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From listings to all-tenant rents: a probabilistic model

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Abstract

Rents are the largest component of the Consumer Price Index (CPI) in many countries, making accurate and timely measurements of rental price developments essential for inflation monitoring and policy decisions. Market (asking) rent indices are often available in near real-time and with high detail, but differ substantially from the rents paid by the overall tenant population, as typically measured in the CPI. This paper proposes a model to bridge the gap between asking and all-tenant rents. First, using rental-unit listings for Switzerland, we construct timely, granular, and high-frequency indices of asking rents. Second, using a probabilistic model that accounts for the duration of tenants' stays, we estimate all-tenant rents based on historical asking rents. Additionally, we incorporate rent changes during ongoing tenancies. For Switzerland, this corresponds to adjustments permitted under Swiss tenancy law in response to changes in the mortgage reference rate and inflation. This allows us to provide weekly, real-time, and highly disaggregated estimates of all-tenant rents, which are highly correlated with the official quarterly survey-based rental index in the Swiss CPI. Our approach provides a tool for timely rental price monitoring and forecasting that can be adapted for use in other countries.

JEL classifications: R31, E31, E37

Keywords: Asking rents, rent indices, duration model, shelter inflation

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1 Introduction

Rents are the most significant single component of the Consumer Price Index (CPI) in many economies, making their accurate measurement crucial for both inflation tracking and economic policy. However, existing rental price data may suffer from significant delay and limited granularity. In Switzerland, for instance, the rental CPI is surveyed quarterly and published without disaggregation, which prevents inference about developments within subpopulations of rental market units. In parallel, asking rental price data are often readily available near real-time and at high geographic resolution, as well as for different unit characteristics (e.g., by number of rooms). This paper proposes a probabilistic model to derive all-tenant rent developments from market rent developments.

Motivation. Previous research has shown that almost all the differences between asking rents and all-tenant rent measures can be attributed to the higher rent growth rates experienced by new tenants compared to the overall tenant population [Adams et al., 2024]. Since new-tenant rents gradually flow into the existing rent stock, asking rents can be seen as a leading indicator of future developments in the all-tenant rent index [Ambrose et al., 2015]. The following thought experiment illustrates this dynamic. Assume rental prices only change when tenants move in or out. If asking rents were frozen at the value a at time t, then the all-tenant rent index would only converge to a, when every tenant had moved at least once, a process that takes a long time. This motivates our strategy of modelling all-tenant rental prices.

Methodology. We start by constructing detailed indices of asking rents based on online listings. These asking rent indices are not readily available for Switzerland at the desired level of disaggregation by location and dwellings. We use real estate listings for rental units (apartments and houses) from Comparis, a Swiss online comparison company offering the largest real estate portal for Switzerland, for the period between 2005 and July 2025. We begin by cleaning the raw listings, removing implausible values and outliers so that the sample reflects a realistic distribution of rental properties. Next, we adjust rents for observable characteristics using a hedonic model, which isolates the unexplained, time-varying component of rents. Finally, we aggregate these signals into detailed sub-indices by canton[1] and room count, rebase them to a common reference year, and construct an overall index weighted by the population distribution of households across rental unit types. The resulting indices capture the evolution of prices for the dwellings currently available on the market.

Once the asking rent indices are built, we provide a theoretical and empirical framework to understand how market-level price signals relate to the broader stock of rental contracts. As an intermediate step, we assume that rental prices only change when tenants move out and new ones move in. Under this assumption, the average existing rent at any given point in time corresponds to the historical asking rents of all rental units, evaluated at the last time each unit was listed for rent. Since our data does not identify individual dwellings over time, we cannot directly observe these histories. To address this, we model the duration of tenants' stays, that is, the time that renters stay in a given unit. Under mild assumptions, we express the average existing rent as a weighted sum of past asking rents, where the weights reflect the probability that a unit listed in the past is still occupied. We empirically estimate all components necessary to implement this model and derive

[1] Switzerland is divided into 26 cantons that are the member states of the Swiss Confederation.

a baseline estimate of all-tenant rents based on market listings, assuming prices change only upon tenant turnover. At this stage, we compare the resulting all-tenant rent index with the Swiss Federal Statistical Office's (FSO) quarterly CPI rent index, obtaining a correlation coefficient of 0.86.

In a second step, we extend this turnover-only model by incorporating Swiss-specific legal and institutional rules governing rent adjustments for occupied units. In particular, rents for existing tenancies can be adjusted in response to changes in the reference mortgage rate and inflation. We estimate the impact of these mechanisms on average rents using rent CPI data and integrate these effects into our model. This enables us to continuously update all-tenant rent indices in real-time, even without direct survey data. Importantly, this component can be extended to other countries by considering the country-specific legislation on rental prices. After incorporating these Swiss-specific legal aspects into the model, the existing correlation between the rent index and the official CPI rent increases to 0.92. Although the improvement in correlation is not statistically significant, the figures suggest that modelling reference rates is important, particularly for periods around changes in the mortgage rate. Nevertheless, given the high correlation between the intermediate all-tenant rent index and the rent CPI, we conclude that modelling rental price changes of units on the market is more important for Switzerland.

Results. In addition to providing much greater detail, our rent price indices are constructed weekly and published the following Monday, offering near real-time insights into all-tenant rents. For Switzerland, this provides new insights into the rental market, laying the groundwork for studying the effects of rent control policies. Furthermore, we demonstrate that modelling all-tenant rents through the lens of asking rents yields forecasting gains of approximately 25% for the rent component of the CPI, highlighting how high-frequency and timely market data can enhance economic monitoring and policymaking.[2]

Literature review. Existing research has established that the discrepancy between asking rents and all-tenant rents is an important factor in measuring rental prices [Adams et al., 2024]. They show that for the United States, this divergence is primarily driven by tenant turnover, where new leases incorporate market conditions faster than existing contracts, creating a delay in rent CPI responsiveness. Specifically, using the U.S. Bureau of Labor Statistics (BLS) housing survey, they construct two rent price indices: the All-Tenant Repeat Rent Index (ATRR) and the New-Tenant Repeat Rent Index (NTRR). The former measures the rents of all tenants, while the latter measures the rents of new tenants. By holding the methodology and sample constant, they conclude that the divergence between market rent indices and rent CPI are due to differences in scope. Similarly, Ambrose et al. [2015] construct a repeat rent index by tracking units through time to measure the rental market conditions – akin to our asking rent indices. Again, they conclude that different scopes primarily drive the divergence between their repeat rent index and rent CPI, which measures all tenants' rents versus market rents. This provides a general explanation for the difference between market-oriented indices and the corresponding rent CPI, commonly referred to as the rent gap. For the US, among others, notable indices include the Zillow Observed Rent Index [Clark, 2022] and the Marginal Rent Index (MRI) [Ambrose et al., 2023]. For Switzerland, these include indices such as the Asking Rent

[2]Importantly, the aim is not to replace the official rent CPI, which provides highly accurate and consistent statistics, but to complement it with timelier, more frequent, and more granular indicators. While less precise, these measures are reliable enough to offer early signals. We therefore compare our index to the official rent CPI throughout the paper to validate our approach and highlight its added value.

Index of WuestPartner [WuestPartner, 2025] and the Rent Index of Homegate [Homegate, 2025]. Finally, Loewenstein et al. [2024] employ the described insights to model rent CPI explicitly from past market prices. Using the share of new tenants at each time, they express rent CPI as a weighted average of all-tenant rents and market rents. Further, they assume that all-tenant rents are generated as a distributed lag of past new tenant rents with a 40% pass-through of past market rents. By varying the growth rates of market rents, mobility shares and the pass-through, they create a range of sensible rent CPI projections. The ideas presented in the Economic Commentary by Loewenstein et al. [2024] align with those of this study in spirit, yet the conceptualisation and modelling approaches differ markedly. Finally, Ball and Koh [2025] model the transmission from market rents to rent CPI inflation in the U.S., constructing an all-tenant rent series through a structural lag framework. A key parameter in their model is calibrated to maximise congruence with rent CPI inflation. Our approach instead builds the all-tenant rent index directly from micro-data, using hedonic asking rent indices, survival mappings, and rent adjustments of occupied rental units, without using the target of rent CPI in the construction.[3]

The construction of the asking rent index draws heavily from the extensive literature on hedonic adjustments. A good summary thereof can be found in Triplett and Bosworth [2006]. The hedonic adjustment methodology, as well as details on the construction of the rent CPI for Switzerland, are provided by the FSO [FSO, 2022a,b]. For additional sources of constructing asking rent indices from listing data not allowing tracking of rental units through time, consider Boeing et al. [2023]. Similarly, Loberto et al. [2022] use housing listing data to analyse market dynamics, demonstrating how unlinked cross-sectional data can still provide meaningful insights into housing price trends.

The effects of monetary policy shocks on various housing market outcomes in Switzerland have been studied in detail by Koeniger et al. [2022]. Similarly, Vonlanthen [2023] estimates the impact of different interest rates on the Swiss housing market, including rental prices. However, neither Koeniger et al. [2022] nor Vonlanthen [2023] estimate the joint effect of changes in the CPI and the reference interest rate on all-tenant rents. We address this gap by estimating the joint effect to better model rental price dynamics for already-occupied rental units.

Structure of the paper. The remainder of the paper is structured as follows. Section 2 describes the data and methodology used to construct the asking rent indices. Section 3 presents the model that links asking and all-tenant rents and outlines the construction of the all-tenant rent indices. Section 4 evaluates the performance of our all-tenant rent index relative to official measures.

2 Asking rent index

In this section, we first describe the data underlying our analysis and then outline the methodology used to construct the asking rent indices.

[3] Note that we use the rental component of the CPI to estimate how reference rate changes affect rents in Section 3.4. This analysis is entirely separate from the construction of the all-tenant rent index and can be viewed as independent research on rent policy in Switzerland.

2.1 Data

We obtain data from two sources. The main data are real estate listings of private household rental units from Comparis, a private online comparison company in Switzerland. The second data component consists of official statistics on the rental market in Switzerland, including information on the average duration of stay in a rental unit, as well as the number of people residing in each geographic region and the type of rental unit they occupy.

The real estate listings encompass all listed rental properties in Switzerland compiled by the online comparison company Comparis for the period from January 2005 to July 2025. Comparis offers the largest real estate portal for Switzerland. The listings are obtained through two channels: either by landlords entering the respective units directly on their website or by scraping listings from competing companies in Switzerland. For each listing, we observe the date the unit was put onto the rental market, whether it is a flat or a house, the monthly gross rent in Swiss francs (CHF), the zip code of the location, the living space size, the number of rooms, the floor and the year of construction of the unit.[4] Note that not all attributes are available for every listing. Table 1 displays the characteristics and the corresponding summary statistics, including the percentage of missing values.

We enrich the listing data with crucial rental market information that is not available in the listing data. First, we gather yearly data on the number of people living in rented or self-owned accommodations, for each canton of Switzerland.[5] Second, we collect data on the yearly and cantonal shares of people living in a unit with a given number of rooms. Third, we collect yearly data on the percentage of renters that move within a given year, by number of rooms of the rental unit [FSO, 2025].[6]

Attribute	Average	Std. deviation	Missing (%)
Gross rent (CHF)	1851	588	0
Number of rooms	3.4	1.48	0
Living space m^2	84.9	29.6	0
Floor	1.9	1.5	21.1
Year of construction	1982	31.1	53.8

Table 1: Descriptive statistics of the rental unit listings between 1 January 2005 and 1 August 2025. Additionally, each observation is associated with the date the listing is put on the market, the zip code of the location, and an identifier whether it is a flat or a house. We observe a total of $N = 3'759'427$ observations.

2.2 Methodology

A central component of rental price developments is rent adjustments that occur at tenant turnover. To model rental price changes coinciding with tenant changes, we need to track

[4] A zip code (postal code) refers to the numerical code assigned to a specific geographic area for mail delivery.

[5] The data can be accessed here: https://www.bfs.admin.ch/bfs/de/home/statistiken/katalog.assetdetail.33947407.html

[6] The data can be accessed here: https://www.bfs.admin.ch/bfs/en/home/statistics/construction-housing/dwellings/home-moves.assetdetail.33249785.html

rental price developments of units on the market. Measures that track these dynamics are commonly referred to as asking rent indices. To construct reliable asking rent indices from listings, we must address several challenges inherent to the raw data. Specifically, these include heterogeneity in unit characteristics, extreme outliers, and shifts in the composition of observed listings over time. We aim to derive an asking rent measure that is comparable week-to-week, robust to quality differences in market units, and representative of the conditions renters face in the market. We proceed in three steps.

First, we clean the raw listings by removing implausible values and distributional outliers, ensuring that the sample accurately reflects a realistic market distribution of rental units. Second, we adjust rents for observed unit characteristics, using a hedonic adjustment strategy. This isolates the unexplained, time-varying component of rents. Third, we aggregate these latent asking rent signals into granular sub-indices by canton and room count. To ensure representativeness, we rebase the sub-indices to a common reference year and construct an overall index using population-based weights that reflect the distribution of households across rental unit types.

