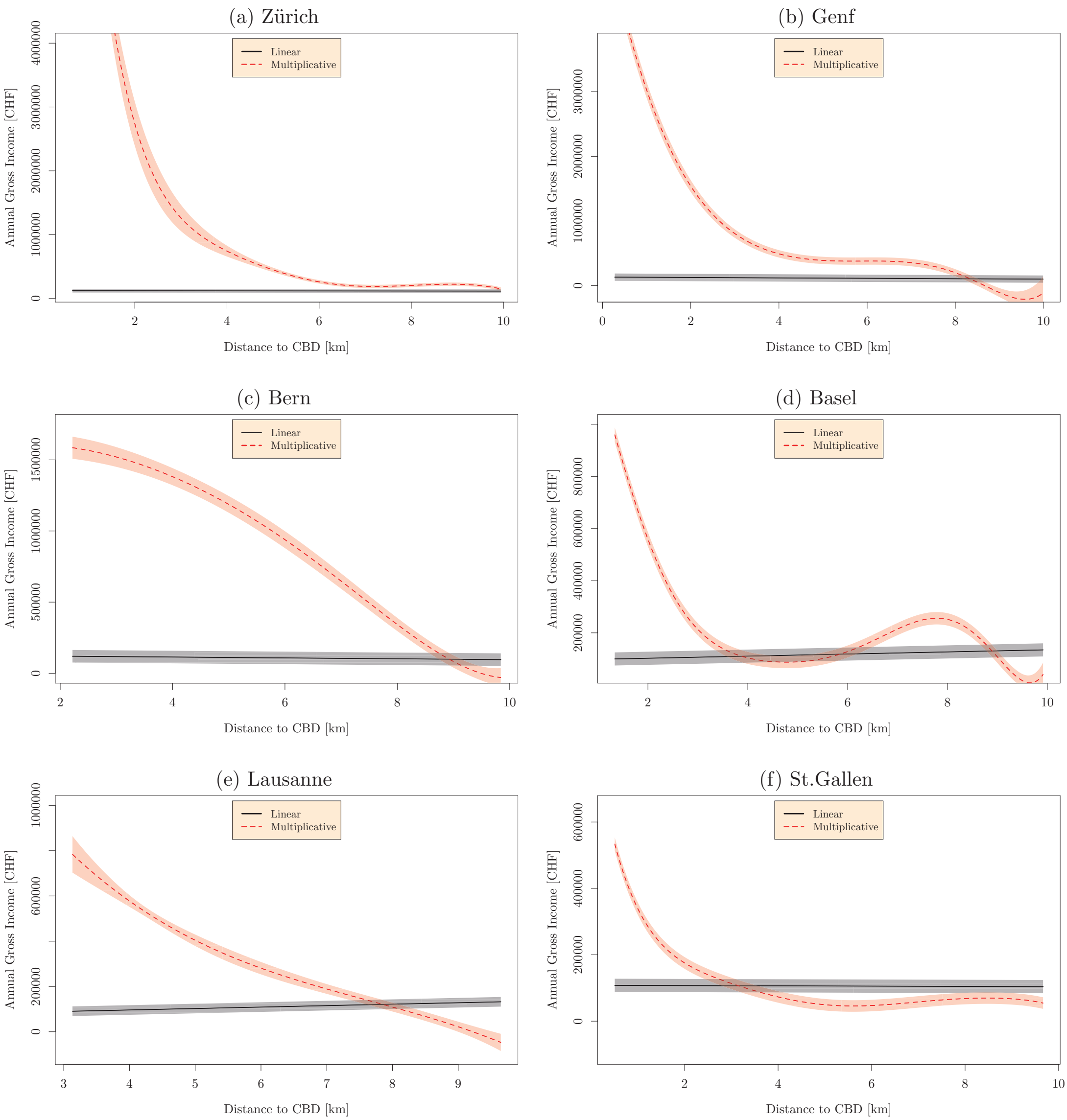
The table shows individual city regressions of log(distance to CBD) on log(income), household characteristics and various amenities for recently moving households. The dependent variable in all regressions is the log(distance to CBD). The regressors *lake* and *border* are included in each panel. The coefficients are estimated with pooled OLS. Standard errors are robust to unknown forms of heteroscedasticity

	Zürich (1) (1)	Genf (2) (2)	Bern (2) (3)	Basel (2) (4)	Lausanne (2) (5)	St. Gallen (3) (6)	Luzern (3) (7)	Aarau (3) (8)
a) "Endogenous amenities"								
log(Income)	−0.011**	−0.075*	−0.055*	0.033	0.003	0.314***	0.062*	0.220**
log(Tax)	0.264	−13.696***	-6.552***	−5.242***	−7.235***	-6.424***	−5.602***	1.840***
log(Area House Price)	−0.373***	−0.013	−1.368***	−0.668***	0.004	-1.905***	−0.566***	−1.106***
Amenities	x	x	x	x	x	x	x	x
Household char.	x	x	x	x	x	x	x	x
Amenities×char.	x	x	x	x	x	x	x	x
Observations	1,393	647	646	753	1,608	469	569	502
Adjusted R^2	0.952	0.808	0.656	0.788	0.500	0.644	0.731	0.507
b) "Exogenous amenities"								
log(Income)	−0.031	−0.083*	−0.034	0.059*	0.004	0.302***	0.126***	0.236***
Transportation	0.033***	0.341***	0.118***	0.497***	0.026*	0.117***	0.195**	0.190***
log(Tax)	−4.965***	−11.956***	−6.916***	−7.886***	−6.048***	−6.977***	1.346***	1.987***
log(Area House Price)	-0.700***	0.056***	-1.411***	−0.689***	0.004	−1.930***	−1.088***	−1.005***
Amenities (outdoor)	x	x	x	x	x	x	x	x
Household char.	x	x	x	x	x	x	x	x
Amenities×Household char.	x	x	x	x	x	x	x	x
Observations	1,393	647	646	753	1,608	469	569	502
Adjusted R^2	0.868	0.828	0.662	0.786	0.471	0.632	0.562	0.514
c) "Exogenous amenities" and Housing size								
log(Income)	−0.072**	−0.132**	−0.038	0.037	0.004	0.273*	0.120***	0.012
Transportation	0.032*	0.359***	0.121***	0.476***	0.025*	0.120***	0.194**	0.189***
log(Size)	0.166***	0.236***	0.016***	0.153***	−0.003	0.273*	0.044	0.676***
log(Tax)	−4.769***	−11.774***	−6.869***	−7.721***	−6.114***	−6.615***	1.305	1.636***
log(Area House Price)	−0.670***	0.088	−1.395***	−0.698***	0.005	−1.959***	−1.082***	−1.105***
Amenities (outdoor)	x	x	x	x	x	x	x	x
Household char.	x	x	x	x	x	x	x	x
Amenities×Household char.	x	x	x	x	x	x	x	x
Observations	1,393	647	646	753	1,608	469	569	502
Adjusted R^2	0.873	0.831	0.663	0.789	0.560	0.636	0.560	0.562

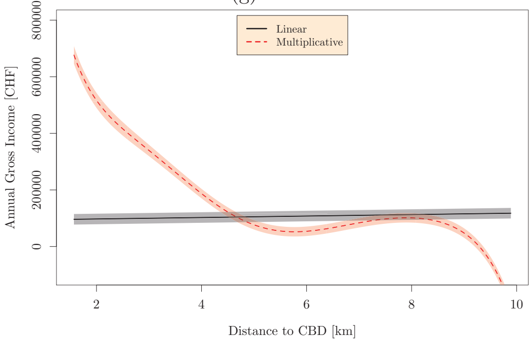
Note: *p<0.1; **p<0.05; ***p<0.01

Figure 6. Partial Income Gradient and Distance to CBD

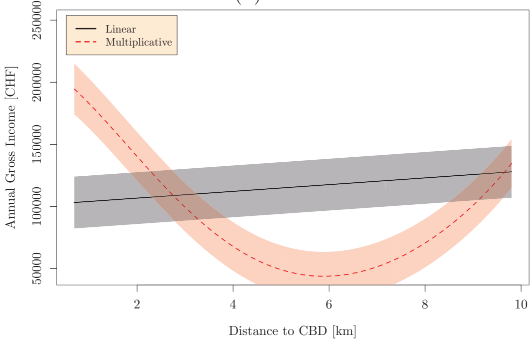
This figure depicts the results from linear and multiplicative regression for each city. A univariate linear model is represented by the solid black line.



(g) Luzern



(h) Aarau



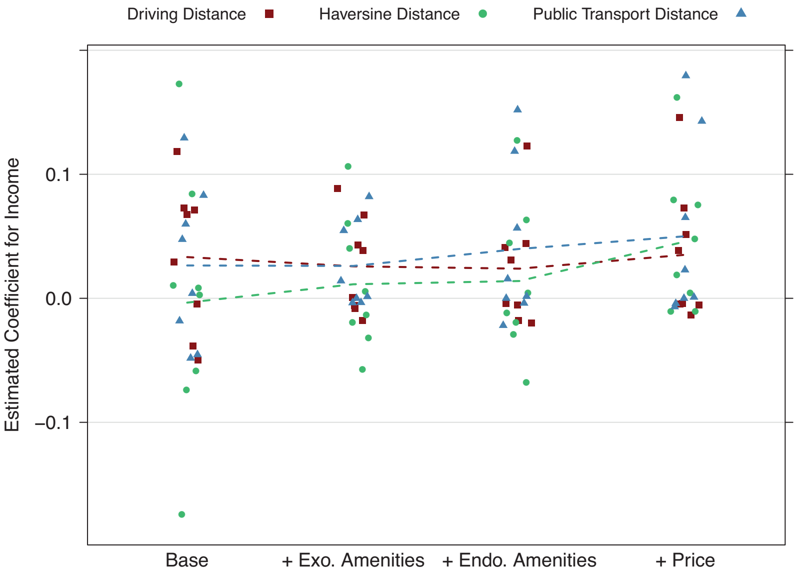
B.3. The distance from CBD assumption and Urban area size

Another assumption of the model is that households respond equally to distances to city centers measured in meters in the larger urban area. While the haversine distance has become standard in the literature, this section tests whether our results are sensitive to driving distance or travelling distance based on public transportation. Additionally, we evaluate the extent to which the estimated income gradients depend on the inclusion of "exogenous amenities", "endogenous amenities" and prices. Figure 7 addresses both of these issues. The y-axis measures the estimated income coefficient. In the base case, a simple regression of log(distance) on log(income) and household characteristics is estimated. Each point represents the coefficient estimate for one city, with the three distance measures highlighted using different symbols. The x-axis shows how the regression specification is expanded by sequentially adding exogenous amenities, endogenous amenities, and finally the area house price.

