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Stable and Reliable Monthly Repeat Rent Indices: A Robust Approach

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Abstract

Repeat rent indices measure changes in rent prices over time by tracking the same rental units across different lease periods, thereby isolating pure rent inflation unaffected by shifts in housing quality or composition. Their main advantage is that they accurately capture the end-of-month cost of private tenancy without requiring additional information on dwelling characteristics. This explains their popularity as an input for the calculation of the consumer price index. A disadvantage is that their traditional implementation using ordinary least squares (OLS) estimation at a monthly frequency shows high sensitivity to revisions as the information in newly signed contracts require updating the prior rent evolution. In an extensive application to Belgian rent price data, we find that, using a robust M-estimator in combination with lease signature dates results in indices that share the same trend, but display significantly lower revision variability than the standard OLS-based indices.

Keywords: Repeat Rent Index, Robust Estimation, Index Revision, Monthly Index.

1. Introduction

Policy makers, house owners and renters need reliable end-of-month indices tracking the total cost of private tenancy. A workhorse approach is to use the repeat rent methodology in which the observed evolution of cost of individual lease contracts is extrapolated to an aggregate number using an ordinary least squares (OLS) regression. The approach was pioneered for house sale prices by Bailey et al. (1963) proposing a framework (BMN) where house price indices are measured based on individual units appearing at least twice over a given period, ensuring relative stability in the underlying housing features. The ease of implementation (as only prices and addresses are needed) led various other scholars to refine the approach and publish methods of their own (Case & Shiller 1987, Shiller 1991, Goetzman 1992, Calhoun 1996). Ambrose et al. (2015) applied the framework to repeat rent indices.

The conceptual simplicity of a repeat rent index belies several inherent data challenges. First, the index is designed to measure changes in rental prices while holding dwelling characteristics constant. Although this assumption is valid for most rental contracts, it is occasionally violated when substantial renovations or other quality altering improvements occur. Additional sources of outliers include changes in ownership, which may prompt atypical rent adjustments, as well as data errors that arise in the collection or reporting of contract information. Second, the timing of rent observations is not naturally aligned with the frequency at which the index is constructed. In this study, we target a monthly frequency, which is aligned with the calculation frequency of the Consumer Price Index (CPI), but contrasts with the typical renewal cycle of rental contracts that is usually one year or longer. As a result, successive updates to the index require the revision of previously estimated rents as new observations provide incremental information on underlying price dynamics. Moreover, at any month end only a subset of relevant rent observations is available. In small samples that may also contain outliers, reliance on ordinary least squares amplifies these issues because the estimator is well documented to be sensitive to extreme values.

The resulting excess variability of the monthly updated repeat rent index is problematic for several reasons. First, frequent revisions to historical index levels undermine their usefulness as stable reference points (Clapham et al., 2006). Second, the implied growth in private-sector rents from the initial index estimate feeds directly into the CPI basket, making reduced revision variability desirable for more accurate consumer price measurement. Third, market participants, including landlords and tenants, require near real time and reliable signals to support price discovery and efficient matching. Large swings in estimated rental growth rates can therefore translate into unnecessary volatility in transacted rents and weaken market functioning.

In this paper we investigate whether the monthly revision variability of repeat rent indices can be reduced using a robust M-estimator as proposed by Bourassa et al. (2013). Bourassa et al. (2013) apply robust estimators to quarterly single-family repeat sale transactions for the US city of Louisville over a 12-year span. The main findings are that distressed sales and house flips lead to outliers and that therefore outlier robust estimators track the market movement better than OLS-based estimators. Furthermore, robust estimators are found to reduce both the magnitude and volatility of revisions to repeat sale indices. Our paper investigates in depth whether the reduction in index revision magnitude and volatility achieved through robust estimation also holds for monthly repeat rent indices.

We apply the proposed robust estimator to Belgian rent data. The data set spans the entire country and consists of 863,289 signed rental leases for the period January 2014 – March 2025. The data is compiled from manually registered rental contracts collected by the Confederation of Real Estate Agents (CIB), the country's largest real estate professional association, in collaboration with the insurance provider Korfine. Given CIB's dominant position in the sector, the data covers a wide geographic spread and can be considered broadly representative of the national housing market. The dataset contains rental prices, service fees, addresses as well as tenant and landlords' id's, contract durations, start and signature dates.

Our main contribution is to demonstrate the benefits of using robust estimators when constructing monthly repeat rent indices. The motivation for this work is closely related to Adams et al. (2024), who highlight the importance of accurate rent measurement for reliable inflation statistics. Their analysis shows that discrepancies between CPI rent indices and alternative measures largely stem from differences in rent growth for new versus existing tenants. Building on Bourassa et al. (2013), Clapham et al. (2006), and Van de Minne et al. (2020), we focus on the issue of index stability. Repeat sale indices are inherently revision-prone: sale pairs can span several decades, and new observations may substantially alter long-standing index values. Although rent indices are typically less affected, they share this fundamental limitation. Using our novel dataset, which records both lease signature and start dates, we assess how a robust M-estimator with Huber loss compares to standard OLS estimation in terms of stability and revision variability. We find that robustly estimated BMN indices produce markedly more stable growth-rate estimates: the gap between initial real-time assessments and subsequent revisions is significantly smaller than under OLS.

Our analysis connects to a broader literature on the design of repeat rent and sale indices while also connecting to previous work on the Belgian market. Related work for Belgium is that of Vastmans & de Vries (2012) and Reusens et al. (2023). Vastmans & de Vries (2012) cover repeat rent indices for the entire Belgian housing stock spanning the period 1990-2010 covering over half a million homes. The number of repeat rent homes however amounts to only 30.000 instances (~6%) and the indices are built on a yearly timescale marginalizing the differences between lease signature and start dates. Reusens et al. (2023) develop a hedonic model for sale prices on Belgian data, incorporating changes in housing quality and their associated premia in a house price index. We contribute to this literature by showing the advantages of robust estimators in the context of repeat rent indices. We also investigate if constructing monthly repeat rent indices on either temporal marker (lease sign or start-date) influences the obtained repeat rent indices and the index revision results.