We observe a collection of rental units indexed by $i \in [N]$, where $[N] \coloneqq \{1, \ldots, N\}$. Every observation is associated with a date on which the unit is published on the listing homepage, which we aggregate to a weekly frequency, indexed by $t \in [T]$. For every entry, we observe a possibly incomplete set of characteristics denoted by $X_{i,t}$, indicating whether it is a house or a flat, the corresponding zip code, the number of rooms, the living space, the floor and the year of construction of the building. Similarly, we observe the corresponding monthly gross rent in CHF, denoted by $Y_{i,t} \in \mathbb{R}_+$. Note that we cannot link later re-listings of the same unit. Each observation is defined by a unit's appearance at a specific point in time, so reappearances enter the data as new rental units. That is, for every week t in our sample, we have access to a sample of size N_t of the joint distribution $\mathbb{P}_{Y,X}$, denoted by $(Y_{i,t}, X_{i,t})_{i=1}^{N_t}$, such that $N = \sum_{t \in [T]} N_t$.

2.2.1 Outlier removal

We begin by removing two types of outliers. The first consists of obvious data-entry errors (e.g., a listing recorded with 35 instead of 3.5 rooms). The second consists of observations that appear extreme relative to the distribution of gross rents $Y_{i,t}$ conditional on rental unit characteristics $X_{i,t}$, partially due to missing information. For example, elevated rent can be due to unobserved amenities such as a roof terrace or a pool.

For the first type, which we term marginal-based outliers, we apply threshold-based plausibility checks and drop units with a gross rent below 300 CHF (0.1% of observations), more than 10 rooms (0.04% of observations), less than $8m^2$ of living space (0.05% of observations), or less than $5m^2$ average room size (0.07% of observations). For the second type, we adopt a model-based approach to flag observations identified as out-of-distribution relative to the conditional distribution $\mathbb{P}_{Y|X}$. Suppose the rental price of a unit is generated via

$$Y_{i,t} = f(X_{i,t}) + \lambda_{i,t}, \;\; i \in [N] \tag{1}$$

where $\lambda_{i,t}$ is a composite error term composed of the time-varying market rent dynamics, and a mean-zero stochastic error term. Consider Section 2.2.2 for more details. We estimate f, denoted by $\widehat{f}$, using outlier-robust linear regression and form the realized-to-predicted rent ratios $r_{i,t} := Y_{i,t}/\widehat{f}(X_{i,t}),\ i \in [N]$.[7] Observations with a ratio not contained in the interval between 0.5 and 2, i.e., realised gross rents less than half or more than twice the predicted values, are flagged as outliers, indicating a substantial deviation from $\mathbb{P}_{Y|X}$.[8] Concretely, we estimate f by estimating the parameters of the following specification for the conditional expectation of gross rents $Y_{i,t}$[9]

$$\begin{aligned} f(x) := \mathbb{E}[Y_{i,t} \mid X_{i,t} = x] = & \sum_{g \in \mathcal{G}} \beta_{0,g} \mathbb{1}\{\text{group} = g\} \\ & + \sum_{g \in \mathcal{G}} \beta_{1,g} \text{living space} \times \mathbb{1}\{\text{group} = g\} \\ := & x^\top \eta, \end{aligned} \tag{2}$$

where $\mathcal{G}$ is the set of groups defined by the corresponding zip code, unit type (house/flat), and the number of rooms, see Appendix A.1 for more details. Further, x denotes the $(2|\mathcal{G}| \times 1)$-dimensional vector of observable characteristics of the rental unit i, and η is a vector of parameters.[10] We estimate the parameters $\eta = (\beta_{0,g}, \beta_{1,g})_{g \in \mathcal{G}}$ of Equation (2) using the outlier-robust Huber loss-function while forcing all coefficients to be non-negative since gross rents $Y_{i,t}$ are positive. See Appendix B.1 for more details on the estimation procedure.

Crucially, we re-estimate the parameters every calendar year using data from that year only and apply the model to the subsequent year. This captures the upward trend of gross rents in Switzerland and yields the interpretation that an observation is an outlier if the price is extreme compared to a similar unit (flat/house) with the same characteristics in terms of zip code, living space, and number of rooms in the previous year. Overall, we remove 1.3% of observations through outlier detection, retaining a total of $3,700,000$ observations, indexed by $i \in [N']$. Figure 1.a visualises the different types of outliers, while Figure 1.b shows the cut-off applied in the model-based outlier detection.

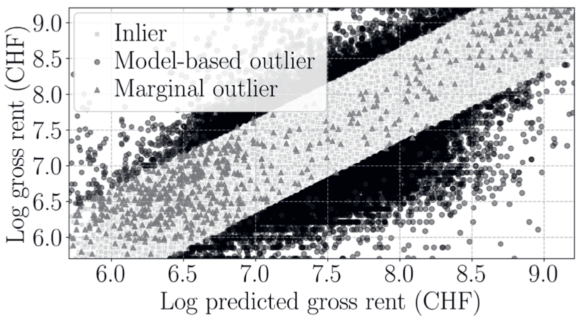
2.2.2 Hedonic adjustment

Asking rent indices are designed to measure changes in the rental prices of properties currently offered on the market. Ideally, they follow the rents of a fixed set of units over time. This approach eliminates quality differences that arise when comparing different rental units and isolates the time-varying component of asking rents that is of primary interest. To replicate this and adjust for quality effects when using unlinked listing data, we proceed as follows.

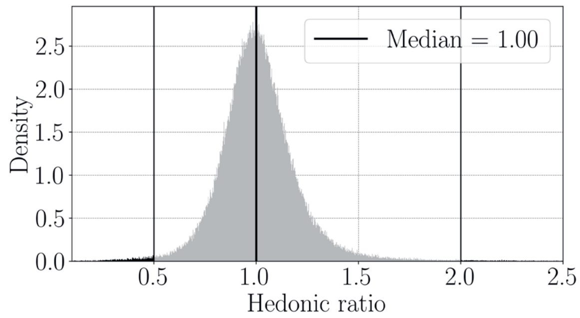
Conceptually, assume the generating Equation (1) of gross rents can be linearly decomposed into

$$Y_{i,t} = f(X_{i,t}) + \underbrace{\nu_t + \varepsilon_{i,t}}_{=\lambda_{i,t}},\ i \in [N'] \tag{3}$$

[7] Although Equation (1) is presented additively, we report results as rent ratios for clearer interpretation and consistency with standard hedonic practice.
[8] We consider different thresholds to define outliers, for details see Appendix D.
[9] Consider Section 2.2.2 for a detailed discussion of the covariates $X_{i,t}$.
[10] We relax the assumption of linearity in Appendix D.



1.a. Scatter plot of gross rent against predicted gross rent from a random sample of 200′000 observations. The black dots are model-based outliers, the gray triangles are marginal-based outliers, and the grey dots denote inliers.



1.b. Histogram of realized to predicted gross rent ratios r of $200'000$ randomly sampled observations. The area shaded in black is the model-based outlier region $(-\infty, 0.5] \cup [2, \infty)$.

In this context, f encodes the time-invariant relationship between gross rents and unit characteristics. As described in Section 2.2.1, we include the type of unit (house/flat), zip code, number of rooms, and living space as such factors. The error term $\lambda_{i,t}$ is composed of $\nu_t + \varepsilon_{i,t}$. Here, ν_t represents the latent asking rent development of interest, reflecting shifts in overall market rents, while $\varepsilon_{i,t}$ is a mean-zero, finite-variance noise term capturing unpredictable fluctuations unexplained by other components. Thus, the gross rent of a rental unit consists of a time-invariant component determined by its characteristics and a time-varying component reflecting market conditions and rent dynamics of interest.

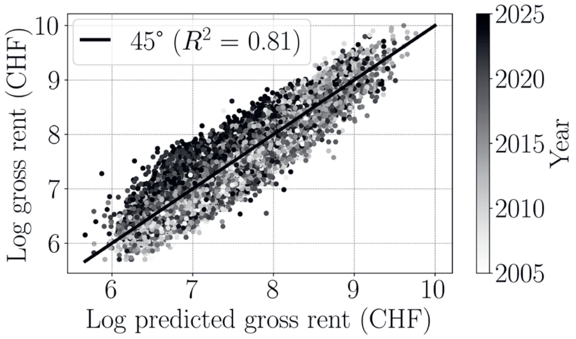
Remark 1 (Heterogeneity in market dynamics ν_t) *The market dynamics ν_t may differ across rental unit types, and can, for example, vary by canton and unit type. For simplicity, we present a common process for all units in this exposition. Further details on heterogeneity are provided in Section 2.2.3.*

As in the outlier detection strategy in Section 2.2.1, we begin by estimating f, which serves to adjust the raw gross rents for observed characteristics. That is, the component of gross rents that is not explained by these unit characteristics is given by

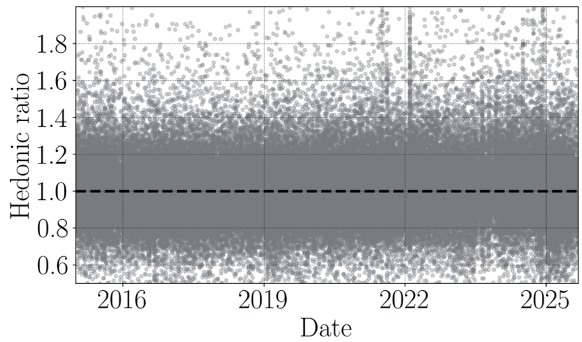
$$r'_{i,t} := Y_{i,t} - \widehat{f}(X_{i,t}), \; i \in [N']. \tag{4}$$

To improve the interpretability of the resulting asking rent indices, we consider a slight modification of $r'_{i,t}$, given by $r_{i,t} := Y_{i,t}/\widehat{f}(X_{i,t}) \cdot 100\%$ as described in Section 2.2.1. This yields ratios that can be interpreted in terms of percentage differences of actual gross rents to predicted gross rents. Details on the estimation of $\widehat{f}$ are provided in Appendix B.2.

In Figure 2.a, we plot predicted gross rents against realised gross rents, achieving an out-of-sample R^2 of 0.81. This is comparable to the FSO's hedonic adjustment for the rent component of the CPI, which attains an out-of-sample R^2 of 0.79 [FSO, 2022a]. While the FSO model includes a substantially larger set of explanatory variables that are not available to us, our ability to control for ZIP-code effects appears to compensate for this difference in model complexity. Figure 2.b further reveals the distribution of realised-to-predicted rent ratios $r_{i,t}$ over time, illustrating the components underlying the asking rent indices constructed in the subsequent Section 2.2.3.



2.a. Scatter plot of gross rent against predicted gross rent of 200′000 randomly sampled observations. The overall out-of-sample R^2 is given by 0.81.



2.b. Random sample of 200′000 hedonic ratios $r_{i,t}$ against the date of market appearance. The hedonic ratios are the basic building blocks of the asking rent indices.

2.2.3 Construction of asking rent index

To study rent dynamics in Switzerland, we construct a granular system of sub-indices, rather than relying on a single national index. Aggregating prices across heterogeneous units can obscure important patterns, such as whether price changes are driven by specific cantons or certain apartment types. Furthermore, by appropriately weighting the sub-indices, we ensure that the national aggregate reflects the actual distribution of tenants across regions and housing types.

We focus on developments for groups of rental units characterised by the canton and the number of rooms. For example, one such group might be two-room rental units in the canton of Zurich. We index these groups by $a \in [A]$, and summarise the distribution of realised-to-predicted rent ratios for each week $t \in [T]$ using the corresponding average

$$I'_{a,t} := \frac{1}{N_{a,t}} \sum_{i \in [N_{a,t}]} r_{i,t}, \tag{5}$$

where $N_{a,t}$ denotes the number of listings belonging to group a in week t.[11] In total, we construct $A = 53$ groups, combining some cantons to ensure enough observations per week and room category. Further details are provided in Appendix B.4. We then rebase all sub-indices to the year 2014, i.e., for all groups $a \in [A]$ and weeks $t \in [T]$

$$I_{a,t} := \frac{I'_{a,t}}{\bar{I'}_{a,T_b}} \cdot 100\%, \tag{6}$$

where $\bar{I'}_{a,T_b}$ denotes the average of $I'_{a,t}$ across the calendar year 2014. This yields the collection of asking-price sub-indices $(I_{a,t})_{a\in[A],t\in[T]}$. We display the set of asking rent sub-indices in Figure 3.b, highlighting the importance of granularity.

Finally, we outline the procedure for aggregating the asking rent sub-indices into an overall asking rent index. This index tracks the average asking rent development of Switzerland over time. Crucially, we want this *average* to reflect developments from the perspective of tenants. That is, it is weighted by the population living in different types of rental units

[11] We also experiment with other summary statistics such as the median – see Appendix D.

rather than simply mirroring the composition of current listings.[12]

To implement this, we draw on the transportability literature in causal inference [Pearl and Bareinboim, 2011]. In essence, we have group-level sub-indices for each canton-room group, estimated from listing data. We aim to apply these estimates to a target population, specifically Swiss tenants. The key assumption is that we can accurately estimate the asking rent index for each such group, while the weights of these groups, derived from listings, may arbitrarily diverge from Swiss tenant weights. We display the weights over cantons derived from listings and official statistics in Figure 3.a, which highlights the differences between both measures. We transport the sub-indices to the population of Swiss tenants by using the law of total expectation

$$\mathbb{E}[\nu_t] = \sum_{a\in[A]} \mathbb{E}[\nu_t \mid A = a]p(a), \tag{7}$$

where $p(a)$ is the probability mass function over groups in the target population of Swiss tenants.