Figure 7 demonstrates that the choice of distance measure does not substantially affect the main results of the paper, as alternative measures yield similar results. This suggests that our findings are robust to different methods of calculating distance. Moreover, the results also indicate that the income -distance gradient estimates are positively and moderately biased when we add the endogenous regressor price. The direction of changes is mixed when adding endogenous amenities.

Finally, we examine the sensitivity of the results when the city edge is placed at various points along the distance scale. The majority of the Swiss territory is occupied by the

Figure 7. Income Coefficients with Sequentially added variables
This figure shows the estimated coefficients from distance to CBD on income for the full dataset. Three different distance measures are used as the dependent variable: driving distance by car, straight-line haversine distance, and distance by public transportation. Each point in the plot represents the estimated coefficient for a specific city. The points in the first column come from a simple regression of log(distance) on log(income) and household characteristics. The second column shows the same income coefficients when "exogenous amenities" are added as control variables. The third column adds "endogenous amenities" as control variables. The forth column adds the area house price.



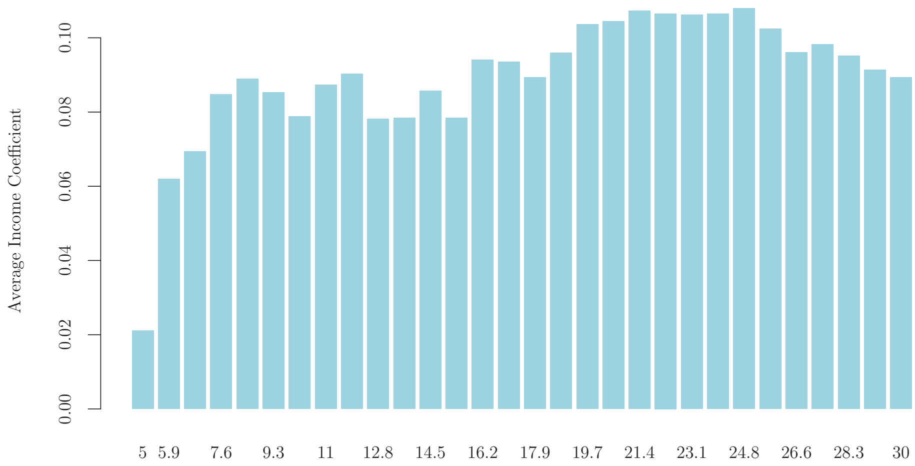
Alps, so cities in Switzerland are concentrated in a dense urban area on the alpine plateau. Additionally, the average city size is small compared to international standards. We decided to place the city edge at 10 km from the city center. Although this cut-off is somewhat arbitrary, it reflects the trade-off between adequately covering the city's land surface and including regions that belong to a neighboring city. We assess the sensitivity of the income coefficient for different distance levels at which municipalities are no longer considered part of the city edge.

Figure 8 shows the simple income gradient estimated from a uni-variate regression of log(distance) on log(income) for different cut-off points and averaged over all cities. The average simple income gradient is fairly robust for different cut-off values. Using 10 km as in our analysis or 30 km has little effect on the estimated income coefficient.[18]. Only very short distances of 5 km, which are still close to the city center, seem to affect the coefficient

[18]Since our cities are located in close proximity, a cut-off value of, say, 30-40 km would lead to overlapping city borders of Zürich – St. Gallen, and Geneva – Lausanne.

estimates. From Figure 8, we conclude that choosing a specific cut-off value within the plausible range is not likely to drive our empirical results.

Figure 8. Sensitivity of Income Coefficient to Distance Cut-Off Value
This figure shows the sensitivity of the income coefficient with respect to the cut-off value for the city edge. Each bar shows the result from a simple regression of log(distance) on log(income), averaged over all eight cities and for a given distance. The benchmark cut-off value used throughout the paper is 10 km.



VI. Conclusion

The main contribution of this paper is the empirical examination of the income gradient in the larger urban area surrounding amenity-rich and amenity-poor city centers. Although their concentration may be related in a complex way to other fundamental drivers, our findings reinforce the importance of amenities for household location choice. The key finding is the estimated inverse relationship between amenity concentration and income gradient, which becomes even more pronounced when several simplifying assumptions are relaxed. Furthermore, our research implies substantial household relocation responses to changes in transportation and taxes at the city's edge. However, not all households respond by locating further from the CBD when the amenity value of the city edge increases in the same way. Our empirical results align with predictions from an extended canonical urban model, where the bid-rent function is studied to show that the intra-city distribution of amenities may lead to a violation of the traditional urban model's negative income gradient hypothesis. We conclude with an illustrative empirical analysis involving the non-linear interactions of housing sizes, location, and access to nature.

Our results contribute to the limited existing research on European cities. Along with countries such as U.S and France, evidence suggests that Switzerland has experienced increasingly sprawled urban areas in recent years, where population growth outside the city centers and in commuting zones has far exceeded growth in the urban core (Veneri, 2018).[19] Swiss cities are small relative to cities in the U.S. and several other European cities, are located in close proximity, and tends to be well-connected by an efficient public transportation network. While these cities have unique traits, the urban amenity theory opens for anticipating similar patterns in other countries once adjustments are made for city-specific factors. One limitation of our analysis is that we measure amenities at a single point in time, six years after the end of the household data spell. While the supply and composition of amenities in a city change rather slowly over time (Duranton and Puga (2015)), this approach might overlook significant changes in amenities and their value over time. Finally, future research could also benefit from exploring a richer set of instruments to address the endogeneity of urban amenities, prices, and location choice, or estimate more complex models.

[19] The study considers the time period 2001-2011.

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VII. Appendix

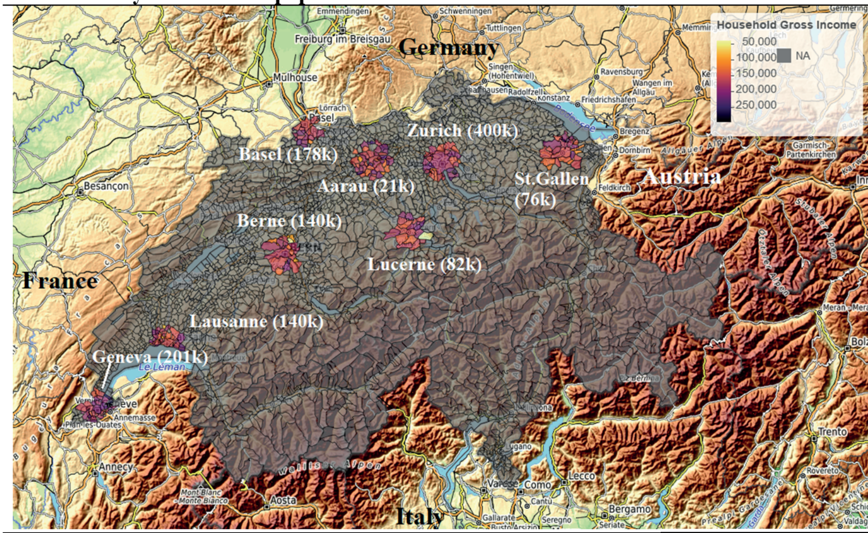
Table A1 Variable description
This table provides an overview of the dependant variable and all explanatory variables of interest.

Variable	Variable description
Dependent Variable	
Linear distance to CBD	Linear distance (meters) from household to the CBD using the Haversine formula.
Car distance and time	Google Maps API was used to estimate the distance and time by car from the centroid of each municipal to the CBD.
Transit distance and time	Google Maps API was used to estimate the distance and time by public transportation from the centroid of each municipal to the CBD.
Explanatory Variables	
Household Characteristics	
Annual gross income	Annual gross income in CHF from all sources.
Age	Age of the household head.
Kids	Number of kids living in the household.
Education [Years]	Number of years spent at school or University
Female	=1 if head of household is female; zero otherwise.
Married	=1 if head of household is married; zero otherwise.
Homeowner	=1 if head of household is a homeowner; zero otherwise.
Unemployed	=1 if head of household is unemployed; zero otherwise.
Swiss	=1 if head of household is Swiss; zero otherwise.
Amenities	
Tax	Municipal tax shifter.
House prices	House price index at the municipal level obtained from Fahrländer Partner Raumentwicklung.
Entertainment	Total number of art centers, casinos, cinemas, nightclubs, and theatres in a municipal.
Eating out	Total number of restaurants, pubs, bars, biergarten, and cafés in a municipal.
Outdoor	Total number of parks, playgrounds, firepits, and gardens in a municipal.
Public services	Total number of schools (kindergarten, primary, middle, and secondary schools) and health facilities (clinic, dentists, doctors, and hospitals) in a municipal.
Transportation	Total number of platforms (place where passengers wait for the public transport) in a municipal.
Sport	Total number of fitness centers, sports centers, and swimming facilities in a municipal.
Lake	=1 if the municipality borders on a lake; zero otherwise.
National border	=1 if the municipality borders on a national border; zero otherwise.

Figure A1. Spatial Income Distribution and City Size

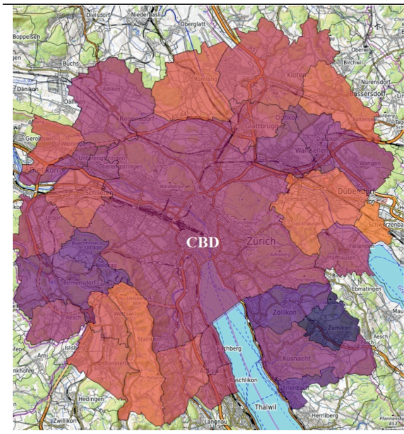
The figure shows the spatial distribution of average gross income on the aggregate municipality level within 10 kilometers of the city center. Panel A shows the location of the eight cities used in our sample together with city population. Panel B highlights the spatial distribution of household income for Zurich and Geneva.