The remainder of the paper is organized as follows. Section 2 describes the dataset, cleaning procedures, and summary statistics. Section 3 reviews the standard repeat-based index methods and outlines our methodological framework. Section 4 compares the performance of robust (Huber) and OLS-based monthly repeat rent indices and relates them to the rent component in the official consumer price index (RCPI). Section 5 presents robustness checks regarding the choice of temporal marker (lease signature or start date) and the tuning of the Huber-loss parameter. Section 6 concludes.

2. Data

Constructing a repeat rent index for Belgium ideally requires a large longitudinal dataset with repeated rental contract observations. Statbel, Belgium's national statistical office, collects all registered rental contracts to construct the end-of-month CPI rental component. However, this administrative dataset is not accessible for research. Fortunately, a representative dataset is available from the Confederation of Real Estate Agents (CIB), the country's largest real estate professional association, in collaboration with the insurance provider Korfine. This dataset provides nationwide coverage and contains the variables required to construct monthly repeat rent indices. In this section we first explain how we construct our dataset and then provide the relevant summary statistics.

2.1 Constructing a Repeat Rent Dataset

The dataset consists of 863,289 rental contracts, geographically sampling the entire Belgian market between January 2014 and March 2025. Following a multi-stage cleaning process we retain 329,697 observations suitable for a repeat rent index. Each retained observation corresponds to a signed rental contract associated with a physical unit that appeared on the market at least twice during this 10-year period. For each lease in our repeat sample dataset we observe key characteristics including rental fees, service fees, deposits, contract signature date, move-in date, tenancy duration and realtor. We also observe anonymized tenant and landlord identifiers (including age). In compliance with GDPR guidelines, personal identifiers as names and national register numbers are in a SHA-256 hashed format. We also observe property level attributes such as street, number, letterbox, postal code and real estate type. Our data cleaning process consists of three stages: general data cleaning, matching rental units to the national building register at the house number level, and finally linking individual units within multi-unit buildings using letterbox information. The final step is crucial to distinguish apartment units within a building, allowing our index to go beyond single-family housing (individual house) coverage.

2.1.1 General Data Cleaning

Our goal is to create an index that tracks the total cost of tenancy over more than ten years and across the entire country. We are therefore interested in the out-of-pocket expenses that domiciled, registered renting household incur each month. To ensure data consistency over the full period, we first combine rental fees and service charges into a monthly variable (total cost of tenancy), as landlords may reallocate costs between both categories, which would affect the repeat rent index.

We subsequently remove duplicate and erroneous entries, which are pervasive in our dataset because it consists of raw, manually entered records collected from thousands of distinct real estate agents. The goal is to retain only 'realistic prices' for private market contracts, excluding social housing, rent-free leases, and non-residential units. In a first step, we drop observations with a monthly total cost of tenancy below €100 or above €10,000 (1,090 cases) as such values are implausible for the private rental market. In a second step, we address additional data-entry errors (e.g., misallocated service charges, deposits, postal codes, or mismatched time periods).[1] For this purpose, we compute the median and standard deviation of log total cost of tenancy within a 12-month rolling window. Observations more than two standard deviations below, or five standard deviations above, the rolling median are removed (7,765 cases). In total we remove approximately 1% of the raw dataset, retaining 767,240 datapoints.

[1] Belgian postal codes consist of a four number digit (e.g. 8900) which could be reported as rental fee. Additionally, rental contracts specify the rental fee for a given time basis (e.g. €2000/month), in many cases the amount or time basis has been entered erroneously.

2.1.2 Matching Data to the National Building Register

To ensure that raw datapoints are attributed to the correct location, we match the dataset to the Belgian building register using reported postal codes and standardized street names.[2] Approximately 4% of contracts (30,791 cases) cannot be matched, primarily due to erroneous postal codes, delays in registry updates for newly constructed units, or substantial spelling inconsistencies in the manually entered data. Leases are then linked to house numbers within each postal code–street combination, using all available information from reported house and letterbox numbers. An additional 4.3% of contracts (33,156 cases) cannot be matched to a valid postal code–street–house number combination, which serve as our unique building identifier. After removing 744 duplicate entries across data providers, the final matched dataset contains 702,545 contracts linked to unique building locations, supplemented with geographical coordinates. For single family housing, matching the data to the building register suffices to identify unique units. To identify distinct apartment units within the same building, the matching procedure needs to be extended to the letterbox level.

2.1.3 Linking Individual Apartment Units on Letterboxes and Filtering Repeat Rent Data

To identify unique rental units within apartment buildings, we rely on reported letterboxes, tenant identifiers, and tenancy duration. This requires imposing a uniform standard on letterbox entries, which are highly heterogeneous and often lack consistent formatting. To avoid misclassifications, we conservatively exclude 87,311 contracts (12.4%) with ambiguous letterbox information.[3] We then remove 249,051 single-appearance units (35.4%), as these do not contribute to repeat rent identification (standardizing and mapping letterboxes is necessary before determining whether a unit appears only once). Contracts signed or commencing in the same month for the same unit (5,945 cases, or 0.8%) are also excluded, as they are unlikely to represent normal tenancy behavior.[4] We further remove 9,274 contracts (1.3%) involving incumbent tenants, which may bias rent levels. Finally, student housing is excluded: 20,043 contracts (2.8%) are identified either directly as student leases or inferred from neighborhoods dominated by young tenants (<26 years), short contracts (≤1 year), or similar rental costs. Excluding student housing is essential, given its non-negligible share in repeat rent data, to construct an index reflecting the total cost of tenancy for domiciled, registered renting households. Appendix A provides a visual example of the matching procedure on letterbox level.