We use official statistics as described in Section 2.1 to derive the corresponding weights as estimates of $p(a)$. That is, the weight $w_{a,t}$ of any group a in week t is given by the (normalised) share of people living in a rental unit belonging to group a in the two previous calendar years, assuming the share of renters is equal for different numbers of rooms.[13] Normalised refers to weights summing to 1 for each $t \in [T]$. We use the share from two years prior, as the most recent data is not yet available due to publication delays. Thus, the overall asking rent index for any week $t \in [T]$ is given by

$$I_t := \sum_{a\in[A]} I_{a,t} w_{a,t}. \tag{8}$$

Remark 2 (Tenant distribution weights) *If the indices are not explicitly weighted, $p(a)$ is implicitly determined by the relative frequency of listings in group a during week t. This approach yields week-dependent weights driven by the number of listings. In contrast, we aim for more time-stable weights based on the empirical distribution of people living in each type of unit.*

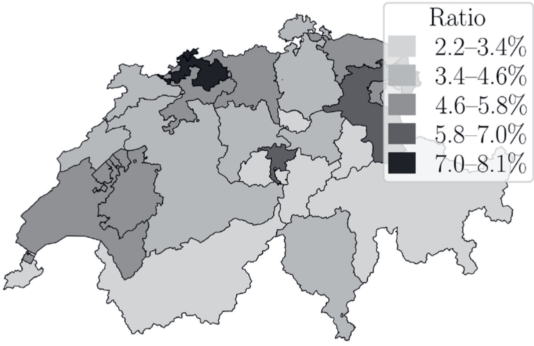
We visualise the overall asking rent index I_t in Figure 3.b.

3 All-tenant rent index

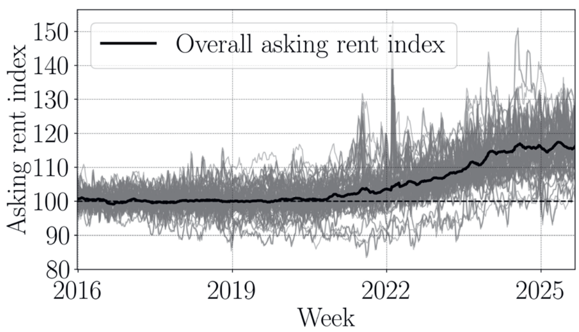
In this section, we describe how we build all-tenant rent indices. First, we provide intuition and motivation behind how we construct the all-tenant rent index. Then, we present the model and describe the resulting all-tenant rent indices.

[12] Both perspectives are meaningful. A listing weighted index can reveal dynamics on the supply side, while a population weighted index captures price changes as they matter for tenants. However, since we must use population-based weights when constructing the index for all-tenant rents, we introduce the former weighting approach to ensure consistency.

[13] This assumption is required since, for Switzerland, we have information on the share of people living in a unit with a given number of rooms per canton and information on the share of renters per canton, but no joint information.



3.a. Representativeness of observed listing frequency compared to the number of rental units by canton, for the year of 2023. The value for a canton is given by the ratio of the number of listings to the total number of rental units for the year 2023.



3.b. Asking rent sub-indices defined by canton and number of rooms and the overall asking rent index. For more details on the grouping of cantons and the number of rooms, consider Appendix B.4.

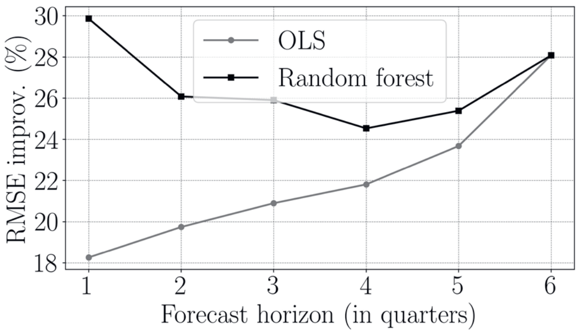
3.1 Motivation

Previous research has shown that nearly all differences between asking rents and all-tenant rent measures can be attributed to the higher rent growth rates experienced by new tenants compared to the overall tenant population [Adams et al., 2024]. Since new tenant rents gradually flow into the existing rent stock, asking rents can be seen as a leading indicator of future developments in the all-tenant rent index [Ambrose et al., 2015]. The following thought experiment illustrates this dynamic. Assume rental prices only change when new tenants move in. If asking rents were frozen at a value a at time t, the all-tenant rent index would only converge to a once every tenant had moved at least once, a process that takes a long time. This motivates our strategy of modelling all-tenant rental prices. As in the thought experiment, we first model all-tenant rents using past asking rents, assuming that rental prices change only when tenants do. Later, we relax this assumption and also model rental price changes for occupied units.

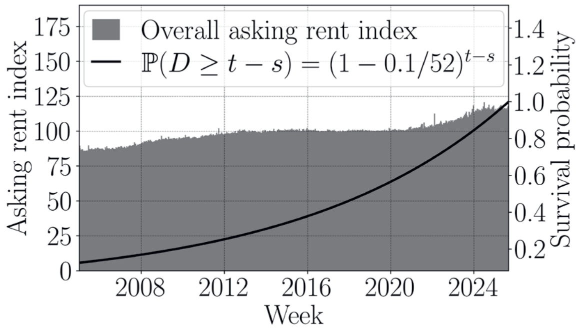
To further motivate the importance of asking rent developments for subsequent all-tenant rent developments, consider the following forecasting exercise. We forecast quarterly first difference of rent CPI (denoted by $\Delta c^r_{t+h} \coloneqq c^r_{t+h} - c^r_{t+h-1}$) in Switzerland once using past rent CPI values ($\Delta c^r_{t-\ell}, \ell = 0, \dots, q$), and once using past rent CPI values, and past asking rents ($\Delta I_{t-\ell}, \ell = 0, \dots, q$). We estimate both a linear regression model and a Random Forest regression model on the training set indexed by $t \in [T']$, and evaluate their performance on the test set $t \in [T] \setminus [T']$ [Breiman, 2001]. Figure 4.a displays the percentage improvements on the order of 25% regarding the empirical RMSE of the enhanced information set. For more details, see Appendix E. This is a consequence of the slow transmission of market rent prices into existing rents, resulting in the observed lead-lag relationship between asking and existing rents.

3.2 Model

The all-tenant rent index aims to track average rental prices over time. Importantly, it measures rental prices of the full collection of rental units – contrary to asking rents, which



4.a. Percentage RMSE improvements (%) of forecasting rent CPI gained through including the asking rent index in addition to past rent CPI, by forecast horizon and method of estimation.



4.b. The overall weekly asking rent index is displayed on the left y-axis. The right y-axis displays the geometric survival function for a weekly moving probability of 0.1/52, where 0.1 (10%) is roughly the average yearly moving quote in Switzerland.

refer to rental prices of units on the market. In the absence of surveys, all-tenant rents are inherently latent. However, in almost all countries, alterations in rental prices are governed by laws and may hence be attractive to model. Crucially, the biggest changes in rental prices occur when tenants change – at which point the unit appears on the market, making the new rental price observable. Conceptually, to construct an all-tenant rent index, we require access to a random sample of rental units and corresponding changes in gross rent, as depicted in Figure 5. There are two distinct types of gross rent changes. First, rental price changes coincide with the unit appearing on the market, and second, rental price changes of occupied units. In the following sections, we demonstrate how to model both types of price changes.

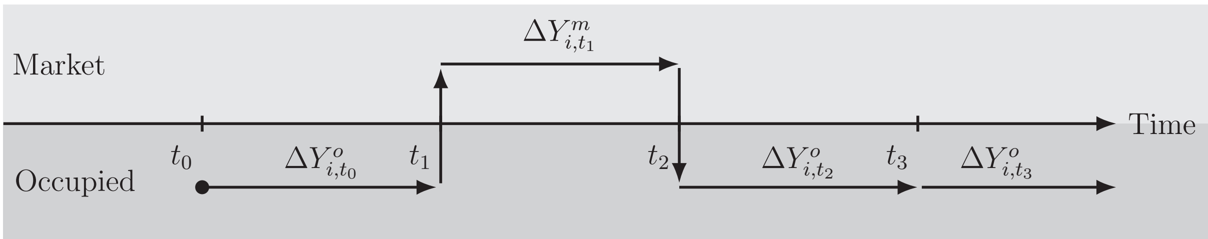


Figure 5: State transitions of rental units. If any unit $i \in [n]$ is in the occupied state in week t, it is occupied by the same tenants as in week $t-1$. If any unit is in the market state, it is currently listed on the market. Lastly, $\Delta Y^m_{i,t}$ denotes the change in gross rent of the unit i in week t, where m (respectively o) indicates that it is a change of gross rent while in the market state (occupied state).

3.3 Rent changes of units on the market

Rental price changes of the first kind are well-suited for modelling using listings data. If every rental unit is uniquely identified, the task reduces to collecting changes in rental prices for all such units whenever any of these units reappears on the market. However, as explained in Section 2, we do not have access to time-independent unit identifiers and thus must take a different approach. For now, suppose that changing tenants and, therefore, market appearance are the sole reasons for alterations in rental prices. This assumption is lifted in the subsequent Section 3.4.

Assumption 1 (Intermediate: rents of occupied units) *Rents may only change when the unit appears on the market, i.e., tenants change.*

Let $S \in \mathbb{N}$ be a random variable governing when a rental unit is put onto the market. Let $D \in \mathbb{N}$ be a random variable of the duration with which tenants stay in the unit, and let $Y \in \mathbb{R}_+$ be the random variable of the gross rent. Every listing is a sample from the joint distribution of (S, D, Y), denoted by $\mathbb{P}$. However, the duration of occupancy for each unit is not observed. For every week $t \in [T]$, we aim to identify

$$\mathbb{E}_t [Y \mid A = a] := \mathbb{E}[Y \mid A = a, S \leq t, D \geq t - S], \tag{9}$$

where $a \in [A]$ indexes the groups defined by canton and the number of rooms. In words, this is the expectation of gross rent over *uncensored* units in week t for the different groups. Uncensored, i.e., the event $E := \{S \leq t, D \geq t - S\}$ ensures that only the most recent gross rent of each unit is considered, since rents may change upon market appearance. In particular, $S + D < t$ implies that the unit reappeared on the market at some point in the past, indicating that the associated gross rent Y may have changed.

Since we cannot identify rental units reappearing on the market, the duration of stay is unobserved. To identify the unit of interest of Equation (9), we need to place an assumption on the duration of stay. We assume that, for each rental unit group $a \in [A]$ and starting week $s \in [S]$ of the tenancy, the latent duration of stay is independent of rental price.

Assumption 2 (Conditional independence of D, Y) *For any group $a \in [A]$ and week $s \in [S]$, the duration of stay D is independent of the gross rent Y, i.e.,*

$$D \perp Y \mid A = a, S = s \tag{10}$$

The assumption is motivated by the following points.[14] First, acquiring knowledge about whether you under- or overpay as a tenant is difficult, since it requires access to rental prices of comparable rental units in terms of location and other characteristics. Second, the monetary and emotional costs of moving are high. Third, finding an adequate replacement for the previous rental unit is hard, especially when there is a shortage of rental units.

Remark 3 (Linked listings and duration of stay) *If market appearances of rental units can be tracked over time using rental unit identifiers, then $\mathbb{E}_t[Y \mid A = a]$ is trivially estimated as the average over the most current gross rents of all units of group $A = a$.*

For simplicity, since the arguments follow through unaltered, we develop the ideas for the unconditional version $\mathbb{E}_t[Y]$ instead of $\mathbb{E}_t[Y \mid A = a]$. Under Assumptions 1 and 2, we

[14]Technically, we merely need to assume the following independence: $Y \perp \mathbb{1}_{\{D \geq t-s\}} \mid A = a, S = s$. However, we choose Assumption 2 for readability.

express

$$
\begin{aligned}
\mathbb{E}_t[Y] &:= \mathbb{E}[Y \mid S \leq t, D \geq t-S] \\
&= \frac{\mathbb{E}[Y \mathbb{1}_{\{S \leq t, D \geq t-S\}}]}{\mathbb{P}(S \leq t, D \geq t-S)} \\
&= \frac{\sum_{s=0}^{t} \mathbb{E}[Y \mathbb{1}_{\{D \geq t-s\}} \mid S=s]\mathbb{P}(S=s)}{\sum_{s=0}^{t} \mathbb{P}(D \geq t-s \mid S=s)\mathbb{P}(S=s)} \\
&= \frac{\sum_{s=0}^{t} \mathbb{E}[Y \mid S=s]\mathbb{E}[\mathbb{1}_{\{D \geq t-s\}} \mid S=s]\mathbb{P}(S=s)}{\sum_{s=0}^{t} \mathbb{P}(D \geq t-s \mid S=s)\mathbb{P}(S=s)} \\
&= \frac{\sum_{s=0}^{t} \mathbb{E}[Y \mid S=s]\mathbb{P}(D \geq t-s \mid S=s)\mathbb{P}(S=s)}{\sum_{s=0}^{t} \mathbb{P}(D \geq t-s \mid S=s)\mathbb{P}(S=s)} \\
&:= \psi_t',
\end{aligned}
\tag{11}
$$

where we used the law of total expectation and probability in the third line, Assumption 2 in the fourth line as $\mathbb{E}[XY \mid S=s] = \mathbb{E}[X \mid S=s]\mathbb{E}[Y \mid S=s]$ if $X \perp Y \mid S=s$, and $\mathbb{E}[\mathbb{1}_{\{A\}}] = \mathbb{P}(A)$ in the fifth line. That is, the all-tenant rent in week t is a weighted average of past asking rents, with weights determined by the probability that a unit has been occupied since then.