Panel A: City location and population size



Panel B: Spatial income distribution for selected cities

Zurich



Geneva

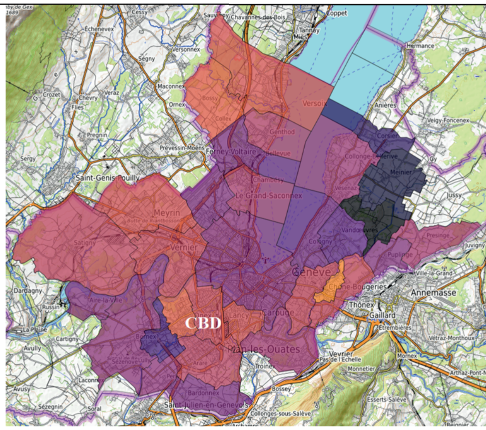


Figure A2. Tax Rate Distribution for Cantons and Municipalities

The figure shows the spatial distribution of annual income taxes across all Swiss municipalities. Taxes are calculated for a married, single-income household with two children and an annual gross income of CHF 150,000. The lowest tax burden occurs in Baar in the canton of Zug, with a tax burden of 3.46% of gross income. The highest tax burden is in Les Verières in the canton of Neuchâtel, with a tax burden of 15.94% of gross income. The data is obtained from the federal tax administration ("Eidgenössische Steuerverwaltung")]

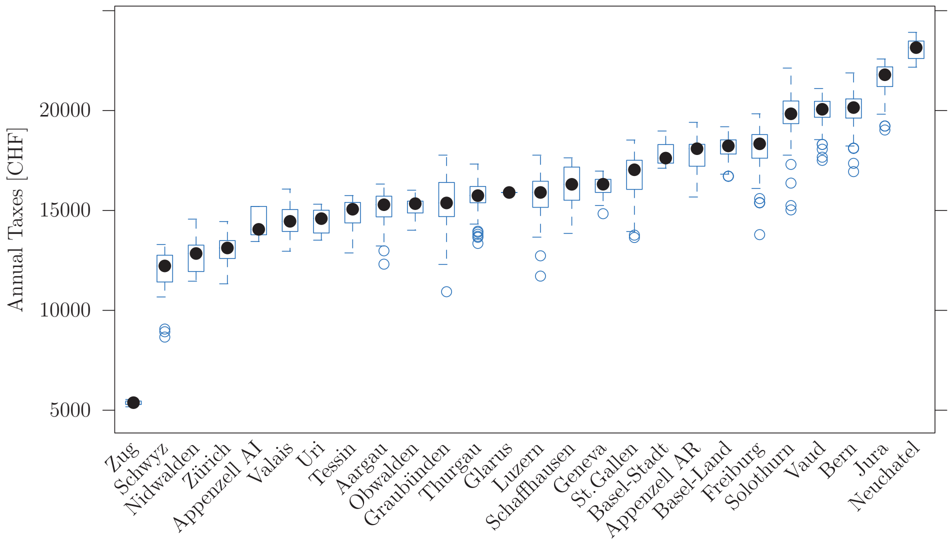


Table A2 2SLS Regressions with Supply elasticity instrument

The table shows individual city regressions of log(distance to CBD) on log(income) and the same variables as in Equation 1 less area housing prices. 'Eating out' amenities are instrumented with supply elasticity estimates. The coefficients are estimated with pooled 2SLS. Standard errors are robust to unknown forms of heteroscedasticity. *a*.The column reports the test statistic.

	Dependent variable:							
	log(distance to CBD)							
	Zürich (1)	Genf (2)	Bern (2)	Basel (2)	Lausanne (2)	St. Gallen (3)	Luzern (3)	Aarau (3)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Income)	−0.009*	−1.215*	0.013*	0.0966***	0.005	0.118***	0.384*	0.102***
Eating Out	−0.153***	−9.261*	0.798***	1.354***	0.000	0.956***	5.747***	0.201***
Amenities (transportation)	x	x	x	x	x	x	x	x
Lake, Border	x	x	x	x	x	x	x	x
Household char.	x	x	x	x	x	x	x	x
Observations	4,571	2,511	1,752	2,556	5,175	1,989	1,830	1,681
Weak instruments^a	286,526	10.49	81.2	714.8	110,647	897	147.1	1,717.1
p-value	(0.000***)	(0.0012**)	(0.000***)	(0.000***)	(0.000***)	(0.000***)	(0.000***)	(0.000***)
Note:								*p<0.1; **p<0.05; ***p<0.01

6 Paper IV

There is an emergent global crisis of urban housing affordability and affordable housing provision. This crisis results from the fact that housing-related household expenses are rising faster than salary and wage increases in many urban centres around the world.

Wetzstein, 2017

Housing Affordability of a Representative Local First-Time Buyer*

Mari O. Mamre†

Published in *Tidsskrift for Boligforskning* (2021)

ABSTRACT

House prices have soared in urban areas over the past two decades, and significantly more than disposable income. This article calculates a purchasing power index based on maximum borrowing for representative single first-time buyers and transaction prices in 43 Norwegian municipalities between 2003 and 2019. This is called the First-time Buyers' Purchasing Power Index (FKI). This method provides multiple gains compared to simpler measures that are often used, such as price-income rates, and is also suited to regular updates. The calculations are compared with the development in actual first-time purchases and may indicate that many young people go far beyond what the limits for their own finances dictate. While a typical single first-time buyer would be able to afford 29 percent of homes sold in the six largest Norwegian cities in 2010, the corresponding figure is 7 percent of homes sold in 2019.[1] A pro-cyclical lending practice increases maximum borrowing during boom periods and weakens maximum borrowing during bust periods. The results indicate that it is not only in Oslo where the barriers to home ownership have increased, but that the geographical spread is greater. At the same time, the great regional differences are illustrated.

Keywords: Housing markets, first-time buyers, housing affordability, actuarial model, index

JEL Classifications: R20, R21, R30

*The index presented in this article is updated annually and published by the Co-operative Housing Federation of Norway (NBBL). Thanks to Dag Einar Sommervoll and Christian F. Bjerknes for their valuable comments to the paper. The paper is published in Norwegian. Although some of the text have been altered in translation, the core message of the original text and analysis is maintained. Several of the figures have Norwegian labels, these are explained in the figure caption.

†Norwegian University of Life Sciences, School of Economics and Business, Ås; Tel.: +47 90787163; E-mail address: mari.olsen.mamre@nmbu.no.

[1] This results is a weighted average by transaction volume in each city.

I. Introduction

Following the Financial Crisis, many countries experienced high credit and housing price growth due to a period of historically low interest rates. This led to the implementation of stricter measures to limit credit risk in the economy, such as targeted regulations on lending for home purchases (Cerutti, Dagher, and Dell'Ariccia (2017b); Cerutti, Claessens, and Laeven (2017a)). However, the combination of high house price growth and tighter credit regulations has increased barriers to ownership. As a result, the purchasing power of young and vulnerable groups is under pressure in many locations. Surveys, such as Living Conditions and EU-Silc, suggest that homeownership rates among young adults have fallen in most EEA countries, including Norway, over the past decade.[2] This trend has sparked a widespread debate about whether cities are becoming too expensive for younger generations and the potential costs of an exclusionary housing market. In Norway, however, the evidence is mixed, as indicated by the volume of first-time purchases.[3] This article presents the methodology behind a new index for the purchasing power of typical single first-time buyers from 2003 to 2019 and compares the results to other existing data, such as home ownership rates and purchase volumes. The focus is particularly on Oslo.

The literature aiming to explain why housing in cities often becomes relatively expensive is abundant. The classical monocentric model (Alonso–Muth–Mills model, see for instance Alonso (1964)) posits an inverse relationship between housing prices or rents and travel distance to the central labor market and attractive city core. More recent contributions examine the dynamics between booming cities and the rest of the country. Research on U.S. urban areas (Gyourko, Mayer, and Sinai (2013)) documents how population growth and prosperity nationwide tend to be concentrated into 'superstar cities', productive urban regions where many desire to live and work, thereby driving up housing prices. The authors also reveal significant costs for superstar cities in the form of reduced productivity, which in turn leads to diminished economic growth for the entire country, as fewer households can afford to live and work in the city. This marks the starting point for this article. The combination of high housing price growth in Norwegian urban regions and insight into the potential costs if fewer young individuals can afford city living, motivates this research.

The "First-time Buyers' Purchasing Power Index" (FKI) aims to measure housing purchasing power. It is defined as the proportion of housing transactions a representative first-time buyer in Norwegian municipalities should be able to afford. This is based on their financial status and the lending practices of banks, and it allows for comparisons between

[2]This development is described in Revold (2019).

[3]See a description in section IV.

areas and over time. Housing purchasing power in a region is defined by the maximum calculated loan uptake in an actuarial model, where banks' lending practices for housing purposes vary across several dimensions. The analysis uses relatively aggregated information about housing buyers' income, expenses, and deductions. Assumptions are made in the construction of the representative buyers about the relevant income and age distribution in cities and more rural peripheral areas, and about the lending practices applicable for the majority of banks. Thus, the need for standardization and simplicity means that important distributional and site-specific nuances may be lost.

The findings indicate that in many areas, housing prices have outpaced the first-time buyer index in recent years, a trend that becomes particularly noticeable from 2016 onwards. The most challenging situation is faced by a representative local first-time buyer in Oslo, who can afford 2.6 % of sold houses, followed by neighboring areas Bærum (3 %), Asker (4 %), Lørenskog (6 %), and then Tromsø (7 %). The gap between the FKI and transaction prices has generally widened in the cities. For instance, while a representative first-time buyer could afford 29 % of transacted houses in the six largest cities in 2010, by 2019, the same buyer could only afford 7 % of transacted homes. There is a close association between calculated purchasing power and actual first-time purchases in the most expensive municipalities. This is evidenced by a steady decline in the FKI estimate coinciding with a decrease in the first-time buyer share in the local housing market. Moreover, the variation in calculated FKI across municipalities also follows ownership rates for individuals of similar age closely.[4] The results are sensitive to the income figures used, but less so if the gap between housing price and purchasing power is significant, as has been the case in areas like Oslo and Tromsø in recent years.

The combination of the calculated FKI presented here, along with information about ownership rates, migration flows, and purchase volumes, can collectively provide a more nuanced understanding of the inclusiveness of the housing market and the barriers faced by younger individuals. Observing falling ownership rates alone does not provide information about the expected gap between housing prices and the purchasing power of younger generations, or the existence of any breakpoints[5] that may indicate how far young people are willing to stretch their finances. The purchasing power index is also a statistically significant variable in models[6] for ownership rates and first-time purchase volumes. Regular updates of

[4]In this article primarily figures for people living in owned housing are used. For adult age groups, it is a good indicator of ownership rates, but only provides an estimate. For Oslo, figures for ownership rates from the Living Conditions Survey are used.