Summarized, we obtain a cleaned dataset of 329,697 signed leases spanning 2014–2025, covering Belgium and including both single-family and multi-unit dwellings. By retaining only residential leases, excluding social housing, and using the total cost of tenancy as a metric (rent plus service charges), we ensure that the sample accurately reflects the private rental market.

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[2] The Belgian land registry does not have a uniform standard for street names (e.g. abbreviations, streets containing multiple names) nor housing numbers (e.g. strictly numbers, letter number combinations), making this step cumbersome.

[3] For example, 1, 0.01, 00/1, and B001 can all be mapped to the value 001 when the official house number includes a 'B'. However, if all letterboxes are missing or identical for overlapping tenancy periods, we cannot reliably map them to unique units that occur repeatedly.

[4] Note that each subsequent filtration step has the possible impact of reducing the signed rental lease on the housing unit level below 2 instances, thus removing the unit from the repeat rent index.

2.2 Summary Statistics

Table 1 compares the full dataset with the repeat rent subsample. Starting from a cleaned sample of 660,840 contracts, we identify 329,697 repeat rent observations (49.9%).[5] For context, Vastmans and de Vries (2012) report a ratio of 6% for Belgium in a comparable study. We attribute the markedly higher share in our data to the richness of the underlying source material and to our extensive cleaning and matching procedures, particularly at the letterbox level for apartment units. The repeat-rent dataset covers 135,584 unique properties, of which 95,650 (70.5%) are apartments. Table 1 reports these figures both at the national level and by province. This predominance of apartments contrasts with the repeat sales literature, which typically focuses on single-family properties, and underscores the importance of accurately matching units within multi-family buildings.

To assess how filtering our cleaned sample (full dataset) for repeat rent observations affects the proportion of datapoints across provinces, we perform a Pearson chi-squared test for homogeneity. We find that the distribution of observations across provinces is statistically indistinguishable between the full and repeat-rent datasets, with a χ^2 score of 2.6 ($p = 0.99$) based on the provincial proportions reported in Table 1. Figure 1, which displays the CPI-adjusted total cost of tenancy for the full dataset (left) and the repeat-rent dataset (right), visually confirms the nationwide representativeness of both datasets and the homogeneity in geographic coverage. The large difference in the number of datapoints between regions, notably between the North and the South, reflects underlying population density across Belgian's ten provinces. The color scheme (jet) highlights geographic variability in monthly total cost of tenancy, with neighborhoods in Brussels (capital city) exhibiting values more than five times higher than those in other provinces.

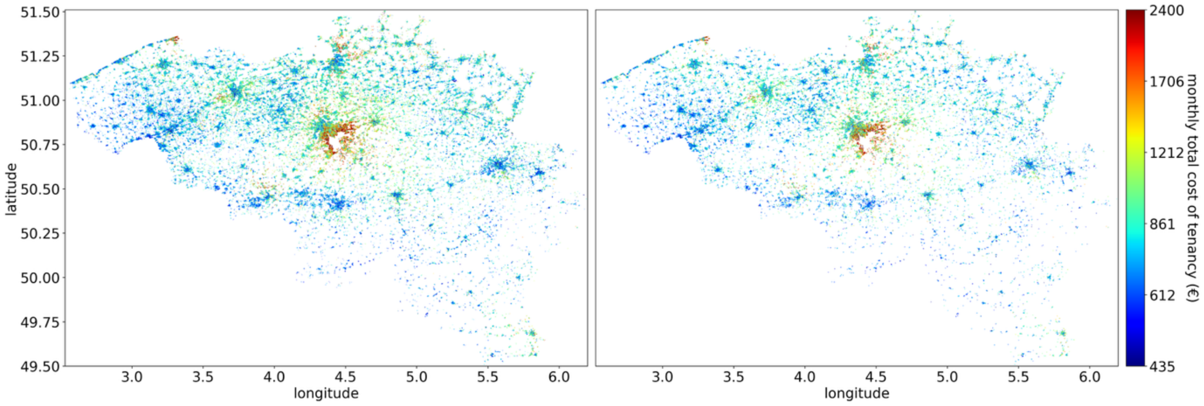
Table 1. Summary Statistics of the Full and Repeat-Filtered Rent Dataset.

Region	Full Dataset		Repeat Rent Dataset					
	# leases	% leases	# leases	% leases	# units	% units	# ap. units	% ap. units
Antwerpen	113,037	17.11	56,153	17.03	23,384	17.25	19,151	14.12
Brabant Wallon	16,670	2.52	7,328	2.22	3,140	2.32	2,054	1.51
Brussels	80,382	12.16	26,987	8.19	11,031	8.14	9,211	6.79
Hainaut	47,468	7.18	23,842	7.23	9,798	7.23	6,146	4.53
Limburg	44,541	6.74	25,048	7.60	10,249	7.56	7,798	5.75
Liège	24,226	3.67	10,480	3.18	4,461	3.29	3,275	2.42
Luxembourg	11,364	1.72	5,794	1.76	2,337	1.72	1,525	1.12
Namur	17,519	2.65	7,857	2.38	3,271	2.41	2,209	1.63
Oost-Vlaanderen	127,270	19.26	71,499	21.69	29,054	21.43	19,771	14.58
Vlaams-Brabant	60,240	9.12	29,380	8.91	12,304	9.07	8,100	5.97
West-Vlaanderen	118,123	17.87	65,329	19.81	26,555	19.59	16,410	12.10
Belgium	660,840	100	329,697	100	135,584	100	95,650	70.55

In the first table 'Full Dataset' we show the number and percentage of leases for each province and the total for the country (Belgium). In the second table 'Repeat Rent Dataset' we show the number and percentage of leases for each province in the repeat rent-filtered dataset, as well as the number of individual rental units and the number/percentage of units identified as an apartment within the repeat rent dataset.