In detail, the final expression ψ_t' contains three components. The *first* component $\mathbb{E}[Y \mid S=s]$ is the expected asking rent of rental units placed on the market in week $S=s$, described and estimated in Section 2. The *second* component of ψ_t' is the conditional survival function of the tenant's duration of stay, given by $\mathbb{P}(D \geq t-s \mid S=s)$. It captures the probability that a rental unit is still being occupied by the tenants who moved in during week $S=s$. Since durations are unobserved in our data, we rely on external sources to estimate this survival function. The Swiss Statistical Office (FSO) publishes yearly moving quotes p for rental units of different number of rooms, as displayed in Figure 6.a.[15] A moving quote of 10% in a given year for one-room units means that 10% of renters living in one-room units moved within that year.[16] Each week can be viewed as a Bernoulli trial, where the tenant moves out with probability $p/52$ and stays with probability $1-p/52$. Under this interpretation, the duration of stay follows a geometric distribution.

Assumption 3 (Duration of stay is geometrically distributed) *The duration of stay after moving in during week $S=s$ for a unit with a number of $R=r$ rooms is geometrically distributed, with the probability of moving being determined by the observed moving quote $p_{s,r}$, i.e.,*

$$D \mid S=s, R=r \sim \text{Geom}(p_{s,r}). \tag{12}$$

From Assumption 3, it follows that the conditional survival function is given by

$$\mathbb{P}(D \geq t-s \mid S=s, R=r) = (1-p_{s,r})^{t-s}, \text{ for all } t-s \in \mathbb{N}. \tag{13}$$

The *third* component of ψ_t' is the marginal distribution of starting dates of listings, denoted by $\mathbb{P}(S=s)$. This is identifiable since we observe the number of listings put onto the

[15]Unfortunately, there is no joint information on the moving quotes by canton and the number of rooms.

[16]To convert this to weekly frequency, we assume that the movers are uniformly distributed over the year with 52 weeks, meaning that 10%/52 ≈ 0.2% of people move in every week in the corresponding year.

market every week $s \in [T]$. Empirically, we find that the distribution of starting dates is close to uniform $\mathbb{P}(S = s) \approx 1/T$ for the period between 2015 and 2025, with seldom outliers and some seasonal patterns. When considering the full period from 2005 to 2025, we observe an increase in the number of listings per week. This is a result of internal changes that enable the listing company to cover an increased market share of listings. In light of these findings, we forgo estimating the marginal distribution and assume that $\mathbb{P}(S = s) = 1/T$, leading to $\mathbb{P}(S = s)$ canceling in ψ'_t. We denote the subsequent expression by ψ_t.

This implies the following, straightforward estimation of the all-tenant rent sub-indices, denoted by $I^{e\prime}_{a,t}$. For any given week $t \in [T]$ and all groups $a \in [A]$, we define

$$I^{e\prime}_{a,t} := \frac{\sum_{s=0}^{t} I_{a,t}(1 - p_{s,r})^{t-s}}{\sum_{s=0}^{t}(1 - p_{s,r})^{t-s}}, \tag{14}$$

where the number of rooms r align with the number of rooms component of group a. Finally, the granular sub-indices are aggregated as described in Section 2.2.3. This yields an overall all-tenant rent index relative to all tenants in Switzerland. That is, for all weeks t, we compute

$$I^{e\prime}_{t} := \sum_{a \in [A]} w_{a,t} I^{e\prime}_{a,t}. \tag{15}$$

Furthermore, we show that the all-tenant rent estimator in Equation (15) possesses desirable statistical properties. Under mild assumptions, we establish its consistency. Further details are provided in Appendix F.

Theorem 1 (Consistency of all-tenant rent index) *Under Assumptions 1 to 3, for any fixed week $t \in [T]$, as $N_{a,t} \to \infty$ for all $a \in [A]$, it holds*

$$I^{e\prime}_{t} \xrightarrow{\mathbb{P}} \psi_t, \tag{16}$$

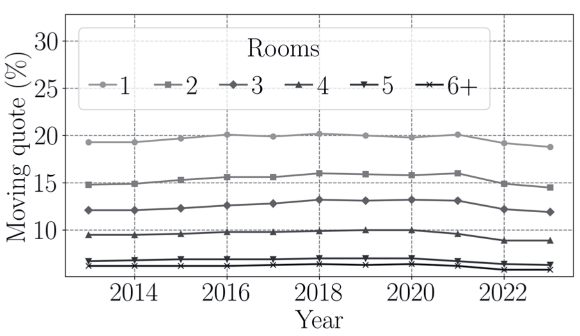
where $\xrightarrow{\mathbb{P}}$ denotes convergence in probability.

Proof. See Appendix F. ∎

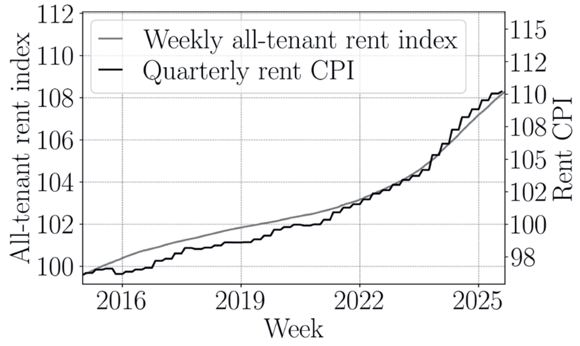
Figure 6.b compares the preliminary weekly all-tenant rent index I^e_t with the official quarterly rent CPI. Aggregating I^e_t to quarterly frequency yields a Pearson correlation coefficient of 0.99 with the rent CPI, indicating an almost perfect linear association. For the corresponding year-over-year growth rates, the correlation remains high at 0.86, suggesting that the index closely tracks both the level and the dynamics of official rent price measures.

3.4 Rent changes of occupied units

In Section 3.3, we describe how to estimate the collection of all-tenant rent expectations $\mathbb{E}_t[Y \mid A = a]$ for all weeks $t \in [T]$ and all groups $a \in [A]$. This was developed under the intermediate Assumption 1 that rental prices change only when tenants change. As indicated in Figure 5, there may be rental price changes in occupied units. As in most countries, conditions for such price changes are governed by laws. In Switzerland, changing rental prices in occupied units is allowed for the following four reasons.



6.a. Yearly moving quote by number of rooms for 2013 – 2023. The more rooms a rental unit has, the longer people stay on average.



6.b. Preliminary weekly all-tenant rent index $I_t^{e\prime}$ compared to quarterly rent CPI. The Pearson correlations in levels are 0.99 and 0.86 for the year-on-year series.

1. Changes in reference interest rate
2. Changes in CPI
3. Changes in maintenance and operating costs
4. Major non-value preserving conversions or renovations

We first demonstrate how to model the former two reasons and subsequently discuss the latter two reasons.[17]

Switzerland introduced the reference interest rate in September 2008 to harmonise claims for rental price changes arising from movements in mortgage interest rates. The quarterly reference interest rate r_q is the volume-weighted average interest rate of all domestic mortgages granted by banks in Switzerland, rounded to the nearest quarter of a percent. If a rental contract is signed under the reference rate $r_{q'}$, or the currently denominated reference rate in the contract is $r_{q'}$, then a rental price adjustment may be claimed. Specifically, landlords may increase rent by 3% for every 0.25 percentage point increase in r_q, while tenants may request a reduction of 2.91% for every 0.25 percentage point decrease. For example, if $r_q = 0.50\%$ and $r_{q'} = 0.25\%$, a rent increase of $0.25 \cdot 3\% = 0.75\%$ can be claimed. The claim must be sent to the counterpart in writing, and upon agreement, it will take effect after the current notice period has passed.[18]

The concept is similar for changes in CPI. Let c_t' denote the CPI value currently denominated in the contract, while the current value is c_t. This justifies a percentage point change of the rental price of

$$\frac{c_t - c_{t'}}{c_{t'}} \cdot 40\%. \tag{17}$$

Since both CPI and the reference interest rate are observed, we aim to estimate the effect of changes in these components on average rents. We use the official rental price index

[17]Other possible grounds for rent adjustments include expiring temporary rent reductions, increases in landlord taxes or public charges, corrections of abusive initial rents, or adjustments to bring rents in line with prevailing market levels. These cases occur less often and are therefore not considered here.

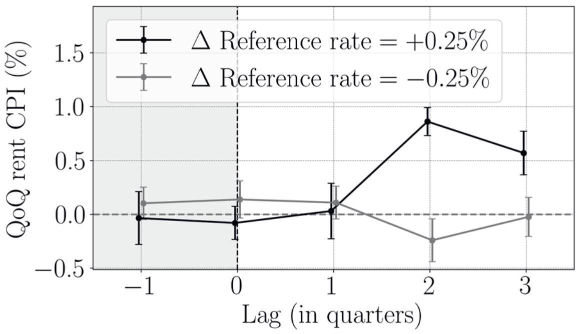
[18]For full details, including adjustments when the reference rate exceeds certain thresholds, see the guidelines of the Swiss Federal Office for Housing: https://www.bwo.admin.ch/bwo/en/home/Wohnungssuche/mietzins/mietzinsreduktion.html.

provided by FSO as the measurement for rent developments. We denote the rental price index, which is of quarterly frequency and constructed survey-based by c_q^r.

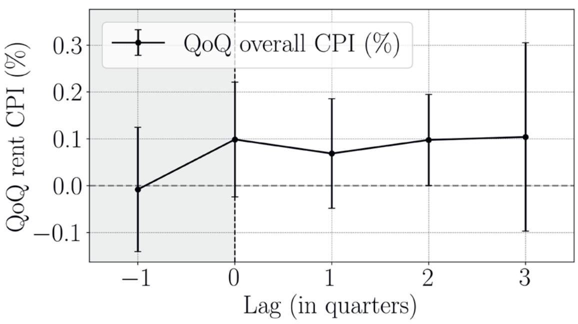
We now turn to the identification assumptions and estimation of the effects of interest. Assume the generating equation of the rental price index c_q^r is linear in the logs of past reference rates and past CPI values and has an auto-regressive structure, specifically,

$$\begin{aligned} \Delta \log c_q^r = \alpha_0 &+ \sum_{\ell_0 \in L_0} \alpha_{\ell_0} \Delta \log c_{q-\ell_0}^r \\ &+ \sum_{\ell_1 \in L_1} \alpha_{\ell_1} \mathbb{1}\{\Delta r_{q-\ell_1} = 0.025\} \\ &+ \sum_{\ell_2 \in L_2} \alpha_{\ell_2} \mathbb{1}\{\Delta r_{q-\ell_2} = -0.025\} \\ &+ \sum_{\ell_3 \in L_3} \alpha_{\ell_3} \Delta \log c_{q-\ell_3} + \epsilon_q, \end{aligned} \tag{18}$$

where $\Delta \log X_q := \log(X_q) - \log(X_{q-1})$ and ϵ_q being a mean-zero, finite variance noise term. The set of lags $L_0 = \{1, 2, 3, 4\}$ is chosen to capture the auto-regressive nature of $\Delta \log c_q^r$, while $(\alpha_{\ell_1})_{\ell_1 \in L_1}$ are the dynamic coefficients of interest for increases in the reference rate. Conversely, $(\alpha_{\ell_2})_{\ell_2 \in L2}$ denote the dynamic coefficients of interest for decreases in the reference rate. We estimate the effects of increases and decreases separately, as, although they should be nearly equal by law, the probability of enforcing the change differs in both cases. Lastly, $(\alpha_{\ell_3})_{\ell_3 \in L_3}$ denote the dynamic coefficients of interest for changes in CPI. We use $L_1 = L_2 = L_3 = \{-1, 0, 1, 2, 3\}$ since the effects of changes in the reference rate and inflation rate ought to translate to rent CPI c^r within a year. Furthermore, the lags $\ell \in \{-1, 0, 1\}$ serve as placebo periods as enforcing rent changes takes at least 3 months. We estimate the parameters of Equation (18) using OLS while employing heteroskedasticity and autocorrelation (HAC) robust standard errors [Newey and West, 1987].[19] We assume that the effects of both the reference rate and CPI are homogeneous in the period of analysis.



7.a. Estimated effects of changes in the reference rate on quarter-on-quarter rent CPI growth (%) along with 95% confidence intervals.



7.b. Estimated effects of changes in the inflation rate on quarter-on-quarter rent CPI growth (%) along with 95% confidence intervals.

We find that the two- and three-quarter-ahead effects of increases in the reference rate are significantly different from zero at a significance level of 5%, while the two-quarter-ahead effect of decreases in the reference rate is also significant. The impact of changes in

[19] We employ a bandwidth of 4 quarters according to the autocorrelation of $\Delta \log c_q^r$.

inflation is not deemed significantly different from 0, for any of the lags. Consider Figure 7.a and Figure 7.b for an overview.