[5]Evidence from cities in other countries, such as the London area where housing prices have risen rapidly, suggests that there are tipping points for price relative to purchasing power beyond which younger households are more likely to leave the city and relocate.

[6]These results are available upon request. Further work remains in this area, and this article includes

indexes such as the FKI can provide valuable guidance in the ongoing development of new policy tools.

Section II outlines the relationship with previous literature. Section III provides a brief description of calculated lending practices. Section IV details the data basis and V describes the methodology. Results and a discussion of the assumptions in the analysis are included in VI, along with some alternative scenarios. Section VII discusses the findings and suggests areas for future research.

II. Related Literature

A portion of the literature concerning housing purchasing power is grounded in the family of micro economic models which relate the decision about tenure status (primarily owning or renting) to a financial analysis of an individual's or household's various options. Housing costs are typically estimated via an actuarial calculation of the maximum loan amount. This calculation takes into account various factors, including lending practices and the need to maintain a cash flow sufficient to service the loan and, to varying degrees, other consumption and additional costs (see Coulombel (2010) for a literature review). This body of literature is particularly relevant to our work as it provides the theoretical basis for our analysis of housing purchasing power.

This analysis is also related to an expanding body of literature centered around agent-based models which facilitate the explicit modeling of different economic actors, such as first-time buyers. In the agent-based model of the housing market outlined in Baptista, Farmer, Hinterschweiger, Low, Tang, and Uluc (2016), households consist among others of first-time buyers, established buyers, and investors. An external party determines the prevailing mortgage regulations, and a banking sector determines the maximum loan uptake, taking into account various factors such as lending rules and repayment capacity. The model estimated in this analysis is closely related to parts of this framework. Since this article remains silent about the demand from potential first-time buyers, the transition from maximum housing loan to housing purchasing power implies an assumption that average first-time buyers are credit rationed (for a discussion of credit rationing over the housing cycle, see Borgersen and Sommervoll (2006)).

As pointed out by Ben-Shahar, Gabriel, and Golan (2020), not all homes are suitable for all households. Therefore, pure matches of purchasing power and units based on prices can be misleading. The authors' research, which covers the period from 2000 to 2015 in

stylized results that combine the decline in ownership rates and purchase volume.

the Tel Aviv region, compares the necessary income increase to afford a house of equivalent quality (same size, type, and more) with how far from the center different types of households must move to afford such a home. and find a significant tightening of housing purchasing power. Additionally, they segment homes according to their suitability for various types of households, such as the requirement for more bedrooms for families with children. In contrast, this article focuses solely on single first-time buyers but does consider the location of the homes within the municipality.

Other Norwegian studies calculate purchasing power in the housing market for different parts of the population, such as varying age groups or specific occupational groups.[7] The approach of Lindquist and Vatne (2019), which addresses the distribution of housing purchasing power among households in different age groups, aligns with this article's methodology. Both base calculations on maximum loan uptake, determined by the calculated disposable income available to service a mortgage, without considering wealth. However, the analysis presented in this article differs by relying on aggregated information about representative single first-time buyers, without any distributional analysis. Furthermore, this article places a greater emphasis on the regional dimension compared to the mentioned research and contrasts the estimated purchasing power index with actual first-time purchases. Finally, it addresses some of the variation in banks' lending practices over time, even before the enforcement of the mortgage regulations.

III. Banks' Lending Practices

For Norwegian households, private banks serve as the primary source of financing when purchasing a home. The term lending practice refers to the necessary steps a bank or loan applicant must undertake before a potential mortgage can be granted. Prior to 2010, each individual bank in Norway had the autonomy to determine its lending practice, so long as these practices adhered to the Basel framework.[8] However, in response to a significant increase in households' debt burden and a steady rise in the loan-to-value ratio on mortgages, the Financial Supervisory Authority introduced guidelines for housing loans in 2010. These guidelines were also a response to the growing trend of loans without installments and the systemic risks highlighted by the Financial crisis, particularly when the loan object itself is used as mortgage collateral. Left alone, households' credit rationing in the mortgage market could assume a pro-cyclical character. This scenario could lead to a mutually reinforcing

[7]See also Lund (2018).

[8]The Basel framework consists of three pillars: a minimum requirement for solidity, the requirement for risk management and internal control, and the requirement for public disclosure of information.

Table I Guidelines and Mortgage Regulations

	Guidelines I	Guidelines II	Regulations I	Regulations II
To - From	3.10-12.11	12.11-6.15	7.15-1.17	1.17-1.21
Maximal LTV	90%	85%	85%	85%
Maximal LTV Deductions	-	70%	70%	60%
Maximal LTI	300%	-	-	500%
Interest surcharge	-	5pp.	5pp	5pp.
Maximal excepted	-	-	10%	10%(8% in Oslo)

Source: Regjeringen.no, 9/11/2020. The table shows the guidelines and mortgage regulations in Norway between 2010-2021. *LTV* is Loan-to-Value, *LTI* is Loan-to-Income.

cycle where higher housing prices and increased loans for housing purchases stimulate each other, posing potential risks to the economy (Borgersen and Sommervoll (2006); Borgersen and Hungnes (2009)).

If the lending practices of Norwegian banks towards new mortgage customers varied significantly before the guidelines and regulations were established, this could notably impact the purchasing power in the market for loan-restricted households such as first-time buyers in particular. A review of the annual housing loan survey by the Financial Supervisory Authority (2003–2020) suggests that both the average repayment period and the extra charge added to the base interest rate (interest rate surcharge) had a pro-cyclical development before the introduction of the mortgage regulations in 2015.[9] In addition, a tendency towards shorter repayment times is observed early in the period (see table A3 in the Appendix). Interestingly, the variations in the interest rate surcharge seem to have had a counterbalancing function against high interest rates in certain years, with a lower surcharge applied when interest rates were particularly high. The mortgage regulations appear to have resulted in less year-to-year fluctuation in observed lending practices. Some elements of the lending practice, such as the possibility of additional collateral security and co-borrowers, are more challenging to capture in a single model. There will also be some proportion of the loans that are exempt from these limits (see table I for details).

[9] In this analysis, a strong period in the housing market is defined as a period with high housing price growth relative to the risk-free interest rate.

IV. Data

This section describes the data sources used in this study and discusses their strengths and potential limitations.

A. *Microdata for First-Time Purchases and Housing Transactions*

The first dataset for this study comprises registry data from Ambita ASA, capturing housing transfers to individuals in Norway who have not previously owned a home—first-time buyers—between January 2010 and September 2019. Both Ambita and Statistics Norway draw from the Property Registry and the Cadastre from the Norwegian Mapping Authority, ensuring high data quality.[10] The dataset includes 731,664 first-time purchases, with details about the buyer's age, ownership share, type of housing, location, purpose of the purchase (residential, commercial/office, leisure), type of transfer (free sale, inheritance, gift), and transfer date. For the purpose of this analysis, we focused on first-time purchases for homes bought through free sale and where the first-time buyer has a minimum ownership share of 25 %. This selection criteria, chosen to ensure the analysis focuses on significant home ownership, reduced the dataset to 564,030 observations. Data for housing transactions are sourced from Eiendomsverdi ASA. The full dataset includes 760,014 broker-confirmed transactions for the municipalities in total, of which 205,544 are in Oslo. These transactions, recorded between 2003–2019, include geographical coordinates, housing prices, and housing characteristics. Potential limitations in combining these data include the time delays of a few months from the transaction to the transfer of the house.

B. *Aggregated data for income, consumption, lending practices, and other debt*

The register data for actual purchases by first-time buyers provide information of the age distribution among first-time buyers in each municipality, which is used as the basis to estimate age-distributed income. This part of the analysis is based on relatively aggregated information about potential home buyers' income and deductions. The actuarial calculations of maximum loan uptake are based on consumption estimates from Consumption Research Norway (the official SIFO consumption budget used by banks and intermediaries, see Austgulen and Borgeraas (2020)) while calculations of disposable income, other housing costs, interest on new loans, and the level of student debt, are all based on data from Statistics

[10] Ambita has further enhanced this dataset by linking properties to houses where data quality in the Cadastre is low.

Norway. The SIFO consumption budget does not vary across municipalities. Estimates for the average repayment period and interest rate surcharge are based on the Housing Loan Surveys of the Financial Supervisory Authority. Choosing the most suitable income data for this analysis is not straightforward. Several alternatives present distinct advantages and disadvantages:

Gross income: This is defined as taxable income, primarily from wages and capital, and does not include tax-free benefits such as child benefits and other stable tax-free incomes. The advantage of using gross income is that it is at the individual level, which aligns well with our focus.

Disposable income after tax: This is another alternative, obtained from income and wealth statistics for households, minus interest expenses. However, this would necessitate choosing single households, excluding potential first-time buyers who still live with their parents, in a collective living arrangement, or are cohabiting before their first purchase.

Specific average wage incomes: These can be drawn from various occupational groups' wages early in their careers. While this could offer a more specific picture, the gross income series used in this analysis align quite well with various typical income groups' starting salaries and follow the trend in the aggregated income development closely.

The income estimates used are annual gross income per two-year age group between 26 and 39 years, less net tax after interest deductions and other deductions, gathered from Statistics Norway. Gross income exhibits strong growth in the years preceding the Financial crisis in most areas, followed by moderate annual income growth after the crisis. Factors such as tax adjustments in 2005–2006 and fluctuations in capital income in certain areas like Asker and Bærum affect the income level. Despite these fluctuations, gross income figures are quite well suited for our purposes. Finally, data for student debt, house transactions, and estimates for housing costs are gathered from Statistics Norway and the National Federation of House Owners in Norway.

A typical challenge in estimating housing purchasing power for first-time buyers and other groups is the integration of both income and wealth data into the analysis. Often, data related to wealth or transfers from family and others are incomplete or unavailable, creating a potential bias in the analysis. Solheim and Vatne document how Norwegian households finance their property purchases in 2015 based on tax return figures (Solheim and Vatne (2018)). According to their analysis, first-time buyers had an average of NOK

276,000 in bank deposits at the end of 2014 and purchased their first home during 2015 for an average price of NOK 2,264,000. Therefore, they had on average 12.2 % of the purchase sum in bank deposits at the start of the year. Interestingly, only a small proportion of first-time buyers reported having inherited wealth. This suggests that transfers and unrecorded advances on inheritance might be significant sources of financing for home purchases, which are not fully captured in the available data. For first-time buyers, about 80 % of the purchase sum was debt-financed in 2015. This number is lower than the assumption of 85 % used in this analysis, which may reflect the proportion of the loans that are exempt from the LTV-limit.