[5] The full dataset in Table 1 shows all cleaned leases (after the general data cleaning: section 2.1.1, and matching the data to the land register: section 2.1.2) with same lease signature-start-date, incumbent tenancy bias and student housing immediately removed (a total of 41,705 leases are omitted), resulting in a 'Full dataset" with 660,840 contracts. In section 2.1.3 we gave the natural sequence of cleaning data for repeat rent purposes where we first remove ambiguous letterboxes and single unit appearances, before applying the subsequent repeat rent cleaning steps as these are required for identification. Here we directly report the grand total of datapoints that are suitable for a total cost of domiciled registered renting households.

Figure 1. CPI-Adjusted Total Cost of Tenancy for All Observation vs. only the Repeat Rent Observations



Geographic coordinates of the full cleaned dataset (left) and the repeat rent dataset (right), matched to the National building registry. The logarithm of total monthly rental cost (rent and service fees) is winsorized at the 1st and 99th percentile, visualized via a jet colormap.

3. Methodology

In this section, we provide an overview of the two basic index methods used in the repeat-rent price index literature: the Time Product Dummy (TPD) method and the Bailey, Muth, and Nourse (BMN) approach.[6] For an in-depth discussion, we refer the reader to Nagaraja et al. (2014) and de Haan & van de Laar (2021). Next, we introduce the robust M-estimator, which is employed in the remainder of the paper to construct our robust repeat rent indices. We then discuss the benchmark choice for evaluating the quality of our indices. Finally, we present our metric for measuring index revision variability (RV).

3.1 Time Product Dummy Regression

Assume a standard model in which rent is decomposed into unit-specific hedonic features and a general rent price index. Let p_i^t denote the log rent of unit i at time t, γ_i a unit-specific fixed effect (capturing unobserved, and in the paper absent, hedonic features), and $\exp(\delta^t)$ the rent index. Following de Haan & van de Laar (2021), we consider a Time Product Dummy specification for a set of N unique housing units over the period (0, T):

$$p_i^t = \alpha + \sum_{i=1}^{N-1} \gamma_i D_i + \sum_{t=1}^{T} \delta^t D^t + \varepsilon_i^t \tag{1}$$

where D_i is a unit dummy (1 if the observation belongs to unit i, 0 otherwise) and D^t is a dummy activated at time t (based on either the lease start or signature date) when a contract occurs. In total, we have $T + N$ parameters in this regression model. The period-over-period growth in the rental market (index) is given by:

$$exp(\delta^{t+1} - \delta^t) - 1 \tag{2}$$

[6] Both methods were developed and are used extensively in the setting of repeat sale single family house price indices. For this reason we keep the notation of price (P) although this can easily be read as rental price, and houses can be interpreted as any rental unit (e.g., apartment).

3.2 Bailey, Muth & Nourse's Repeat Rent Regression

As an alternative representation of the time product dummy regression model in (1), Bailey et al. (1963) propose to directly model the difference in log-prices of a repeat rent observation. This has the advantage of reducing the number of parameters to estimate. The underlying assumption is still the general hedonic rent model assuming the hedonic house characteristics to remain the same between two consecutive rental contracts. Assuming our sample contains *N* unique housing units for which we observe repeat rents (i.e., rental leases recorded at least twice for the same property; t' denotes the timing of a subsequent lease for unit *i*), we can then express the change in log rent as:

$$p_i^{t'} - p_i^t = \delta^{t'} - \delta^t + \varepsilon_i^{t\prime} - \varepsilon_i^t \,. \tag{3}$$

In this framework, an *n*-tuple of rent contracts observed for the same housing unit yields *n-1* distinct repeat rent pairs (e.g., a triplet yields two pairs, a quadruple yields three pairs). Such tuples naturally occur more frequently in rental contracts than in sale contracts. The resulting BMN index has *T-1* parameters to estimate. In this paper, we favor the original repeat sale method of Bailey et al. (1963) for its simplicity, particularly given the lack of hedonic covariates in our setting (a differencing approach rather than estimating fixed effects, as in the TPD model).

3.3 OLS vs. M-estimator

The standard estimator for both the Time Product Dummy and Repeat Rent regression is Ordinary Least Squares. This approach is highly sensitive to the reality of outliers in the data. Inspired by Bourassa et al. (2013), we consider the alternative uses of an M-estimator to estimate (3) using the Huber loss function (Huber, 1964). For simplicity of notation, let us assume that we have one repeat rent observation per unit. We then estimate the rent-level coefficients δ^t by minimizing

$$\sum_{i=1}^{N} \rho_{huber}\left(\frac{\varepsilon_i^{t'} - \varepsilon_i^t}{\sigma}\right), \tag{4}$$

where the Huber loss controls the impact of outliers through a piecewise penalty function:

$$\rho_{huber}(z) = \begin{cases} \frac{1}{2}z^2 & if\ |z| \leq \theta \\ \theta\left(|z| - \frac{1}{2}\theta\right) & if\ |z| > \theta. \end{cases} \tag{5}$$

Small standardized residuals ($|z| \leq \theta$) receive a quadratic penalty, while for larger residuals ($|z| > \theta$) the part exceeding the threshold θ receives a linear penalty.[7] The scale parameter σ is estimated via the median absolute deviation (MAD) on $\varepsilon_i^{t'} - \varepsilon_i^t$.