Not seeing effects for inflation is expected, since inflation rates were relatively low over the period of estimation of $2008-2025$ and increasing rental prices as a reaction to inflation spikes is uncommon in Switzerland. It is more common to enforce this rule at arbitrary points in time – or to bundle such claims with increases of the reference rate to lower the administrative burden. Thus, we decide not to model the effect of changes in CPI on rental prices, since we cannot reject the null hypothesis of there being no channel of influence. The estimates for the impact of changes in the reference rates are also confirmatory. Not being able to reject the null-hypothesis for the current and subsequent quarter is in line with Swiss law since, after contacting the landlord (tenant), and agreeing upon such a change, it is put into place after the current period of notice, which is normally 3 months in Switzerland.[20]

Remark 4 (Interpretation of coefficients) *The estimated coefficients of the reference rate and CPI changes bear an interesting interpretation. Let $J \in \{0,1\}$ denote whether a change in the rental price is justified, based on the reference rate denominated in the contract and the current reference rate. Let $E \in \{0,1\}$ denote whether such a change is enforced. For a fixed change $\delta \in \{-0.25, 0.25\}$ of the reference rate r, defining $w_{e,j} \coloneqq \mathbb{P}(E = e \mid J = j)\mathbb{P}(J = j)$, the corresponding coefficient $\alpha(\delta) \in \{2.91\%, 3\%\}$ for a given lag ℓ of Equation (18) estimates*

$$
\begin{aligned}
&\mathbb{E}[c^r \mid R_{ref} = r + \delta] - \mathbb{E}[c^r \mid R_{ref} = r] \\
&\quad= \sum_{j\in\{0,1\}} \sum_{e\in\{0,1\}} \mathbb{E}[c^r \mid R_{ref} = r + \delta, E = e, J = j]w_{e,j} - \mathbb{E}[c^r \mid R_{ref} = r, E = e, J = j]w_{e,j} \\
&\quad= \sum_{j\in\{0,1\}} \mathbb{P}(E = 1 \mid J = j)\mathbb{P}(J = j)\left(\mathbb{E}[c^r \mid R_{ref} = r + \delta, J = j] - \mathbb{E}[c^r \mid R_{ref} = r, J = j]\right) \\
&\quad= \sum_{j\in\{0,1\}} \mathbb{P}(E = 1 \mid J = j)\mathbb{P}(J = j)\alpha(\delta)\delta \\
&\quad= \mathbb{P}(E = 1)\alpha(\delta)\delta,
\end{aligned} \tag{19}
$$

where we used the law of total expectation in the first line, $\mathbb{E}[c^r \mid R_{ref} = r + \delta, E = 0] = \mathbb{E}[c^r \mid R_{ref} = r, E = 0]$ in the second line, and the assumed linearity of the conditional expectation in line three. For $\delta = 0.25\%$, we have that $\delta \cdot \alpha(\delta) = 0.25 \cdot 3\% = 0.75\%$. Conversely, $\delta \cdot \alpha(\delta) = -0.73\%$ for a change of the reference rate of -0.25%. That is, if we observe asymmetries in $\widehat{\alpha}$ between increases and decreases of the reference rate that exceed the small legal difference between 0.75% and −0.73%, they must be driven by the fraction of tenants who can justifiably request a change and by the share for which such a change is actually implemented. The same interpretation holds for changes due to CPI.

To incorporate the effects of reference rate changes on the all-tenant rent sub-indices, we take the estimated dynamic effects that are deemed different from 0 at a confidence level of 5% and add them to the growth rates of the all-tenant rent sub-indices. That is, we

[20] Contemporaneous effects are not possible, since reference rate changes are communicated quarterly in March, June, September, and December, while the rental index of CPI is adjusted quarterly in February, May, August, and November.

assign, for all $a \in [A]$, $t \in [T]$, $\delta_2 = 0.025, \delta_3 = -0.025$ and $j = 2, 3$

$$\Delta \log I^e_{a,t} \coloneqq \Delta \log I^{e\prime}_{a,t} + \sum_{j \in \{2,3\}} \widehat{\alpha}_{\ell_j} w_t(q) \mathbb{1}\{\Delta r_{t-\ell_j} = \delta_j\}, \tag{20}$$

where $w_t(q)$ are triangular weights distributing the quarterly effects to the different weeks t in the quarter q, and $\Delta r_t \coloneqq \Delta r_q$ for all weeks t in the respective quarter q.[21] Finally, to transform the log-growth rates to levels and rebase each sub-index to 100 in the first period corresponding to the first week of 2015, we compute for all $t \in [T]$ and all groups $a \in [A]$

$$I^e_{a,t} = I^e_{a,t=1} \exp\left(\sum_{s=1}^{t-1} \Delta \log I^e_{a,s+1}\right), \tag{21}$$

where $I^e_{a,t=1} = 100$. Following that, the overall all-tenant rent index is computed as described in Equation (15).

As previously discussed, changes in maintenance costs and general cost increases, as well as major non-value-adding renovations, are also legitimate reasons to increase rental prices. While general price changes could arguably be proxied using publicly available data, we do not model this component as they occur very seldom in Switzerland and, more importantly, are closely linked to changes in rental prices due to changes in the CPI. Renovations of occupied rental properties that increase property value are unobserved and can thus not be modelled. We assume that such renovations do not vary systematically over time and are hence not relevant to the model for capturing average all-tenant rents.[22]

Assumption 4 (Time-Independence of Renovations) *For each group $a \in [A]$, the probability of a unit being renovated and a change in the rental price occurring without tenants changing, is independent of time.*

4 Validation of the all-tenant rent index

In the following, we first benchmark our all-tenant rent index against the official CPI rent component to assess alignment and differences. We then highlight the relevance of the two modelling pillars discussed in Section 3.3 and Section 3.4, respectively. Next, we outline the advantages of our approach with respect to frequency, timeliness, and geographic and structural granularity. Finally, we report a set of robustness checks to validate the stability of our results.

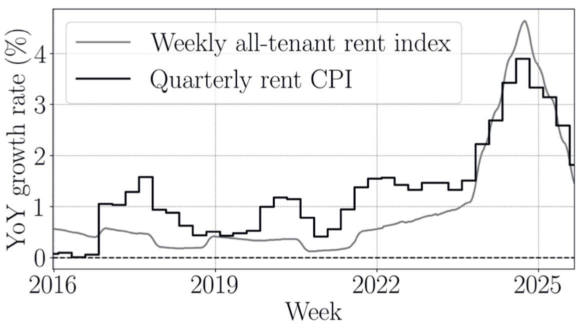
[21] Concretely, for the first week in a quarter q with 12 weeks, we have $w_1(q) = 1/42$ since $1 + 2 + 3 + \cdots + 6 + 6 + \cdots + 2 + 1 = 42$. Thus, the effect builds up gradually (weeks 1–6), stays at its maximum (week 6–7), and then tapers off (weeks 7–12). The triangular weights approximate this diffusion over the quarter. We also consider uniform weights, that is, $w_t(q) = 1/12$ or $w_t(q) = 1/13$, depending on the number of weeks in the quarter, in Appendix D.

[22] This omission is of little relevance in the Swiss context, since major value-enhancing renovations are often not feasible while a unit is occupied, and if undertaken without terminating the lease, landlords must provide detailed justification for any resulting rent increase, including the use of an official adjustment form.

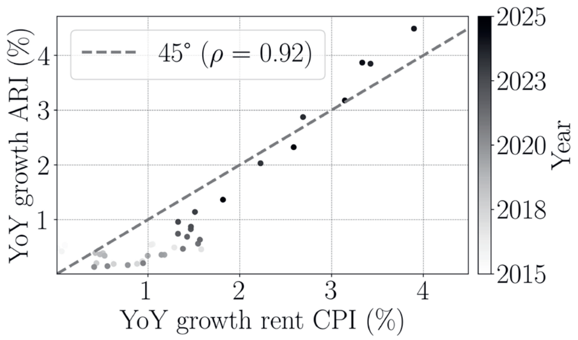
4.1 Comparison with the rent CPI

The all-tenant rent index we construct is conceptually aligned with the official rent CPI, both aiming to capture the evolution of rents for all tenants.[23] To assess their similarity, we convert the overall all-tenant rent index to quarterly frequency by averaging and compare year-over-year (YoY) growth rates of the two series. Over the full period, the correlation between the two YoY series is 0.92. However, our dataset begins in 2005. Thus, we do not have access to granular and weekly asking rent indices pre-2005. We therefore truncate the model for rental price changes of units on the market described in Equation (9) to $t - s \geq 1$ January 2005. This means that asking rents before 2005, which in principle should contribute to the construction of the all-tenant rent index, cannot be taken into account. As time progresses and the weight of these pre-2005 rents diminishes, our index is expected to align even more closely with rent CPI. Under the overall average annual tenant moving rate of 10% displayed in Figure 4.b and Assumption 3, the share of rents originating from asking rents before 2005 falls below 20% roughly 836 weeks ($\approx$ 16 years) later, i.e., by 2021.[24] One might consider the period before the 2021 cutoff as a run-in phase. From 2021 onward, we define the resulting series as the final all-tenant rent index, for which the year-over-year correlation with the rent CPI increases to 0.98, indicating a very strong alignment. See Figure 8.a and Figure 8.b for more details.

Note that our construction underestimates rent growth in the early years of the sample, while it tends to overestimate growth in the more recent years. For forecasting purposes, this bias is of secondary importance, as the main objective is to capture turning points and co-movements with rent CPI. Nevertheless, the issue deserves closer examination in future research, as it is closely linked to how the asking rent indices are indexed.



8.a. YoY growth rate (%) of quarterly rent CPI against the YoY growth rate of the weekly all-tenant rent index.



8.b. YoY growth rate (%) of quarterly rent CPI against YoY growth rate of the quarterly average of the all-tenant rent index (ARI). The Pearson correlation coefficient ρ between the two series is 0.92, resp. 0.98 from 2021 onwards.

4.2 Added value of reference rate adjustments

We investigate the relative importance of modelling rental price changes of units on the market (Section 3.3) and rental price changes of occupied units (Section 3.4). The corre-

[23] Specifically, the housing rentals (rental index) component that captures rents paid by tenants, not the imputed rents for owner-occupied dwellings.

[24] This follows from $(1 - 0.1/52)^t = 0.2 \iff t = \log(0.2)/\log(1 - 0.1/52) \approx 836$.

lation of the YoY growth rates of rent CPI and the intermediate overall all-tenant rent index $I_t^{e\prime}$ is 0.86 (0.92 from 2021 onward), while the correlation of the final overall all-tenant rent index I_t^e with rent CPI is 0.92 (0.98 from 2021 onward). See Figure 8.a for details. We test whether this difference is statistically significant, yielding p-values of 0.22 (0.48 from 2021 onward).[25] Thus, we cannot reject the null-hypothesis of the correlations being equal. However, investigating the figures leads to the conclusion that modelling reference rates is clearly important, and not being able to reject the null-hypothesis is mostly driven by the low number of observations, and hence the lack of power. Nevertheless, considering the high correlation between the intermediate all-tenant rent index and the rent CPI, we conclude that modelling rental price changes of units on the market is more important, at least for Switzerland. This result is encouraging, as modelling rental price changes of units on the market is largely independent of country-specific institutions and legal frameworks, making the approach transferable across different rental markets.

4.3 Granularity, frequency and timeliness

Our all-tenant rent price indices are designed to offer a high level of granularity, enabling the construction of sub-indices for a wide range of market segments. In principle, we can build granular sub-indices wherever equivalent asking rent indices can be constructed, as long as the relevant listing characteristics (such as geographic location or number of rooms) are observable. For example, the existing dimensions of granularity can be extended to distinguish between luxury and lower-priced rental segments by inferring such classifications from the observed gross rental prices. In this paper, we focus on sub-indices by canton and number of rooms as our primary level of aggregation. For Switzerland's most densely populated areas, we extend this further by computing additional sub-indices for the six largest cities.[26] The final aggregate index is based on the canton-by-room combinations. Figure 9.a illustrates the richness of these measures by comparing the all-tenant rent price index for one-room units in Zurich with that for four-room units in the rural canton of Jura. Zurich is Switzerland's largest city and a major economic centre, while Jura is a sparsely populated, predominantly rural canton, making them a useful contrast in terms of housing market conditions. The two series exhibit distinctly different dynamics, underscoring the policy relevance of such granularity. These differences can serve as a foundation for studying substitution effects – how households relocate across regions or apartment types – and how such shifts affect local market demand and prices. Additionally, by jointly analysing sub-indices for asking rents and all-tenant rents, policymakers can disentangle how much of a region's rent dynamics stem from market-listed units versus already occupied units. This distinction is particularly important for evaluating cantonal rent stabilisation policies, which primarily operate by restricting price adjustments for existing tenants, as regulations for price changes in newly listed units are typically hard to enforce. Given the heterogeneity of rental laws across Switzerland, this granular framework offers a valuable tool for assessing the effectiveness of such interventions.