V. Methodology

This study aims to measure the total income y_{tr} of a typical single first-time buyer in each municipality $r \in [1, 43]$ in each year t . This measure of total income is calculated by weighting the average income $y_{tr,i}$ of bi-annual age cohorts[11] $i \in [1, 7]$ between the age of 26 and 39 with the proportion a_{ij} this age group represents over time[12] among actual first-time buyers in region type $j \in [a, c]$. The region types j are (a) Large cities; (b) Smaller cities and villages East; (c) Smaller cities and villages Other. This relationship is described in equation (1):

$$y_{tr} = \sum_{i=1}^{7} (a_{ij} y_{tr,i}) \quad , t = 2003, ..., 2019, \tag{1}$$

where

$$\sum_{i=1}^{7} a_{ij} = 1.$$

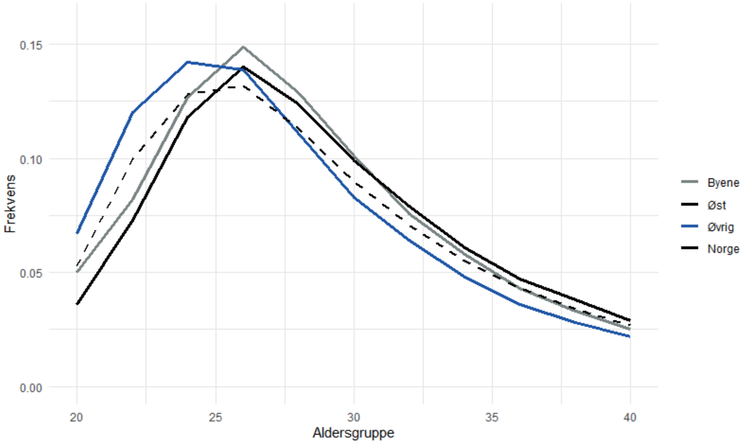
This study uses a method with age-weighted income data based on historical first-time purchases. This approach allows for some regional adjustment, taking into account the varying age distributions of first-time buyers across different regions. However, it is important to note that fine-tuning the age weights to each municipality is not desirable, as it will be difficult to distinguish the differences in age composition and differences in purchasing power in the final results. It is observed that first-time buyers in (c) Smaller cities and villages Other are generally younger than those in (a) Large cities. As a result, the younger income

[11] Bi-annual cohorts are chosen over annual ones due to data availability.
[12] That is, the average share the age group represents among first-time buyers in the ten-year period 2010-2019. In later updates, it is possible to keep this share constant or adjust for significant changes.

groups receive somewhat higher weights in these regions. This age effect can influence the purchasing power and housing affordability in these regions, and should be taken into account when interpreting the results.[13] The distribution of first-time purchases by age per region type, which forms the basis for the weights a_{ij}, is depicted in Figure 1.

Figure 1. First-time buyers by age and region type

Notes: First-time buyers are aged 20-41 years. The figure gives the 10-year average between 2010-2019 a.The division is by two-year age groups from 20-21 years and up to 40-41 years and the youngest in the age group is indicated on the axis. The dotted line shows the average for Norway (43). English translation: Aldersgruppe (Age group), Frekvens (Frequency), Byene (Large Cities), Øst (East), Øvrig (Others), Norge (Norway).



Different regions within a country serve various functions and tend to attract distinct demographic groups. For instance, larger cities often attract a higher proportion of younger and single individuals, while established couples with children more frequently reside in surrounding areas. These demographic trends can significantly impact the housing market dynamics in these regions. Among first-time buyers in 2019, 53 %, 40 %, and 45 % in region types a-c respectively were buyers with an ownership share of 100 %, referred to as the proportion of singles in table II. It shows the development over the ten-year period 2010-2019 for all municipalities combined. Notably, the average age at first-time purchase remains relatively stable around 32-33 years. However, a slight increase in the average age at first-time purchase is observed in Oslo between 2015 and 2019. While the volume of purchases can vary with differing growth in age cohorts, such as a rise in students, living conditions surveys suggest a decline in home ownership rates among young people in the cities (Revold (2019)). This trend may indicate a growing affordability challenge for younger individuals

[13] For a detailed breakdown of the division by region type, see table A1 in the Appendix.

Table II Summary Statistics

Year	HP NOK	Apartments	FTBs	FTB age (single)	FTB HP NOK
2010	2,485,400	0.61	23,845	33.1 (0.41)	1,881,300
2013	3,033,500	0.62	23,045	32.9 (0.40)	2,315,500
2016	3,538,900	0.64	22,093	32.6 (0.42)	2,614,400
2019[a]	4,030,500	0.63	23,500*	32.7 (0.42)	2,989,100

Notes: The table shows summary statistics for transacted homes and the volumes of first-time buyers. It gives the average for all 43 municipalities. *HP* is the average total transaction price and *FTB HP* is the average total transaction price for first-time buyers, rounded to the nearest 100. *Apartments* gives the share of transactions that are apartments. *FTB age* is the average age for the purchase of the first home, for both singles, couples, and others, while the share that is single is given in brackets. This is defined as the share among first-time buyers of all ages who were registered with 100 % ownership. *a*.Data for the first half of 2019. *Data for 2018.

in urban areas.

The disposable income available to service a mortgage for a typical first-time buyer in municipality i in year t, denoted as $y_{d,tr}$, is defined as the income $y_{e,tr}$ after tax adjusted for deductions $T_{t,i}$ depending on age group i, $y_{e,tr} = \sum_1^7(a_{ij}(y_{tr,i} - T_{t,i}))$, minus the minimum expenses for other consumption defined by the SIFO-budget for the relevant age cohort, $SIFO_t$[14] and an estimate for expenses to service other debt, OD_t. Other debt is defines as the average student loan for 25-34-year-olds. Finally, a minimum cost for housing expenses HE_t is subtracted from the disposable income. This is somewhat ad hoc defined to constitute 20 % of annual consumption expenses, thereby accounting for the same CPI adjustment of housing expenses as consumption expenses. For instance, in 2019, the SIFO expenses are calculated to NOK 109,800, housing expenses to NOK 21,960, and servicing of other debt to NOK 10,890. These housing expenses could approximately cover electricity, internet/television, and municipal fees for a small home.[15] This relationship is summarized in equation (2):

$$y_{d,tr} = y_{e,tr} - SIFO_t - OD_t - HE_t. \tag{2}$$

A. Method consisting of two steps

This study employs a two-step method to calculate the maximum mortgage and maximum house price for typical first-time buyers in each municipality.

[14]SIFO operates with broad age groups. Here, annual budgets are defined as the average consumption expenses for a woman or a man between 18 and 60 years without children and without a car. A methodological change at SIFO results in a jump in expenses in 2016, which has been smoothed out and distributed over several years in this calculation.

[15]See a description of typical housing expenses at Huseierne.no

1. **Step 1: Maximum mortgage and maximum house price are calculated for typical first-time buyers in each municipality in an actuarial model**[16]

The bank (actuary) offers different repayment periods N_t in different years. The bank will offer a maximum mortgage Q_t in year t to a representative first-time buyer in each municipality, which is in line with current mortgage regulations and general lending practices defined by requirements for (i) Loan-to-income (LTI), and (ii) Servicing capacity, which is the ability to service the mortgage as well as other consumption and debt at various interest rates. In addition, the bank must set limits for Loan-to-value (LTV). Which of these conditions that minimizes equation (3) determines the results for the maximum offered mortgage and thus the purchasing power of the FTB household in the local market:

$$Q_t = argmin \left(\psi_t^{LTI} y_t - D_t, \quad y_{d,t} \frac{(1-(1+i_t^K)^{-N_t})}{i_t^K} \right) \tag{3}$$

$$P_t = (1 + (1 - \psi_t^{LTV}))Q_t \tag{4}$$

Where
(i) $\psi_t^{LTI} y_t \sim$ LTI-condition. y_t is borrowers total income and ψ_t^{LTI} is the maximal LTI-ratio, first introduced in 2017 and constant $\psi_t^{LTI} = 5$ for the whole period 2017-2019. D_t is the value of other debt included, specifically total student debt.[17]

(ii) $y_{d,t} \frac{(1-(1+i_t^K)^{-N_t}}{i_t^K} \sim$ Serviceability condition. $y_{d,t}$ is the borrower's disposable income for house mortgage payments, i_t^K is the average interest rate issued for new mortgages plus a variable interest rate addition to hedge for future increases, and N_t is a variable down payment period.[18]

(iii) $P_t = (1 + (1 - \psi_t^{LTV}))Q_t \sim$ Maximum house price offer. P_t is the maximum house price available and is determined by Q_t. This formulation of the banks objective implies that the borrower always pays the minimal down payment requirement, at

[16]Equation (3) is strongly inspired by Baptista et al. (2016), which estimate a richer model using data from the UK. The first argument in (3) differs by including student debt. The second argument is an annuity formula, which separates from the above mentioned article by allowing the interest rate markup and the repayment period of the loan to vary with t. Finally, the requirement for equity is not included directly in the equation.
[17]Student debt is included in the LTI requirement in the Norwegian mortgage rules.
[18]See table A3 in the Appendix.

$\psi_t^{LTV} = 0.9$ up until and including 2011, and $\psi_t^{LTV} = 0.85$ from 2012, thus wealth is not a variable factor in this model.

2. **Step 2: Match of calculated housing purchasing power with transaction prices**

   Based on the total prices for transacted homes in each municipality, we determine what proportion of the houses the constructed first-time buyer could afford year by year. Results are also studied for the maximum calculated mortgage Q_t alone, set against the median house price in the municipalities. Any difference must be financed with equity, while meeting the Loan-to-Value (LTV) requirement. An important assumption in this step is that all transacted homes are suitable for first-time buyers. This is less of a strict assumption for singles than for couples with children, as the latter group would have specific requirements for size, number of bedrooms, and other functions, making certain types of housing, such as one-room apartments, unsuitable (see Ben-Shahar et al. (2020)). This assumption implies that no sorting of units by suitability is performed.