[7] In our implementation we apply the standard $\theta = 1.345$ (resulting in a 95% efficiency under normal errors). As Huber loss is non-linear the minimization has no closed form solution and iteratively reweighted least squares is applied with a tolerance of 10^{-7}. Note that if $\theta = \infty$, the M-estimators coincides with the OLS estimator.

In this paper, we deliberately restrict our analysis to methods that can be readily implemented using standardized data inputs. Within these constraints, we experimented with repeat-rent index methods following Goetzmann (1992), Case and Shiller (1987), Shiller (1991), and Calhoun (1996). These approaches primarily address the issue of long intervals between successive repeat sales and provide only negligible improvements over the basic TPD or BMN indices in our setting.

3.4 Comparing the Constructed Repeat Rent Indices to the National Benchmark

We compare our custom-constructed indices with an official benchmark, following Bourassa et al. (2013), Ambrose et al. (2015) and Adams et al. (2024). In our paper, this comparison serves two purposes: (i) to validate the suitability of our dataset for constructing repeat rent indices and for broader academic use, (ii) to assess the implications of applying a robust estimator, relative to a standard OLS estimator, for monthly repeat rent index revisions.

For Belgium, our benchmark is the RCPI index (the private rent and social housing component of the CPI) which is published at the end of each month. It is constructed by running a TPD regression on all registered repeat rent leases over an eight-year window, stratified by province. All end-of-month RCPI figures are final and not subject to revisions. In our dataset, index values are generated at the end of each month, with the available data truncated at that point. For all methods considered, indices are reconstructed each month over the entire horizon spanning from 2014 to the current month and the obtained index values are normalized to January 2017.

For the comparison between BMN indices estimated using a robust (Huber loss) versus an OLS approach, we use the period January 2018 to March 2025 (87 months). For the comparison between our indices and those constructed by the national forecasting agency (also normalized to January 2017), we restrict the period to January 2020 to March 2025 (63 months), as the repeat rent TPD method is only applied by Statbel for the RCPI from 2020 onward.[8]

3.5 Repeat Rent Index Revision Variability

Revision variability in repeat rent indices can be substantial, raising concerns not only for the timely settlement of index-linked instruments (Clapham et al., 2006) but also for the credibility of the index itself. If early releases are systematically subject to large adjustments, market participants may rationally discount the informational value of newly published figures.[9] A natural measure of revision variability (RV) is obtained by taking the squared differences between the revised estimate of monthly rent growth $\hat{g}_i^{t+\Delta}$ and the initial end-of-month estimate $\hat{g}_t^t$. For an index that produces n Δ-month updates relative to the first end-of-month estimate, the index revision variability is defined as:

[8] Until December 2019, data for the rent component of the CPI was collected via a large-scale survey covering 1,800 renting households.

[9] Not only the latest published figures are prone to revision, but the entire span of the already constructed repeat rent index may be affected (Bourassa et al., 2013).

$$RV = \frac{1}{n}\sum_{t=1}^{n}\left(\hat{g}_t^{t+\Delta} - \hat{g}_t^{t}\right)^2. \quad (6)$$

4. Main findings

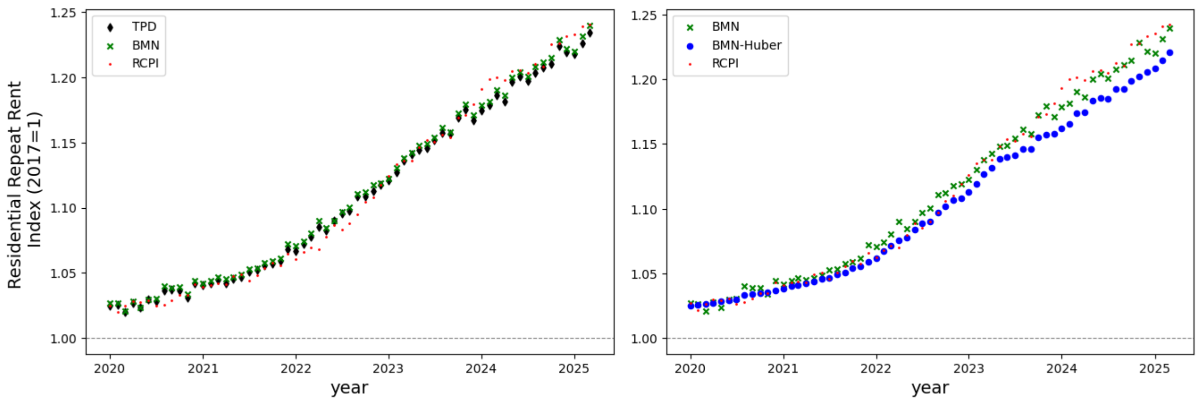
The goal of this section is to study the benefits of using robust estimators for monthly repeat rent indices. We analyze this in three steps: First, we asses that the proposed repeat rent index on our data sample captures nationwide rental market dynamics, as benchmarked against the national RCPI index. Second, we study to what extent the M-estimator reduces the volatility of monthly repeat rent indices as compared to the conventional OLS estimator. Third, we quantify the reduction in revision variability when using the M-estimator.

4.1 Same Methods, Different Data: our Indices Compared to the Benchmark

Our dataset covers a sample of the rental market, excludes social housing and is constructed via a BMN method while the RCPI is based on all registered tenancy agreements and is constructed via a TPD regression on an 8-year rolling window. A first empirical question is how big the differences are between our indices based on our dataset and the index published by the national statistical agency.

In Figure 2 we compare end of month BMN/TPD (estimated using OLS) and BMN-H (using a Huber loss function) based national (Belgium) indices on signature dates against the end of month RCPI index over the period January 2020 – March 2025. We conclude both our TPD and BMN indices on our dataset replicate the RCPI with minimal difference (left hand side). To isolate the impact of the robust estimation procedure we compare the same BMN method using an OLS and an M-estimator (right hand side).