Beyond policy evaluation, having access to granular all-tenant and asking rent indices may enable improved economic monitoring and forecasting, as co-movements and divergences across sub-indices can signal underlying structural changes in the housing market. To highlight the heterogeneous dynamics, we display the following dispersion measure of the

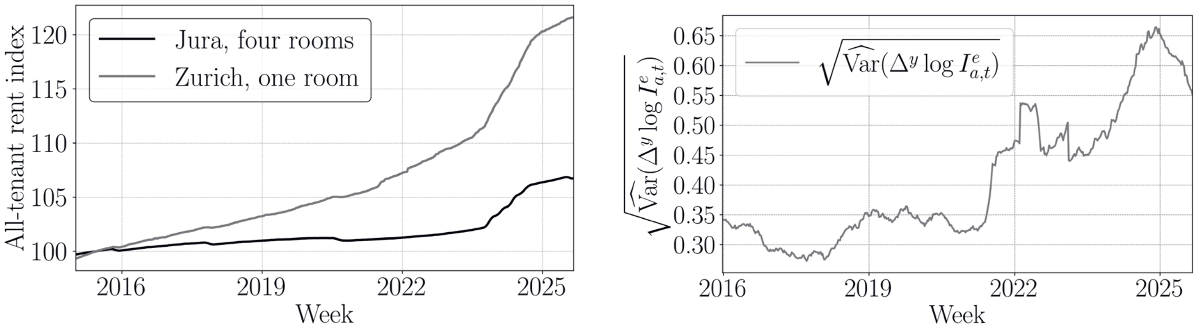
[25] Formally, we test H_0 : correlations are equal and $H_A : \neg H_0$ using Steiger's Z-test.

[26] While these city-level indices are not explicitly used in constructing the overall index, they can be generated in the same manner and are available for analysis.

all-tenant rents, for all weeks $t \in [T]$

$$\sqrt{\widehat{\mathrm{Var}}(\Delta \log^y I^e_{a,t})}, \tag{22}$$

where $\Delta^y \log X_t := \log(X_t) - \log(X_{t-52})$. The results point to a sustained rise in dispersion, while the forces behind this pattern require closer investigation. For a visual overview of the variability of asking rents, consider Figure 3.b.



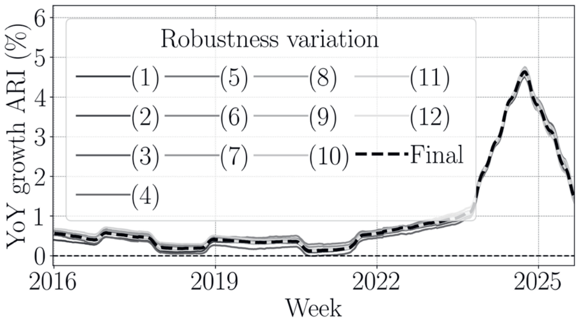
9.a. All-tenant rent index for four-room units in the canton Jura compared to the all-tenant rent index for one-room units in the canton of Zurich.

9.b. Cross-sectional standard deviation across the granular all-tenant rent sub-index YoY log-growth rates for every week in the sample.

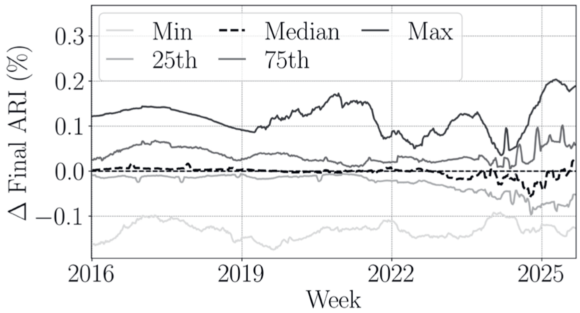
Our all-tenant rent price indices stand out not only for their fine granularity but also for their frequency and timeliness. Each sub-index for week t is computed on the following Monday, enabling near real-time tracking of rental price developments at a weekly frequency with virtually no publication lag. This contrasts with all-tenant rent measures derived from surveys, which are typically available monthly and may be subject to additional delays due to processing and publication. In Switzerland, rent CPI is surveyed quarterly. As a result, when forecasting next month's rent CPI or overall CPI in the third month of a quarter, the most recent rent CPI data corresponds to price information from three to five months prior. By contrast, the indices developed in this paper provide researchers with last week's rents, which can be used as a timely covariate in forecasting models. This dramatic reduction in informational lag is particularly valuable because rent CPI constitutes the largest single component in many consumer price indices, making accurate forecasts crucial for overall CPI projections.

4.4 Robustness checks

Finally, we conduct a comprehensive range of robustness checks to assess the validity of the results in light of inevitable design choices. These include, for example, varying the assumed distribution of durations of stay and relaxing the linearity assumption in the hedonic adjustment. For a comprehensive overview of the robustness checks, see Appendix D. In Figure 10.a, we visualise the collection of YoY growth rates of overall the all-tenant rent indices corresponding to the various robustness checks. Evidently, the resulting indices are strikingly similar. To investigate differences in more detail, we consider the differences in YoY growth rates of all robustness checks to the YoY growth rate of the final all-tenant rent index, for all weeks $t \in [T]$ in Figure 10.b.



10.a. YoY growth rates (%) of the overall all-tenant rent indices (denoted by ARI) corresponding to different robustness variations described in Appendix D.



10.b. Extremes and quartiles of the distribution of differences between the final all-tenant rent index (denoted by ARI) and the robustness variations described in Appendix D. The differences are negligible.

5 Conclusion

Summary. This paper develops a framework for estimating all-tenant rents using only online listings and official statistics, without reliance on tenant surveys. By combining

1. Hedonic-adjusted measures of asking rents
2. A probabilistic model of tenant duration
3. Legal mechanisms governing rent adjustments for occupied dwellings
4. Transport of marginal distributions to ensure representativeness along important dimensions,

we construct weekly and granular indices of all-tenant rents for Switzerland that align closely with the official rent CPI. These indices substantially enhance the timeliness and accuracy of rental price measurement while maintaining consistency with established benchmarks.

From a monetary policy perspective, the results are highly relevant. The new rent indices allow earlier identification of rent inflation turning points, and preliminary evidence points to notable forecasting gains. A comprehensive forecasting analysis is left for future research.

Our findings suggest that the dynamics of all-tenant rents in Switzerland can be largely attributed to the gradual transmission of past asking rents, as tenants move, supplemented by discrete adjustments linked to the mortgage reference rate. The resulting indices replicate the long-run evolution of rent CPI, with correlations exceeding 0.98 after a run-in period, while offering vastly higher frequency and detail. Moreover, we argue that incorporating these indices into forecasting frameworks improves predictive accuracy for rent inflation relative to models relying solely on lagged CPI data, underscoring their value for real-time monitoring and economic analysis.

The methodology also highlights substantial heterogeneity in rental price dynamics across apartment sizes, cantons, and urban versus rural regions. Such granularity opens the door to new strands of research, including the study of substitution patterns across housing segments, the regional impact of interest rate and policy shocks, and the role of market frictions in the pass-through from asking rents to the broader tenant population. These applications demonstrate how listing-based measures can complement official statistics, not only as leading indicators but also as tools for structural analysis.

While the empirical focus is Switzerland, the framework is broadly applicable. The modular structure, which separates the construction of the hedonic index from the modelling of price changes of units on the market and occupied units, facilitates adaptation to other rental markets. Countries with fixed-term leases, stronger rent controls, or different adjustment triggers can be accommodated by modifying the legal and probabilistic components while maintaining the same core approach. This generalisation, coupled with the ability to work with listing datasets that do not track individual units over time, makes the method widely relevant for housing market research.

Limitations. First, since durations of stay are not observed in the listing data, we need to place an assumption on the durations to identify the all-tenant rents of interest. Assumption 2 of the conditional independence of gross rents and durations is strong. However, this allows the construction of timely, high-frequency all-tenant rent indices without observing a fixed sample of units through time. Second, the parametric assumption of geometric survival imposes significant structure. This is necessary because, for Switzerland, there is no publicly available data beyond yearly moving averages along some dimensions of granularity. Third, and connected to the second point, since there are no moving quotes by canton and number of rooms jointly, we assume that the moving quotes by number of rooms are homogeneous across cantons. Fourth, we assume that the transmission of changes in the reference rate to rental prices is homogeneous across cantons and properties, regardless of the number of rooms. This is necessary because there is no publicly available granular data on all-tenant rents in Switzerland that could be used to estimate such heterogeneous effects. The homogeneity of the reference rate effects synchronises the granular sub-indices, per construction.

Future research. First, rather than relying on parametric assumptions such as geometric survival, the distribution of tenant duration of stay could be estimated nonparametrically from the data itself. Second, lifting Assumption 2 of conditional independence of gross rents and durations to an alternative assumption, such as conditional counter-monotonicity of gross rents and durations, constitutes an interesting extension [Dhaene et al., 2002]. Third, considering further dimensions of granularity, such as price class, is very relevant to rental market policy. Fourth, adapting the framework to other countries offers a natural extension. Fifth, the link between asking and all-tenant rents offers untapped opportunities for forecasting. Beyond the aggregate indices used here to motivate the all-tenant rent model, forecasting models could leverage granular sub-indices of asking rent. Finally, the granular asking and all-tenant rent indices developed in this paper can be used for policy research on the Swiss rental market. By exploiting cantonal variation in housing regulations and the timing of legislative changes, researchers can try to use these indices to identify causal effects of rent control laws. Such work would shed light on the efficacy of rental housing policies in a heterogeneous market.

A Appendix: data

We perform several processing steps on the listing data and the data from official statistics, which are described in detail below.

A.1 Listing data

The hedonic model categorises listings into groups defined by unit type (house/flat), number of rooms, and zip code, as specified in Equation (2). We describe how these groups are formed. First, the distribution of listings over unit types and number of rooms is examined, and 10 subsets are defined such that each subset contains enough observations to enable geographic subdivision. The starting subsets are 1 room flats, 2 room flats, etc. Within each subset, groups are formed by aggregating neighbouring zip codes to ensure there are enough observations in each group in the training data, corresponding to listings during the year 2014. Letting *free* zip codes denote not yet assigned zip codes, the algorithm can be described as follows.

Algorithm 1 Grouping of ZIP codes

```
1: Initialize: Mark all zip codes with ≥ 50 observations as a stand-alone
2: Set: Remaining zip codes as free
3: while free zip codes remain do
4:     Seed new group g from free zip code furthest from the geographic centre of CH
5:     while group g has < 20 observations do
6:         Select free zip code closest to the current group's centre
7:         Let d_zip ← distance(zip code, group center)
8:         Let d_alt ← distance to closest grouped zip code
9:         if d_zip ≥ 1.75 × d_alt then
10:            Merge current group into closest group
11:            Break to line 3
12:        else
13:            Add zip code to current group
14:            Update group centre as the average of member coordinates
15:        end if
16:    end while
17: end while
```

A.2 Official statistics

To get the yearly weights of the number of renters by canton and the number of rooms described in Section 2.2.3, we multiply the number of renters in a given canton and year by the number of renters by number of rooms $1, 2, 3, 4, 5$, and 6+. Then, for all weeks, the weights $w_{a,t}$ are created by dividing this number by the sum of all such numbers in the given week. Since this information is only publicly available from 2013 onward, we backwards fill these weights back to 2005.

A.3 Reference rate

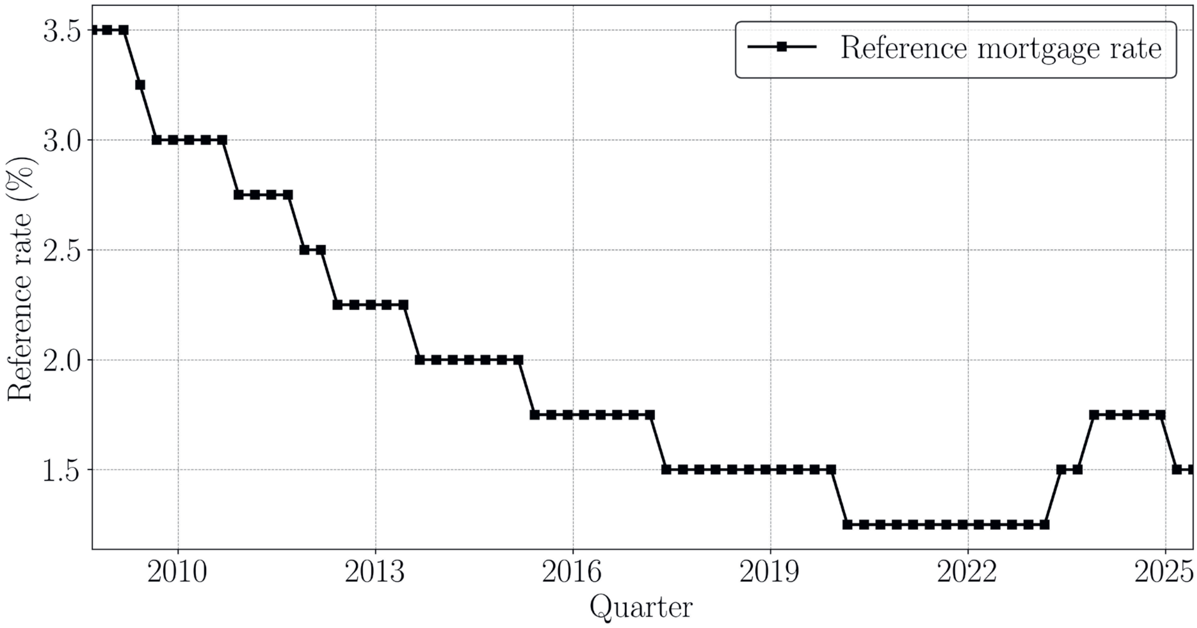


Figure 11: Development of the Swiss reference mortgage rate from its introduction in 2008 to 2025. Consider Section 3.4 for more details on the reference mortgage rate.