VI. Results

A. First-time buyers' purchasing power index (FKI)

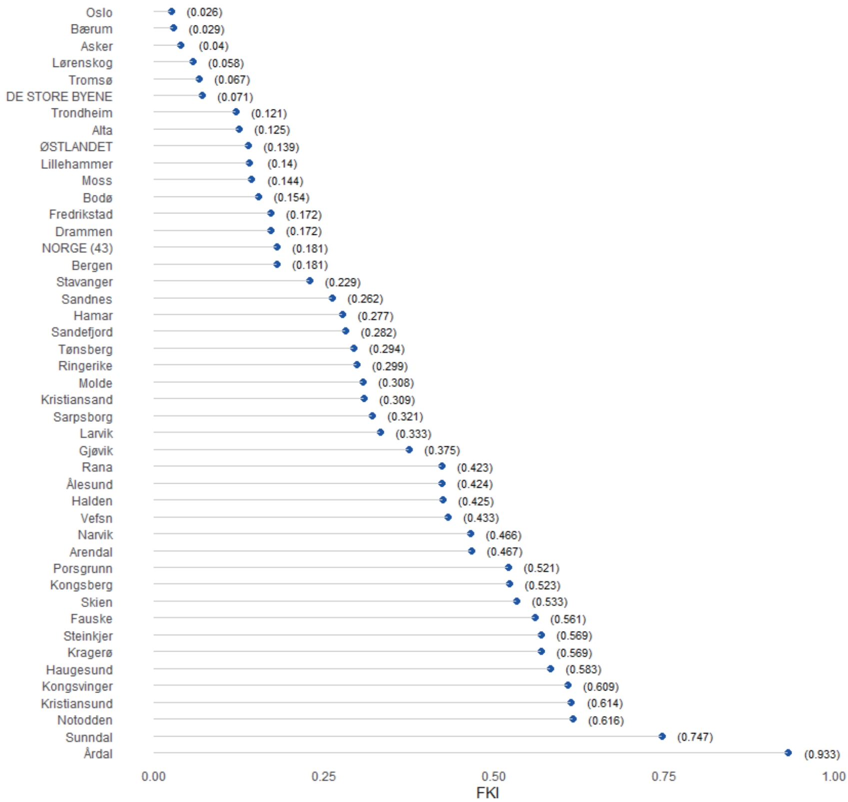
The results of this study indicate a significant weakening of the purchasing power index (FKI) for average local first-time buyers in many regions as of 2019. The lowest FKI is found in Oslo (2.6 %), followed by the nearby areas of Bærum (3 %), Asker (4 %) and Lørenskog (6 %). Then follows Tromsø (7 %). This trend is also observed in most of the large cities. This represents a dramatic shift from 2010, when a typical first-time buyer could afford 29 % of sold homes in the six largest cities. By 2019, the same first-time buyer could only afford 7 % of the homes sold, highlighting the increasing affordability challenges in these urban areas.[19] These findings align with the main message from the literature that suggests that housing markets in urban regions face significant pressure (see e.g., Gyourko et al. (2013)). Similar trends were reported by Lund (2018), who calculated the housing purchasing power of an average nurse in Oslo to be 3.2 % in 2019, and Lindquist and Vatne (2019), who calculated

[19] See table A2 in the Appendix. The figures are based on a weighted average by transaction volume. Thus, cities like Oslo and Bergen receive a higher weight in the total average.

the housing purchasing power of the 50th percentile household between 30 and 35 years to be around 10 % in 2016 (the FKI is estimated to 9.3 %).

Figure 2. First-time buyers' purchasing power index

Notes: The figure displays the results for the FKI by municipality in 2019. The results for DE STORE BYENE (the big cities), ØSTLANDET (Eastern area), and NORGE (Norway) (43) are weighted by transaction volumes.



In the following, we are interested in the implications of changes in lending practices, disposable income to service a mortgage, and house prices, for the results. During the period under review, banks' lending practices have undergone significant changes. Up until 2017, the serviceability requirement generally constrained maximum borrowing for representative first-time buyers. However, post-2017, the Loan-to-Income (LTI) requirement has been more often the binding constraint, although there are notable differences between municipalities. Income growth was particularly weak during the Financial Crisis period of 2008-2009, following strong growth in previous years. This had a significant impact on the purchasing power

Table III Results Oslo

Year	$y_{d,t}\frac{(1-(1+i_t^K)^{-N_t}}{i_t^K}$	$\psi_t^{LTI}y_t - D_t$	P_t	FKI	Median HP
2003	1,475,000	-	1,622,500	0.415	1,800,000
2004	1,625,000	-	1,787,500	0.414	1,979,700
2005	1,775,000	-	1,952,500	0,436	2,130,000
2006	1,575,000	-	1,732,500	0.249	2,375,000
2007	1,675,000	-	1,842,500	0.315	2,200,000
2008	1,600,000	-	1,760,000	0.277	2,258,000
2009	1,725,000	-	1,897,500	0,339	2,282,400
2010	1,825,000	-	2,007,500	0.388	2,284,000
2011	1,825,000	-	2,007,500	0.287	2,492,700
2012	1,775,000	-	2,041,250	0.187	2,750,000
2013	1,800,000	-	2,070,000	0.145	2,850,000
2014	1,850,000	-	2,127,500	0.160	2,887,400
2015	2,100,000	-	2,415,000	0.165	3,268,400
2016	2,250,000	-	2,587,500	0.093	3,714,000
2017	2,200,000	2,062,000	2,371,000	0.018	4,079,400
2018	2,350,000	2,136,500	2,457,000	0.027	4,001,600
2019	2,475,000	2,206,500	2,537,500	0.026	4,216,700

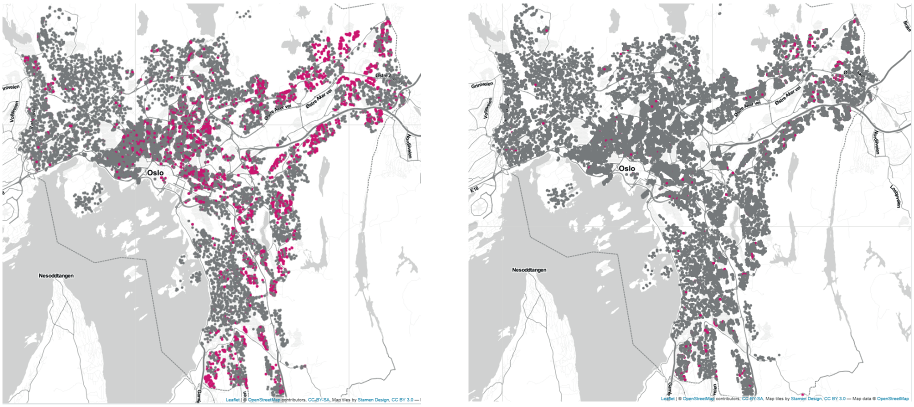
Notes: The table shows the maximum mortgage and estimated housing purchasing power for a single first-time buyer (FKI) in Oslo

index. Similarly, 2016 was a year marked by especially weak income growth. In individual years, consumption price growth has been particularly low, as in 2009 and 2018. High and increasing student debt also limits maximum borrowing, particularly in urban areas. Given these factors, the capital Oslo has the lowest estimated housing purchasing power per 2019. After the introduction of the LTI-condition in 2017, it became the determinant of maximum borrowing, as shown in table IV. It is important to note that these findings are based on simplifying assumptions. For instance, first-time buyers with children and cars would likely have higher expenses than those assumed in this study. Similarly, housing costs would likely vary more than assumed here under more realistic scenarios. These factors should be considered when interpreting the results.

Figure 3 illustrates which of the transacted homes a representative first-time buyer in Oslo could afford, denoted by a pink color on the map. The estimated FKI shows a significant decrease, from around 35 % of transacted homes between 2003 and 2007, to just 4 % between 2016 and 2019. In addition to the decreasing number of affordable homes, these homes are also becoming increasingly decentralized, moving further away from the city center. The median distance to the central area has nearly doubled, from approximately 3.6 km in the

Figure 3. Purchasing power index Oslo
Pink marks transacted houses a typical single first-time buyer could afford based on calculated housing purchasing power and matching with sold properties during the same period. Map made with Leaflet in R.

(a) 2003-2007 (b) 2016-2019



period 2003-2007, to 7.3 km between 2016 and 2019, measured by the Euclidean distance.[20] Overall, the closest homes transacted are around 200 meters from the city center, while the furthest units are about 15 km away. This trend of decentralization of affordable homes could have significant implications for urban development and housing policy in Oslo and other similar cities.

B. *Some stylized facts: FKI compared to other statistics*

This section compares the results for the First-Time Buyers' Purchasing Power Index (FKI) with other data sources, such as actual home purchases. This comparison aims to provide a more comprehensive understanding of housing affordability trends and validate the FKI as a useful measure.[21]

Positive association between FKI and actual first-time purchase shares

The results indicate a positive association between the First-Time Buyers' Purchasing Power Index (FKI) and actual first-time purchases. Figure 4 suggests that areas with higher

[20] Euclidean distance measures a straight line between two points. Here, elevation, public transport options, or accessibility are not taken into account. The city center is defined as the Royal Palace in Oslo. The calculations are done with spDistsN1 in R.

[21] A more in-depth analysis should take into account the development in each municipality and a number of factors such as regional growth, migration flows, and geographical areas that are not independent, but are part of center-periphery clusters.

FKI tend to have higher rates of actual purchases by first-time buyers, as measured by first-time homes as a share of sold properties in 2018/19. This share is just below 40 %, a number that aligns with, but is somewhat above, the share found by Solheim and Vatne (2018) at 36 %.[22] As expected, there is a clear urban component to these results, with central areas experiencing high population growth often ranking low in both FKI and share of purchases. The geographical dimension is also significant, with areas such as Oslo ranking low in both FKI and the actual first-time purchase share. This pattern is consistent when looking at the distribution of the share of 30-39-year-olds living in owned housing, an indicator of home ownership rates. For the top ten most expensive areas measured by FKI in 2019, the reduction in FKI and the reduction in the share of actual first-time purchases also match well, with a correlation coefficient of 0.93 (Pearson's). However, it's important to note that these findings do not control for important factors such as the demographic composition or the student share in the region. Also, the correlation between the reduction in FKI and the reduction in the share of actual first-time purchases appears to be weaker in less expensive areas.