Figure 2. Our Repeat Rent Indices vs. the Benchmark Index.



On the left-hand graph we compare the end of month BMN and TPD based national indices against the end of month RCPI index over the period January 2020 – March 2025. On the right-hand side graph we compare the end of month BMN (OLS) and BMN-H (Huber loss) based national (Belgium) indices against the end of month RCPI index over the period January 2020 – March 2025.

From visual inspection of the left graph in Figure 2, we draw two main conclusions. First, we find that both approaches (BMN and TPD) lead to nearly the same results. Second, their values nearly overlap with the official rent price index published by the national statistical agency confirming the representativeness of our dataset. One exception is the temporary divergence in

2024 where the official index increases more than ours, most likely due to a change in social rent regulation as of January 2024. In the right figure we compare the OLS estimator (denoted as BMN) with the robust Huber M-estimator (denoted by BMN-Huber). The use of a robust M-estimator leads to a slightly lower level of the repeat rent index. This is expected as changes in house characteristics would typically be improvements (e.g. due to refurbishing) leading to substantially higher rental price changes than would be expected if house characteristics would not have changed.

In Table 2 we analyze the statistical significance of the observed differences in mean growth rates (log first differences) of one end of month index estimate vis-à-vis another. For equality of mean growth rates we apply a two-sided Newey-West t-test with HAC standard errors (lags chosen via AIC, Akaike Information Criterium) for which we display the *p*-values. The null hypothesis (equality of mean growth rates) is never rejected in favor of the alternative when comparing indices constructed on different methods on the same dataset (BMN vs. TPD, BMN-H vs. BMN) or between our dataset and the full population of all registered rental contracts (TPD vs. RCPI), across all regions.

Next, we examine whether the indices, constructed using either robust or OLS estimation under the TPD or BMN procedures, share a common long-run trend. We start with a test for presence of a unit root (non-stationarity) in each index. Given our small datasets (max 87 periods), we run an Elliott-Rothenberg-Stock (1996) DF-GLS unit root test, with the lags again selected via AIC. The *p*-values displayed do not reject the null, indicating the series has a unit root (not-stationary), but for two cases in the TPD setting. The two provinces where the null is rejected belong to the lowest sample density regions as per Table 1. Given the absence of stationarity in the majority of the indices, we test for short run pairwise cointegration between the indices via a Johansen-Juselius (1990) test with the lags set at a quarter (3 months). We run a trace test for which we display the test statistics. The null hypothesis of no cointegration is almost universally rejected in favor of the alternative, indicating the presence of cointegration.

Table 2. Growth Rates and Cointegration.

Region	Mean Monthly Log Returns ($\times 10^{-3}$)			p-value Newey-West t-test			p-value DF-GLS			Trace Statistic Johansen-Juselius		
	BMN	BMN-H	TPD	TPD -RCPI	BMN -TPD	BMN-H -BMN	TPD	BMN	BMN-H	TPD -RCPI	BMN -TPD	BMN-H -BMN
Belgium	2.44	2.23	2.40	0.978	0.538	0.382	0.795	0.774	0.327	23.962***	27.642***	28.826***
Antwerpen	3.34	2.52	3.28	0.816	0.656	0.286	0.918	0.881	0.623	24.408***	29.096***	18.636**
Brabant Wallon	2.09	2.40	1.83	0.928	0.577	0.809	0.015	0.259	0.411	27.444***	46.862***	33.385***
Brussels	-0.03	1.74	0.10	0.926	0.870	0.386	0.774	0.656	0.669	22.528**	23.107**	21.139**
Hainaut	2.17	1.94	2.10	0.718	0.846	0.755	0.938	0.918	0.919	31.718***	31.592***	30.198***
Limburg	2.23	2.28	2.19	0.849	0.852	0.957	0.983	0.963	0.419	36.274***	24.286***	26.582***
Liège	2.45	1.75	2.47	0.884	0.948	0.716	0.737	0.739	0.581	16.622*	36.130***	32.053***
Luxembourg	2.33	2.48	2.43	0.860	0.898	0.946	0.203	0.173	0.178	21.001**	44.728***	33.764***
Namur	3.55	3.12	3.52	0.758	0.962	0.698	0.000	0.403	0.774	25.329***	39.044***	23.421***
Oost-Vlaanderen	2.42	2.28	2.32	0.918	0.477	0.744	0.638	0.890	0.539	13.222	31.845***	40.785***
Vlaams-Brabant	2.50	2.32	2.54	0.866	0.873	0.799	0.773	0.905	0.453	32.848***	28.738***	28.214***
West-Vlaanderen	2.43	2.05	2.39	0.731	0.762	0.450	0.809	0.800	0.545	29.106***	29.717***	41.485***

Results are shown for BMN (Bailey, Muth & Nourse, OLS estimated), BMN-H (BMN-Huber Loss estimated) and TPD (Time Product Dummy, OLS estimated) indices. Indices span January 2020 - March 2025 when compared to the RCPI (Rent Component of the National Monthly CPI estimate), otherwise the indices span January 2018 – March 2025. The mean monthly log differences are displayed in the first column. The second column displays the *p*-values of a two-sided Newey-West t-test, with HAC-covariance matrices (lags selected via AIC (Akaike Information Criterium), restricted to 12 months. The third column displays the *p*-values for an Elliott-Rothenberg-Stock (DF-GLS) unit root test. The last column shows the trace test statistic for the Johansen-Juselius test for cointegration with the standard * on 10, 5 and 1% significance level.