B Appendix: details asking rent index

We provide a few details regarding the construction of the asking rent indices that were previously not detailed.

B.1 Outlier detection

Letting $e_{i,t}(\eta) \coloneqq Y_{i,t} - x^\top \eta,\ i \in [N]$ be the residuals using the conditional expectation as specified in Equation (2) for a given η, we solve the following minimisation problem

$$\widehat{\eta} \in \operatorname{argmin}_{\eta \in \mathbb{R}^p_+} \sum_{i \in [N]} \rho(e_{i,t}(\eta)), \tag{23}$$

where $p \coloneqq 2|\mathcal{G}|$ and the Huber loss is $\rho(z) = z^2$ for $|z| < c$ and $\rho(z) = |2z|c - c^2$ for $|z| \geq c$, for some hyper-parameter $c > 0$. Technically, we also select c in a data-dependent manner, as proposed by Huber and Ronchetti [2009]. The loss is quadratic for small residuals and linear for large residuals, which limits the influence of outliers.

B.2 Hedonic adjustment

The latent asking rent process ν_t is not mean-zero, complicating the estimation of f of Equation (3). We select a base period over which $\mathbb{E}[\nu_t] = 0$ holds, allowing the estimation of f. We consider the calendar year 2014 as the base period, and motivate that $\mathbb{E}[\nu_t] = 0$ by showing the residuals $Y_{i,t} - \widehat{f}(X_{i,t})$ are time-invariant in Figure 12. As in Section 2.2.1, we assume f is linear and estimate the parameters of the specification of the conditional expectation of Equation (2) to construct $\widehat{f}$. That is, letting $i \in [N_b']$ index the listings in the base year of estimation 2014, we estimate f by estimating the parameter vector η of

$$\begin{aligned} f(x) \coloneqq \mathbb{E}[Y_{i,t} \mid X_{i,t} = x] &= \mathbb{E}[f(X_{i,t}) \mid X_{i,t} = x] + \mathbb{E}[\lambda_{i,t} \mid X_{i,t} = x],\ i \in [N_b'], \\ &= x^\top \eta, \end{aligned} \tag{24}$$

since $\mathbb{E}[\nu_t \mid X_{i,t} = x] = \mathbb{E}[\varepsilon_{i,t} \mid X_{i,t} = x] = 0$, in the base year. We estimate η using ordinary least squares (OLS) while forcing all coefficients to be non-negative since gross rents are positive. We choose 2014 as the base year since we start constructing the all-tenant rent index beginning in 2015, and we want to prevent using future information to construct the index. Following that, we evaluate $\widehat{f}$ on the whole period to generate the predicted gross rents.

Note that other factors, such as the view, closeness to major roads or calmness of the neighbourhood, are determinants of gross rents.[27] However, since we do not observe these attributes, they cannot be adjusted for. We operate under the assumption that the occurrence of units with such attributes is independent of time. Under said assumption, the average contributions of these additional determinants of gross rents are equal across weeks, which cancel when re-basing the index as described in Section 2.2.3. This is an important distinction, and stems from the fact that we model average prices over time, as opposed to targeting unit-level predictions of the gross-rent. See Appendix F.2 for more details.

[27] We include robustness checks using the year of construction and the floor, which are missing for 54%, respectively 21% of observations in Appendix D.

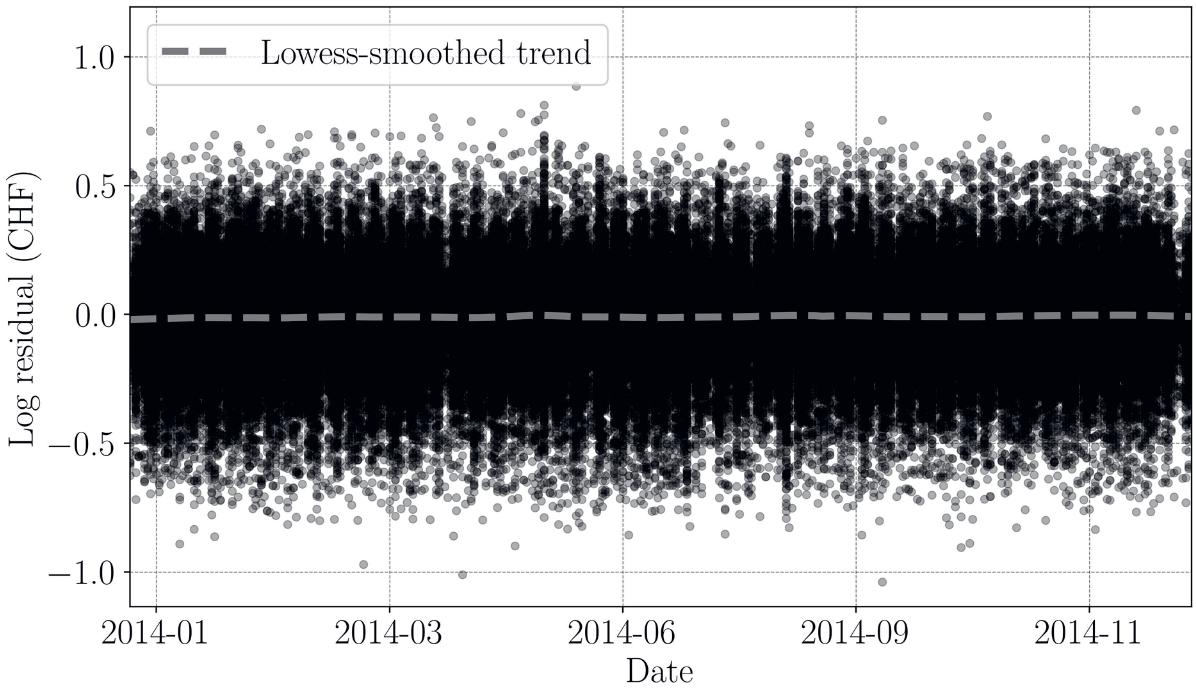


Figure 12: Log hedonic ratio $\log \widehat{Y}_{i,t} - \log Y_{i,t}$ against the date in the year of estimation 2014. The red line is a LOWESS smoothed trend with a low fraction of $d = 10\%$ of observations used to construct the smoothed value.

B.3 Composition of rental units by floor

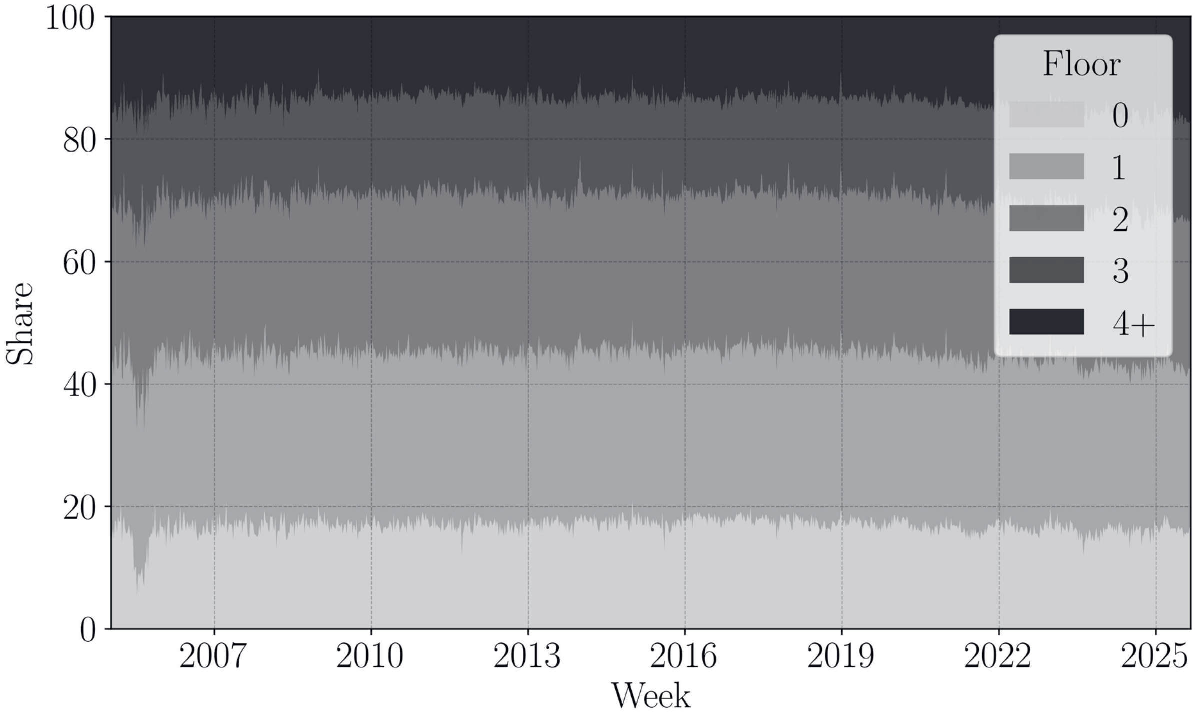


Figure 13: Share of observations by floor over the sample period. The composition remains stable, apart from a brief decrease in ground-floor units in 2005. This justifies the decision not to consider the floor as an observed characteristic in Equation (3), see Appendix F.2.

B.4 Granular asking rents before and after 2015

Cantons	Rooms	Period
ZH, TG, SH, ZG	Any number of rooms	Before 2015
VD, GE, NE	Any number of rooms	Before 2015
BE, FR, JU	Any number of rooms	Before 2015
AG	Any number of rooms	Before 2015
SG, AI, AR	Any number of rooms	Before 2015
GR, UR, GL, SZ	Any number of rooms	Before 2015
TI, VS, LU, OW, NW	Any number of rooms	Before 2015
BS	Any number of rooms	Before 2015
BL, SO	Any number of rooms	Before 2015
ZH, ZG	1 room, 2 rooms, 3 rooms, 4 rooms, 5+ rooms	After 2015
TG, SH	1–2 rooms, 3 rooms, 4+ rooms	After 2015
VD, NE	1 room, 2 rooms, 3 rooms, 4 rooms, 5+ rooms	After 2015
GE	1–2 rooms, 3 rooms, 4 rooms, 5+ rooms	After 2015
JU, BE	1–2 rooms, 3 rooms, 4+ rooms	After 2015
FR	1–2 rooms, 3 rooms, 4+ rooms	After 2015
AG	1 room, 2 rooms, 3 rooms, 4+ rooms	After 2015
SG, AI, AR	1 room, 2 rooms, 3 rooms, 4+ rooms	After 2015
GR, UR, GL, SZ	1–2 rooms, 3 rooms, 4+ rooms	After 2015
TI	1–2 rooms, 3 rooms, 4+ rooms	After 2015
VS	1–2 rooms, 3 rooms, 4+ rooms	After 2015
LU, NW, OW	1–2 rooms, 3 rooms, 4+ rooms	After 2015
BS	1 room, 2 rooms, 3 rooms, 4+ rooms	After 2015
BL	1–2 rooms, 3 rooms, 4+ rooms	After 2015
SO	1–2 rooms, 3 rooms, 4+ rooms	After 2015

Table 2: Aggregation of cantons and the number of rooms into groups for asking rent sub-indices. Less granular groups are used before 2015 due to fewer observations. There are 9 groups pre-2015 while there are 53 groups post-2015.