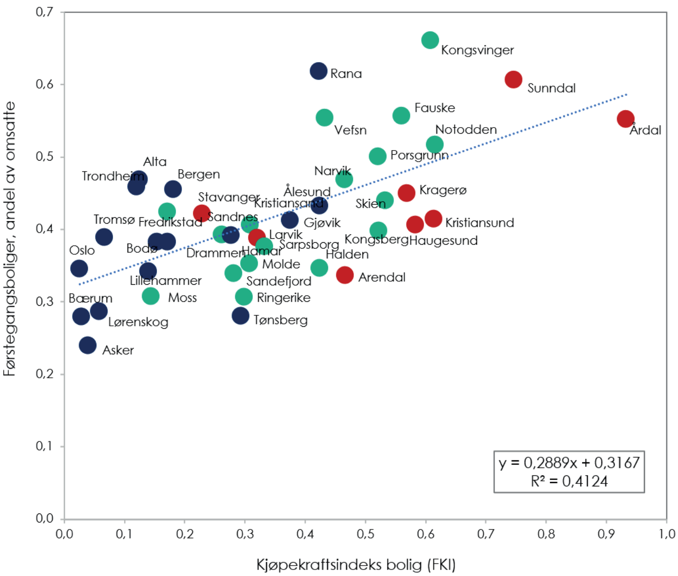
Consistency with home ownership rates

The results indicate a decline in the first-time buyer share aged 20 to 34 years in Oslo. As shown in figure 5 (right graph), the number of first-time buyers in this age group as a share of the total age group fell from 4.4 % in 2010 to 3.1 % in 2017, before increasing slightly until 2019. This share is also affected by shifts in the number of first-time buyers and the number in the age group year by year. Notably, there was an influx of students moving to Oslo during this period, which may have influenced the share. Figure 5 also shows the volume of first-time buyer homes as a share of sales. According to our calculations, this share decreased from 40.5 % in 2010 to 32.2 % in 2017, before increasing slightly in 2018 and decreasing again in 2019. The increase at the end of the period may be partly due to the fact that total transactions increased, contributing to more affordable homes in total. Note that one can expect that the number of total transactions is somewhat higher in reality, which would result in a somewhat lower share.[23] Finally, the volume of first home purchases relative to other purchases display a similar pattern.

[22] See Table 1 in the referenced paper. This corresponds with our numbers in important regions like Oslo and its surroundings, even though the numbers for households and individuals are not directly comparable. Several studies for other countries also operate with numbers around 40 % and slightly below.

[23] Our transaction data covers broker-confirmed sales and do not cover sales made by sellers or other parties.

Figure 4. Actual first-time purchases as a share of sales and purchasing power index (FKI)
The figure displays the actual first-time purchases (y-axis: Førstegangsboliger, andel av omsatte) as a share of sold houses in 2018/2019 and FKI (x-axis). First-time homes are total counts from the registry data for home purchases converted to unique homes via ownership shares. The color indicates population growth in the municipality among the population aged 20-34 years throughout the period 2010-2019. Blue: 15% or more. Green: 5-15%. Red: Below 5%. FKI uses figures for 2019 and first-time purchases for 2018/19.



C. Sensitivity analysis

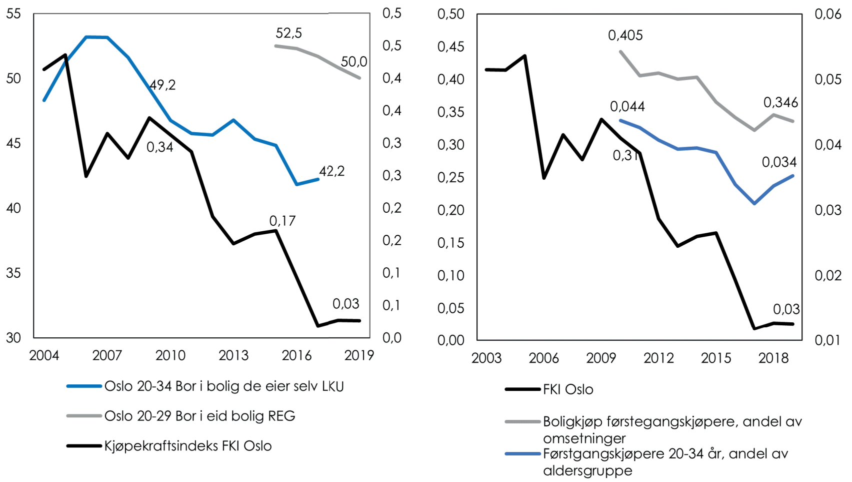
This section explores the sensitivity of the results to the choice of assumptions that influence income figures or lending practices. Specifically, the analysis focuses on the most expensive municipality, Oslo, and assesses the impact of alternative assumptions.

Income Sensitivity

A scenario-analysis is conducted to illustrate the uncertainty in the income estimates. Estimated income y_{tr} varies greatly with age. Three alternative income series are calculated for first-time buyers in Oslo: (a) $y_{t,Oslo}^{HIGH}$ (b) $y_{t,Oslo}^{MED}$ (main scenario) and (c) $y_{t,Oslo}^{LOW}$. These are age-weighted incomes using respectively the 28-39 year, 26-39 year, and 24-39 year cohorts. Under the High scenario (a), the average income in 2019 is approximately NOK 516,000, compared to NOK 478,000 in the Medium scenario (b) and NOK 440,000 in the Low scenario (c). This variation in income is substantial and reflects that lower age groups make up a significant proportion of first-time buyers and thus have a high weight in the income measure.

Figure 5. FKI compared with other statistics
FKI and ownership rates (left graph) and FKI and share of first-time purchases of total transactions (right graph). Register data for the share of 20-29-year-olds living in owned housing (REG) and the share living in owned housing is sourced from the Living Conditions Survey (LKU)/EU-Silc).

(a) FKI and owner rates (b) FKI and share of transactions/age group



As of 2019, the FKI in Oslo varies significantly depending on the income scenario. With low income, the FKI is estimated at 1.0 %, rising to 2.6 % with medium income and 5.5 % with high income. Figure 6a shows more variation in the estimated maximum housing loan in Oslo at different incomes in previous years. This variation is partly due to the requirement for servicing capacity being more income-sensitive than the loan-to-income constraint. Another significant factor is the high housing prices in recent years in Oslo. Furthermore, there are more homes with sales prices close to the estimated maximum affordable price up to 2015/16.

Subsequently, the gap between incomes and affordability have increased, and even large income increases only produces small changes in FKI. This suggests that the income sensitivity of the results is also greater in recent years in municipalities where housing prices are closer to the FKI limit. The income estimates used in the main scenario are closest to the median house price for actual housing purchases made by single first-time buyers in most years. While this could be considered a typical purchase price for successful first-time buyers, it provides less information about the maximum price for all potential first-time buyers.[24] Nonetheless, the close correlation between typical purchase price and calculated typical maximum price between 2012 and 2015 supports the choice to use this as our measure

[24]The market purchase price does not provide information about the reservation price of excluded groups.

Table IV Sensitivity analysis. Income- and lending practice assumptions

Variable	y	ΔQ	FKI
Income			
LOW	516,000	-0.109	0.010
MED (main scenario)	478,000	0	0.026
HIGH	440,000	+0.122	0.055
Lending practice			
Equal	478,000	± 0.037	0.026
Variable (main scenario)	478,000	0	0.026

Notes: Gross income data are from 2019. ΔQ is the estimated average annual change in the maximum mortgage in each scenario relative to the main scenario between 2003 and 2019.

of representative income.

Lending practice sensitivity

Results for Oslo have also been calculated under two scenarios for lending practices: (1) Variable lending practice (variable N and i^K) and (2) Equal lending practice ($N = 25$ and $i^K = i + 5$).

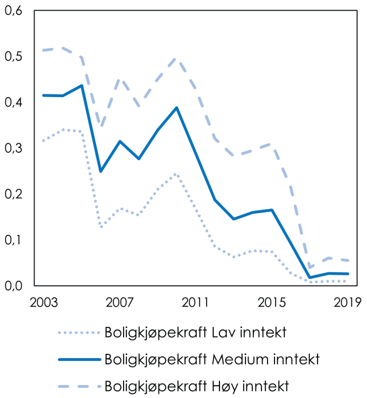
As shown in figure 6b, the assumption of variable lending practice has less impact on the calculated maximum mortgage than in the previous income scenarios. Under variable lending practices, the calculated maximum mortgage excluding equity is equal to or higher compared to a situation with equal lending practices. Also note that the difference in the calculated mortgage is greater in very expansive years in the housing market, such as in 2007 and 2016. This suggests that banks typically have had a pro-cyclical lending practice during these periods.

The calculated maximum mortgage changes by +/- 11-12 % on average between 2003 and 2019 with the alternative income measures, while only 3.7 % on average during the same period with the alternative lending practice (see table IV). However, in recent years, the difference in FKI is smaller for the income scenario, and zero for the lending practice scenario due to the introduction of the LTI constraint. These findings suggests that temporal variation in lending practices is less influential after the mortgage regulations were introduced.

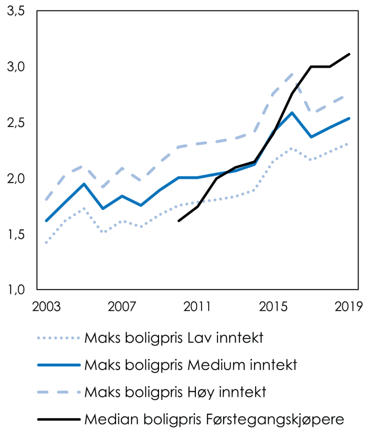
Figure 6. Sensitivity analysis

Panel a) shows FKI at different income levels. Panel b) gives the maximum calculated house price (Maks boligpris) and the median house price (in million NOK) at purchase by single first-time buyers (right graph). Panel c) shows the maximum calculated mortgage excluding equity for equal and variable lending practices. All figures gives results for Oslo. The median house price is based on purchases made by first-time buyers between 26-39 years in Oslo during the same period based on figures from Ambita AS. The different income measures are described above (Low=Lav, MED=Medium, HIGH=Høy). Main scenarios are given by bold lines, while alternative scenarios are given by dashed or dotted lines.