Three results from Table 2 stand out. First, the results from the two-sided Newey-West t-test indicate the mean growth rates per province do not differentiate significantly from the nationwide mean growth rates (RCPI). The automatic indexation of rents tied to the national health CPI growth, which in effect restricts province rent indices to deviate substantially from the national level explains this result. Second, on the national level and across all provinces, we show the Huber Loss estimation procedure does not significantly affect the mean geometric growth rates. Third, the Johansen-Juselius Trace statistics indicate the TPD index based on our dataset and the nationwide RCPI index, also estimated via TPD-OLS but on the full population, to be cointegrated. We find a similar result comparing the Huber and OLS estimated BMN indices, where applying a robust estimator preserves the underlying long-run price dynamic.

4.2 Impact of Robust Estimation vs. OLS Estimation on Repeat Rent Indices

This section examines the impact of employing an M-estimator rather than the conventional OLS estimator in the construction of repeat rent indices for a large-scale dataset. Specifically, we assess the extent to which robust estimation reduces monthly index volatility.

Table 3 measures the differences in volatility of growth rates by applying a one-sided *F*-Test on the HAC adjusted Variance Ratio (lags set to a quarter, 3 months). In the first column we display the HAC adjusted Standard Errors for the mean monthly log differences. The values for BMN and BMN-H are displayed for the period January 2018 – March 20205, those for TPD are displayed for the period January 2020 – March 2025, matching the period of the RCPI index. The *p*-values for the one-sided *F*-Test are directly displayed in the last columns. We find the null, the former index to have a larger or equal variance in growth rates than the latter to be unanimously rejected when comparing the BMN-H (Huber) vs. BMN (OLS) indices, indicating the former to have a lower variance in growth rates. Moreover, when comparing our TPD index with the RCPI counterpart, we can reject the null on the national level at 5% significance. These results could be explained by our exclusion of social and student housing in our dataset.

Table 3. Index Growth Rate Volatility

Region	HAC-Standard Errors Log Diff. ($\times 10^{-3}$)			Variance Ratio		p-Value Variance Ratio Test	
	BMN	BMN-H	TPD	BMN-H / BMN	TPD / RCPI	BMN-H -BMN	TPD -RCPI
Belgium	0.40	0.30	0.38	0.54	0.62	0.002	0.033
Antwerpen	0.97	0.38	0.74	0.15	2.39	0.000	1.000
Brabant Wallon	1.65	1.03	1.79	0.39	13.93	0.000	1.000
Brussels	2.86	1.24	2.27	0.19	22.60	0.000	1.000
Hainaut	1.06	0.56	0.96	0.28	4.06	0.000	1.000
Limburg	0.97	0.45	1.12	0.22	5.46	0.000	1.000
Liège	2.44	1.07	2.36	0.19	24.42	0.000	1.000
Luxembourg	2.97	1.70	2.99	0.33	38.97	0.000	1.000
Namur	2.00	1.31	2.09	0.43	19.04	0.000	1.000
Oost-Vlaanderen	0.56	0.34	0.53	0.36	1.24	0.000	0.795
Vlaams-Brabant	0.94	0.45	1.15	0.23	5.81	0.000	1.000
West-Vlaanderen	0.62	0.36	0.76	0.34	2.51	0.000	1.000

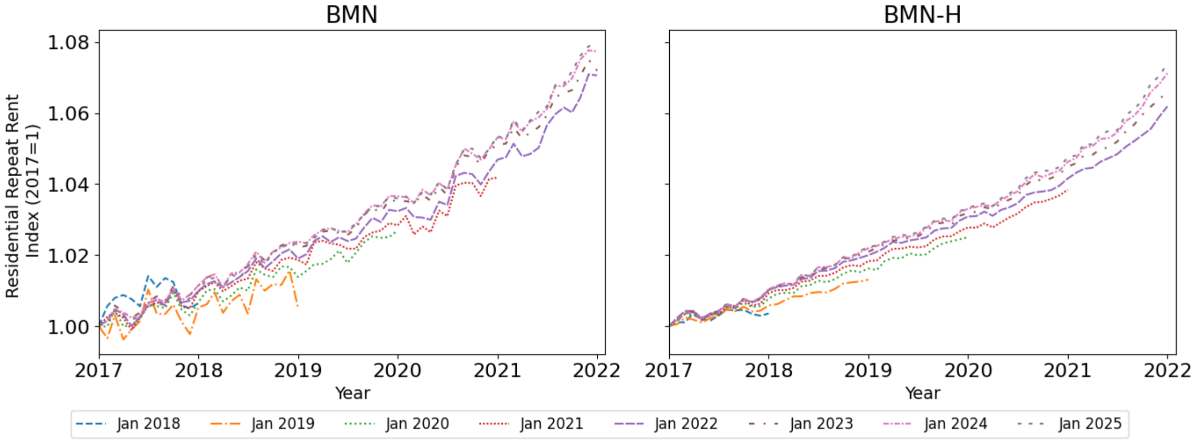
Results are shown for BMN (Bailey, Muth & Nourse, OLS estimated), BMN-H (BMN-Huber Loss estimated) and TPD (Time Product Dummy, OLS estimated) indices. Indices span January 2020 - March 2025 when compared to the RCPI (Rent Component of the National Monthly CPI estimate), otherwise the indices span January 2018 – March 2025. The Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors of mean growth rates with one quarter (3 months) lags are reported in the first column. The variance ratio column shows the ratio of HAC-adjusted variances. The result of the one side F-test for equal Index variance is reported in the third column (p-value).

4.3 Robust Estimation and the Accuracy of Monthly Rent Growth Indices

Accurately estimating monthly rental cost growth is central to the mandate of national statistical agencies. This section investigates which estimation approach (OLS or an M-estimator) yields the most reliable results. We pay particular attention to how the use of a Huber loss function influences the revision variability (6) of repeat rent indices compared to OLS at monthly frequencies. We analyze the indices for 1, 2, 3- and 4-year revision periods, capturing the bulk of the revision effects. Because the national statistical agency does not release historical vintages of the RCPI, our analysis is limited to BMN-based indices constructed from our dataset.