C Appendix: details all-tenant rent index

C.1 All-tenant rent index granularities

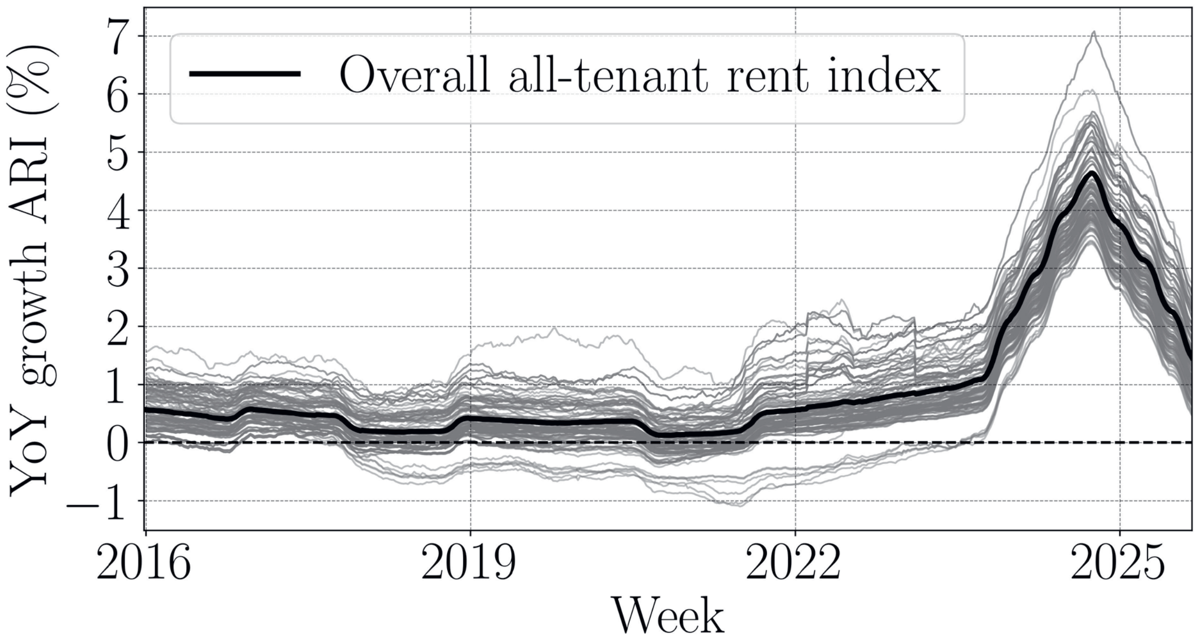


Figure 14: The YoY growth rate (%) of the overall all-tenant rent index (ARI) and the granular disaggregations along cantons and number of rooms as described in Appendix B.4. There are strong global factors, such as changes in reference rates, driving the all-tenant rents across the granular series. At the same time, there are substantial differences in the growth rates across the dimensions of heterogeneity.

D Appendix: robustness checks

ID	Description
1	Equally weighting zip codes within cantons for the sub-index computation
2	Geometric mean aggregation of hedonic ratios instead of arithmetic mean aggregation to construct sub-indices
3	Median aggregation of hedonic ratios instead of arithmetic mean aggregation to construct sub-indices
4	Defining the geographic component in the hedonic model to be cantons instead of zip code aggregations
5	Lifting the positivity assumption of coefficients $(\beta_{0,g}, \beta_{1,g})_{g \in \mathcal{G}}$ in the hedonic model described in Equation (2)
6	Additional additive contributions to the hedonic model based on the floor and age of the building, restricted to observations where this information is available. Explicitly, adding the following terms to Equation (2) $\begin{aligned} \sum_{g \in \mathcal{G}} \beta_{2,g} \mathbb{1}\{\text{is ground floor}\} \mathbb{1}\{\text{group} = g\} & \\ + \sum_{g \in \mathcal{G}} \beta_{3,g} \mathbb{1}\{\text{is less than 10 years old}\} \mathbb{1}\{\text{group} = g\} & \\ + \sum_{g \in \mathcal{G}} \beta_{4,g} \mathbb{1}\{\text{is less than 40 years old}\} \mathbb{1}\{\text{group} = g\}. & \end{aligned}$
7	Additional additive contributions to the hedonic model based on floor for flats and age of the building for houses, restricted to observations where this information is available.
8	Non-linear hedonic adjustment using Random Forest regression using the main specification described in Equation (2). Hyper-parameters are determined by expanding-window cross validation.
9	Extending the inlier region of hedonic ratios for the outlier detection to $[0.2, 5]$.
10	Single outlier-detection model trained in 2014.
11	Log-normal duration of stay with $\mu = 1/p$ and $\widehat{\sigma}$ being set by maximising the correlation of the YoY growth rate of rent CPI and the overall all-tenant rent index ($\widehat{\sigma} \approx 0.5$).
12	Uniform weekly weights of distributing the quarterly reference rate effects onto the weeks in a quarter, i.e., $w_t(q) = 1/12$ or $w_t(q) = 1/13$.

Table 3: Robustness check variations were implemented for both the asking and all-tenant rent constructions. The ID column corresponds to the identifiers employed in Figure 10.a.

E Appendix: forecasting details

We forecast the first difference of the h-horizon ahead quarterly rent CPI Δc^r_{q+h} by estimating f from

$$\Delta c^r_{q+h} = f(X_{q-1}) + \epsilon_{q+h} \text{ and } \Delta c^r_{q+h} = f(X'_{q-1}) + \epsilon_{q+h} \tag{25}$$

where $X_{q-1} \coloneqq (\Delta c^r_{q-1}, \ldots, \Delta c^r_{q-4})$ and $X'_{q-1} \coloneqq (\Delta c^r_{q-1}, \ldots, \Delta c^r_{q-4}, \Delta I_{q-1} \ldots, \Delta I_{q-4})$, for $h = 1, \ldots, 6$. Note that I_q denotes the average overall asking rent index in quarter q. We estimate f using OLS and a Random Forest on the training set from the Q_2 2015 to Q_1 2022. The hyperparameters of the Random Forest regressor are chosen using an expanding window cross-validation approach on the training set. We evaluate the models using the empirical RMSE on the test set from Q_2 2022 to Q_2 2025, and plot the percentage improvement of using the information set X'_{q-1} instead of X_{q-1}.

F Appendix: mathematical details

F.1 Proof of theorem 1

Proof. We first show the consistency of the asking rent sub-indices $I_{a,t}$. For all $a \in [A]$ and $t \in [T]$, we have access to $N_{a,t}$ i.i.d. samples of the distribution of gross rents for the specific group a at the specific time t. Involving the law of large numbers, we conclude that, for all fixed $t \in [T]$ and all groups $a \in [A]$, as $N_{a,t} \to \infty$

$$I_{a,t} \xrightarrow{\mathbb{P}} \mathbb{E}[r \mid A = a, T = t], \tag{26}$$

where $\xrightarrow{\mathbb{P}}$ denotes convergence in probability. Next, we examine the properties of the moving quotes p and the renter population weights w. Since the statistical office provides these, we treat them as fixed, non-random population quantities. If one prefers not to make this assumption, it is sufficient that they be consistent estimators of the corresponding population measures – a property that holds in any case. Finally, consider the overall all-tenant rent index for any $t \in [T]$, given by

$$I_t^{e\prime} := \sum_{a \in [A]} w_{a,t} \frac{\sum_{s=0}^{t} I_{a,t}(1 - p_{s,r})^{t-s}}{\sum_{s=0}^{t}(1 - p_{s,r})^{t-s}}. \tag{27}$$

Note that $g(a_1, \dots, a_k) = \sum_{i=1}^{k} a_i$ and $h(a, b) = a/b$ are continuous if $b \neq 0$. Thus, since $\sum_{s=0}^{t}(1 - p_{s,r})^{t-s} > 0$, we invoke the continuous mapping theorem to prove the claimed consistency of the all-tenant rent index $I_t^{e\prime}$, for any fixed $t \in [T]$ [Vaart, 1998]. ∎

Note that, under suitable conditions on $\widehat{f}$, one could also show that $I_{a,t}$ converges in probability to the population quantity $\mathbb{E}\left[Y/f(X_{i,t}) \mid A = a, T = t\right]$. To avoid distracting from the main goals of the paper, we keep the exposition simple.

F.2 Time-independent probability of market-appearance

Assume the gross rents additionally depend on unobserved characteristics $X'_{i,t}$, i.e.,

$$Y_{i,t} = f(X_{i,t}, X'_{i,t}) + \nu_t + \varepsilon_{i,t}. \tag{28}$$

Conversely, we estimate f using only $X_{i,t}$, and define the missspecified composite error term $\mu_{i,t}$

$$\begin{aligned} \mu_{i,t} &:= Y_{i,t} - f(X_{i,t}) \\ &= \underbrace{f(X_{i,t}, X'_{i,t}) - f(X_{i,t})}_{:=b_{i,t}} + \nu_t + \varepsilon_{i,t}. \end{aligned} \tag{29}$$

Let $S_{i,t} \in \{0, 1\}$ indicate whether a given rental unit is put on the market, meaning it is part of our sample. We assume that the market-appearance probability of a unit with unobserved characteristics $X'_{i,t}$ is time-invariant, meaning

$$\mathbb{P}(S_{i,t} = 1 \mid X'_{i,t} = x) = \zeta(x), \tag{30}$$

where $\zeta(\cdot)$ does not depend on time. Thus, we identify the first difference of the asking rent component ν_t for all units on the market in expectation via

$$\begin{aligned}
\mathbb{E}[\mu_{i,t} - \mu_{i,t-1} \mid S_{i,t} = 1, S_{i,t-1} = 1] &= \underbrace{\mathbb{E}[b_{i,t} - b_{i,t-1} \mid S_{i,t} = 1, S_{i,t-1} = 1]}_{\text{=0 by time-invariant selection on } X'_{i,t}} \\
&\quad + \mathbb{E}[\nu_t - \nu_{t-1} \mid S_{i,t} = 1, S_{i,t-1} = 1] \\
&\quad + \underbrace{\mathbb{E}[\varepsilon_{i,t} - \varepsilon_{i,t-1} \mid S_{i,t} = 1, S_{i,t-1} = 1]}_{\text{=0 by mean-zero noise}} \\
&= \mathbb{E}[\nu_t - \nu_{t-1} \mid S_{i,t} = 1, S_{i,t-1} = 1].
\end{aligned} \tag{31}$$

Importantly, we only identify first differences, as the level of the latent asking rent component may be misspecified. However, since we build an index and rebase the values in any case, this is not relevant.

References

Brian Adams, Lara Loewenstein, Hugh Montag, and Randal Verbrugge. Disentangling rent index differences: Data, methods, and scope. *American Economic Review: Insights*, 6:230–45, June 2024.

Brent W. Ambrose, N. Edward Coulson, and Jiro Yoshida. The repeat rent index. *The Review of Economics and Statistics*, 97:939–950, December 2015.

Brent W. Ambrose, N. Edward Coulson, and Jiro Yoshida. Housing rents and inflation rates. *Journal of Money, Credit and Banking*, 55:975–992, August 2023.

Laurence M. Ball and Kyung Woong Koh. Market rents and cpi shelter inflation. Working Paper 34113, National Bureau of Economic Research, August 2025.

Geoff Boeing, Jake Wegmann, and Junfeng Jiao. Rental housing spot markets: How online information exchanges can supplement transacted-rents data. *Journal of Planning Education and Research*, 43:525–537, February 2023.

Leo Breiman. Random forests. *Machine Learning*, 45:5–32, October 2001.

Joshua Clark. Methodology: Zillow observed rent index. Online Release, September 2022. URL https://www.zillow.com/research/methodology-zori-repeat-rent-27092/. Accessed: December 16, 2025.

J. Dhaene, M. Denuit, M.J. Goovaerts, R. Kaas, and D. Vyncke. The concept of comonotonicity in actuarial science and finance: theory. *Insurance: Mathematics and Economics*, 31:3–33, August 2002.

FSO. *Rent price index: methodology report*. Federal Statistical Office (FSO), Neuchâtel, Mar 2022a. URL https://dam-api.bfs.admin.ch/hub/api/dam/assets/21784250/master. Accessed: December 16, 2025.

FSO. *Consumer Price Index (December 2020 = 100)*. Federal Statistical Office (FSO), Neuchâtel, Apr 2022b. URL https://dam-api.bfs.admin.ch/hub/api/dam/assets/20984928/master. Accessed: December 16, 2025.

FSO. Building and housing statistics (since 2009), 2025. URL https://www.bfs.admin.ch/bfs/de/home/statistiken/bau-wohnungswesen/wohnungen/wohnverhaeltnisse/mieter-eigentuemer.assetdetail.33947407.html. Accessed: December 16, 2025.

Homegate. Homegate mietindex. Online Release, May 2025. URL https://swissmarketplace.group/de/media-release/mietindex-11-2025-de/. Accessed: December 16, 2025.

P.J. Huber and E.M. Ronchetti. *Robust Statistics*. Wiley Series in Probability and Statistics. John Wiley & Sons, January 2009.

Winfried Koeniger, Benedikt Lennartz, and Marc-Antoine Ramelet. On the transmission of monetary policy to the housing market. *European Economic Review*, 145:104–107, June 2022.

Michele Loberto, Andrea Luciani, and Marco Pangallo. What do online listings tell us about the housing market? *International Journal of Central Banking*, 18:236–377, October 2022.

Lara P. Loewenstein, Jason Meyer, and Randal J. Verbrugge. New-tenant rent passthrough and the future of rent inflation. Economic commentary, Federal Reserve Bank of Cleveland, October 2024. URL https://doi.org/10.26509/frbc-ec-202417. Accessed: December 16, 2025.

Whitney K. Newey and Kenneth D. West. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55:703–708, August 1987.

Judea Pearl and Elias Bareinboim. Transportability of causal and statistical relations: A formal approach. *2011 IEEE 11th International Conference on Data Mining Workshops*, 25:247–254, December 2011.

Jack E. Triplett and Barry P. Bosworth. Handbook on hedonic indexes and quality adjustments in price indexes. Technical report, OECD, September 2006.

A. W. van der Vaart. *Asymptotic Statistics*. Cambridge Series in Statistical and Probabilistic Mathematics. Cambridge University Press, June 1998.

Joël Vonlanthen. Interest rates and real estate prices: a panel study. *Swiss Journal of Economics and Statistics*, 159:1–25, April 2023.

WuestPartner. Angebotspreisindex. Online Release, August 2025. URL https://www.wuest.io/online_services_classic/angebotspreisindex/index_e.phtml. Accessed: December 16, 2025.

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