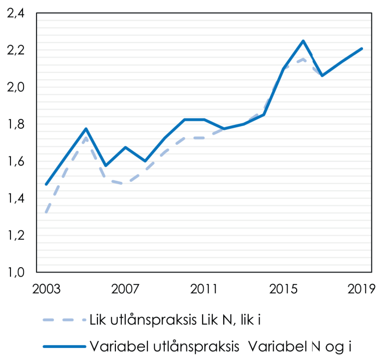
(a) Income scenarios FKI



(b) Income scenarios Price



(c) Lending practice scenarios Mortgage



D. Scenario Analysis

Maximum mortgage without Loan-to-Income (LTI) requirement

The results indicate that without an LTI-requirement, the maximum mortgage would increase. Under this scenario, the maximum mortgage for Oslo is estimated to increase from 2,062,000 to 2,200,000 (6.7 %) in 2017, from 2,136,500 to 2,350,000 (10.0 %) in 2018, and from 2,206,500 to 2,475,000 (12.2 %) in 2019. The increase in the maximum mortgage is primarily driven by low interest rates, muted growth in consumption costs, and a relatively strong income development towards the end of the period. As a result, the servicing capacity based on the criteria in the actuarial model would significantly increase. These estimates suggest that removing the LTI requirement could have a large expansionary effect for first-time buyers in Oslo and other municipalities where housing prices are high relative to income. However, it is important to note that these findings are based on a representative first-time buyer, and the effect of the LTI requirement can vary substantially among different groups of buyers.

Scenario with alternative interest rates

Among the various components in equation (3), the interest rate level plays a significant role in determining the maximum borrowing amount. In a final alternative scenario, the maximum borrowing is calculated with the current interest rate, a mortgage interest rate of 2.5 % for the entire period 2007 to 2019. Under this scenario, today's interest rate level would result in a 32.5 % higher maximum mortgage on average for typical first-time buyers in 2007-2008, when the interest rate was particularly high. Throughout the period 2007-2019, the corresponding increase is 11.1 %. For instance, this corresponds to an increase in the housing mortgage from 1,850,000 to 2,075,000 with a 2.5 % interest rate in 2014. After 2017 the LTI requirement limits the size of the mortgage, thus the interest rate change does not have any effect.[25] These estimates indicate that the current interest rate level plays a significant role in the maximum borrowing amount.

VII. Conclusion

This article presents a new index for the housing purchasing power of local first-time buyers in Norway, known as the FKI. The results indicate that barriers to home ownership have increased in many Norwegian municipalities, as reflected in the decreasing FKI. The

[25] Note that lower interest rates generally would mean higher housing price levels and that the comparison therefore only serves to illustrate the interest rate's importance for the maximum mortgage for credit-limited groups.

FKI corresponds closely with the proportion of first-time purchases out of total sales in a municipality. Furthermore, a reduction in FKI coincides with a decrease in this proportion in the most expensive municipalities. The FKI also aligns well with regional variations in home ownership rates among individuals in their 30s. However, there are significant differences in the proportion of students and place-based functions across regions that should be taken into account in future research. Updates to the FKI will capture changes in income, consumption, and housing expenses, as well as the effects of changes in mortgage regulations, interest rates, and housing prices. A weakness of these calculations is that we do not consider distributional differences. Another challenge is the difficulties in incorporating both income and wealth in the analysis, as well as fully capturing variations in lending practices between banks and over time. Ongoing research considers richer models that address these limitations.

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VIII. Appendix

Table A1 Region type, division by municipality

Large cities	Bergen, Kristiansand, Oslo, Stavanger, Tromsø, Trondheim
Smaller cities and villages East	Asker, Bærum, Drammen, Fredrikstad, Gjøvik, Halden, Hamar, Kongsberg, Kongsvinger, Kragerø, Larvik, Lørenskog, Moss, Sarpsborg, Porsgrunn, Ringerike, Sandefjord, Skien, Tønsberg
Smaller cities and villages Other	Alta, Arendal, Bodø, Fauske, Haugesund, Kristiansund, Lillehammer, Molde, Narvik, Notodden, Rana, Sandnes, Steinkjer, Sunndal, Vefsn, Ålesund, Årdal

Notes: The choice of municipalities is based on, among others, urbanity and geographical distribution.

Figure A1. Purchasing power index (FKI) in the large cities
Notes: A tax-based income adjustment contributes to the reduction in housing purchasing power in 2006, while increased equity requirements contribute to dampening the reduction in the estimated purchasing power index in 2012.

Table A2 Detailed results: First-time buyers' purchasing power index (FKI) in 2010 and 2019

	FKI 2010	FKI 2019	Pop. 20-34 2019
Oslo	0.39	0.03	195,681
Bærum	0.24	0.03	20,659
Asker	0.31	0.04	14,682
Lørenskog	0.27	0.06	8,081
Tromsø	0.24	0.07	18,898
LARGE CITIES	0.29	0.07	-
Trondheim	0.25	0.12	53,962
Alta	0.26	0.13	4,694
Eastern area	0.43	0.14	-
Lillehammer	0.27	0.14	5,836
Moss	0.39	0.14	8,246
Bodø	0.38	0.15	11,498
Fredrikstad	0.51	0.17	15,118
Drammen	0.57	0.17	19,558
Bergen	0.32	0.18	69,544
NORWAY	0.39	0.18	-
Stavanger	0.32	0.23	31,240
Sandnes	0.23	0.26	16,290
Hamar	0.36	0.28	5,928
Sandefjord	0.46	0.28	11,337
Tønsberg	0.43	0.29	10,733
Ringerike	0.64	0.30	5,511
Molde	0.33	0.31	5,932
Kristiansand	0.28	0.31	24,536
Sarpsborg	0.60	0.32	10,341
Larvik	0.48	0.33	7,724
Gjøvik	0.64	0.38	6,116
Rana	0.53	0.42	5,074
Ålesund	0.51	0.42	13,489
Halden	0.66	0.43	5,708
Vefsn	0.66	0.43	2,423
Narvik	0.39	0.47	3,801
Arendal	0.35	0.47	7,758
Porsgrunn	0.67	0.52	6,639
Kongsberg	0.51	0.52	5,088
Skien	0.63	0.53	9,969
Fauske	0.37	0.56	1,653
Kragerø	0.57	0.57	1,580
Steinkjer	0.51	0.57	4,367
Haugesund	0.61	0.58	7,327
Kongsvinger	0.76	0.61	2,920
Kristiansund	0.60	0.61	4,465
Notodden	0.72	0.62	2,361
Sunndal	0.71	0.75	1,133
Årdal	0.80	0.93	815

Notes: The table shows results for FKI in 43 municipalities. FKI is defined as the estimated share of transacted homes a representative single first-time buyer can afford each period.

Table A3 Parameters Oslo

	ΔP (%)	N_t	markup (pp.)
2003	1.8	23	3.0
2004	12.3	23	4.0
2005	9.1	24	4.5
2006	15.3	24	4.5
2007	11.2	26	3.5
2008	-4.2	27	3.5
2009	2.7	25	4.5
2010	8.3	26	4.5
2011	9.0	27	4.5
2012	7.7	26	5.0
2013	4.9	26	5.0
2014	2.3	25	5.0
2015	9.6	26	5.0
2016	8.3	25	4.5
2017	5.7	25	5.0
2018	0.8	25	5.0
2019	2.6	25	4.5

Notes: The table displays the parameters used in this analysis for Oslo. ΔP is annual growth in housing prices based on data from Eiendomsverdi ASA. N_t is an estimate of the average term for new mortgages with an 85-90% loan-to-value ratio. The interest rate markup is the most typical bank interest rate markup per year. The two latter are based on lending surveys of Financial Authorities Norway.

Table A4 Data Processing

First-time buyer data	N
Raw data	731,664
Data 1: Raw data excl. vacation homes	693,837
Data 2: Raw data excl. holiday homes and office/commercial	692,703
Data 3: Raw data excl. holiday homes, office/commercial and homes not sold in free sale[a]	569,900
Model data: Data 3 excl. ownership shares below 25 %	564,030
Transaction data	**N**
Raw data	760,083
Model data: Raw data excl. homes transacted below 200 000 NOK	760,014

Notes: a.Homes sold as gifts, probate settlements, undivided, or other, constitute the other types of sales.

Errata

Errata list			
Page	**Line**	**Change from**	**Change to**
1	2	**69**	69
1	11	**4.1**	4.1
11	5	«…and other challenging prediction problems (Auret & Aldrich, 2012). Auret & Aldrich (2012), in particular…»	«…and other challenging prediction problems. Auret & Aldrich (2012), in particular…»
11	22	«As Williams (2018) elaborates, rational buyers control both their initial screening of listings and subsequent search intensities...»	«As William elaborates, rational buyers control both their initial screening of listings and subsequent search intensities…»
20	23	«As documented by Sommervoll & Sommervoll (2019)…»	«As documented by Sommervoll & Sommervoll…»
24	21	«In line with the theoretical predictions of (Brueckner, et al., 1999)…»	«In line with the theoretical predictions of (Brueckner et al., 1999)…»
110	1	«The theory shows that the relative location of di¤erent income groups...»	«The theory shows that the relative location of different income groups...»

Mari O. Mamre

Mari O. Mamre was born in Oslo, Norway, and grew up in Fredrikstad. She holds a MSc in Economic Theory and Econometric Analysis from the University of Oslo. Her research interests include housing market analysis, urban research, empirical methods, machine learning and economic valuation methods.

The thesis consists of an introduction and four independent research papers. The objectives of this thesis are: (i) to enhance our understanding of housing quality heterogeneity and its impact on housing market models; (ii) to explore how households may trade off housing quality and location during booms and busts; (iii) to address location decisions and spatial sorting by income in cities with different relative amenity levels; and (iv) to construct standardized measures for the housing affordability of representative first-time buyers in disparate regional housing markets.

The results show that accounting for the quality of housing and "the quality of location" provides several benefits, such as better estimates of housing price growth and insights into "ripple effects" in urban areas. The research also documents evidence of income sorting in urban areas, where lower-income groups tend to live further away from attractive centres. Finally, the thesis shows that housing affordability has been significantly reduced in many places in recent years. This research provides important insights for those who monitor housing market developments or aim to influence urban development.

School of Economics and Business
Norwegian University of
Life Sciences (NMBU)
P.O Box 5003
N-1432 Ås, Norway

Institute for Urban and Regional
Research
Oslo Metropolitan University
(OsloMet)
Telephone: +47 90787163

e-mail:
mari.olsen.mamre@nmbu.no
mari.mamre@oslomet.no

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