Figure 3 shows the impact of ‘new data’ on previously established datapoints in both the BMN (OLS) and BMN-H (Huber) framework on the national level. From a visual perspective the robust method clearly returns indices with lower volatility, and consequently less impactful updates. In both cases there is a clear upward trend in the adjustment of previously computed index levels. This underscores our focus on produced month over month growth rates, and their updates, instead of levels. In Table 4 we formally test the hypothesis. In the first column, we display the revision variability (RV) of each index with respect to the revision horizon. In the second column, we apply a one-sided Diebold-Mariano (Diebold-M.) test with HAC errors on the mean squared error between the end of month rent growth estimate and the update n-years later. The null hypothesis is unanimously strongly rejected in favor of the alternative, indicating a lower growth estimate error of BMN-Huber loss-based indices over OLS with respect to all revision horizons. A robust estimation procedure is advised when producing reliable end of month growth rate estimates.

Figure 3. Index Revisions under OLS and Robust (Huber) Estimation



Results are shown for 8 indices constructed on an expanding dataset on the national level (Belgium). The full updated indices are constructed on all time filtered available data at each stage (e.g. for January 2018, the last datapoint is an 'end of month estimate' (see Figure 2); all previous datapoints are based on increasingly larger samples). The left figure displays the BMN (Bailey, Muth & Nourse, OLS estimated) indices, the right figure displays the BMN-H (Huber Loss based with $\theta = 1.345$). The x-axis of the graph is restricted to January 2022 for visual purposes, the indices are normalized in January 2017.

Figure 2 and Figure 3 clearly demonstrate the difference between end of month estimates and the global index revision. In Figure 2, similar to how the RCPI is constructed, a datapoint is constructed at the end of the given month. In Figure 3 the entire index is revised over the entire span based on all available data. Previously computed datapoints shift under the influence of new repeat pairs. Notice how the last datapoint of Figure 3 for each year update aligns with the end of month forecast in Figure 2.

Table 4. Index Revision Volatility.

Region	1Y Revision Horizon			2Y Revision Horizon			3Y Revision Horizon			4Y Revision Horizon		
	RV ($\times 10^{-3}$)		**Diebold–M.**	**RV** ($\times 10^{-3}$)		**Diebold–M.**	**RV** ($\times 10^{-3}$)		**Diebold–M.**	**RV** ($\times 10^{-3}$)		**Diebold–M.**
	BMN	BMN-H	BMN-H -BMN	BMN	BMN-H	BMN-H -BMN	BMN	BMN-H	BMN-H -BMN	BMN	BMN-H	BMN-H -BMN
Belgium	0.08†	1.01†	-5.07***	0.12†	1.42†	-4.94***	0.14†	1.29†	-4.87***	0.14†	1.30†	-3.72***
Antwerpen	0.01	0.08	-5.87***	0.01	0.12	-4.60***	0.01	0.15	-4.03***	0.01	0.12	-3.35***
Brabant Wallon	0.40	1.37	-4.00***	0.31	1.32	-3.90***	0.32	1.41	-3.92***	0.34	1.79	-3.37***
Brussels	0.37	1.44	-3.55***	0.39	1.58	-4.03***	0.34	1.13	-4.26***	0.35	1.34	-4.21***
Hainaut	0.03	0.20	-7.09***	0.03	0.27	-5.75***	0.02	0.26	-4.56***	0.03	0.29	-3.54***
Limburg	0.02	0.24	-4.41***	0.02	0.21	-3.89***	0.02	0.24	-3.95***	0.02	0.34	-2.88***
Liège	0.24	1.44	-4.56***	0.25	1.53	-3.59***	0.31	1.69	-3.54***	0.36	2.42	-3.96***
Luxembourg	0.58	2.05	-2.64***	0.74	2.54	-2.42***	0.85	3.03	-2.55***	0.97	3.34	-2.63***
Namur	0.60	2.01	-3.90***	0.50	1.58	-3.67***	0.63	2.00	-3.35***	0.65	2.35	-3.44***
Oost-Vlaanderen	0.01	0.04	-3.13***	0.01	0.06	-3.92***	0.01	0.07	-4.47***	0.01	0.08	-4.08***
Vlaams-Brabant	0.04	0.20	-3.81***	0.05	0.42	-3.48***	0.05	0.33	-5.08***	0.05	0.37	-3.22***
West-Vlaanderen	0.02	0.08	-3.81***	0.01	0.10	-3.80***	0.02	0.08	-2.93***	0.01	0.11	-3.09***

The first two sub-columns indicate performance with respect to the revision horizon in terms of revision variability[10] for the BMN (Bailey, Muth & Nourse, OLS estimated) and BMN-H (BMN-Huber Loss estimated) indices. The subsequent sub-column displays Diebold-Mariano (Diebold-M.) test values given with the standard * on 10, 5 and 1% significance level. For the 1-year horizon, the original vintages span from January 2018 to March 2024 allowing for a full 1-year update window. The procedure for longer revision horizons is similar, leading to shorter windows

5. Robustness Checks

In the previous section, all indices were constructed using the signature date of rental contracts, as is standard in both industry practice and the academic literature. However, one could also argue for using the contract start date as the temporal reference in repeat rent indices. Adams et al. (2024) explicitly examine this distinction and show that indices based on signature dates naturally lead those based on start dates. The signature-date approach is preferable for real-

[10] Values on the national (Belgium) level (indicated with †) indicate multiplication with 10^{-5} instead of 10^{-3}.

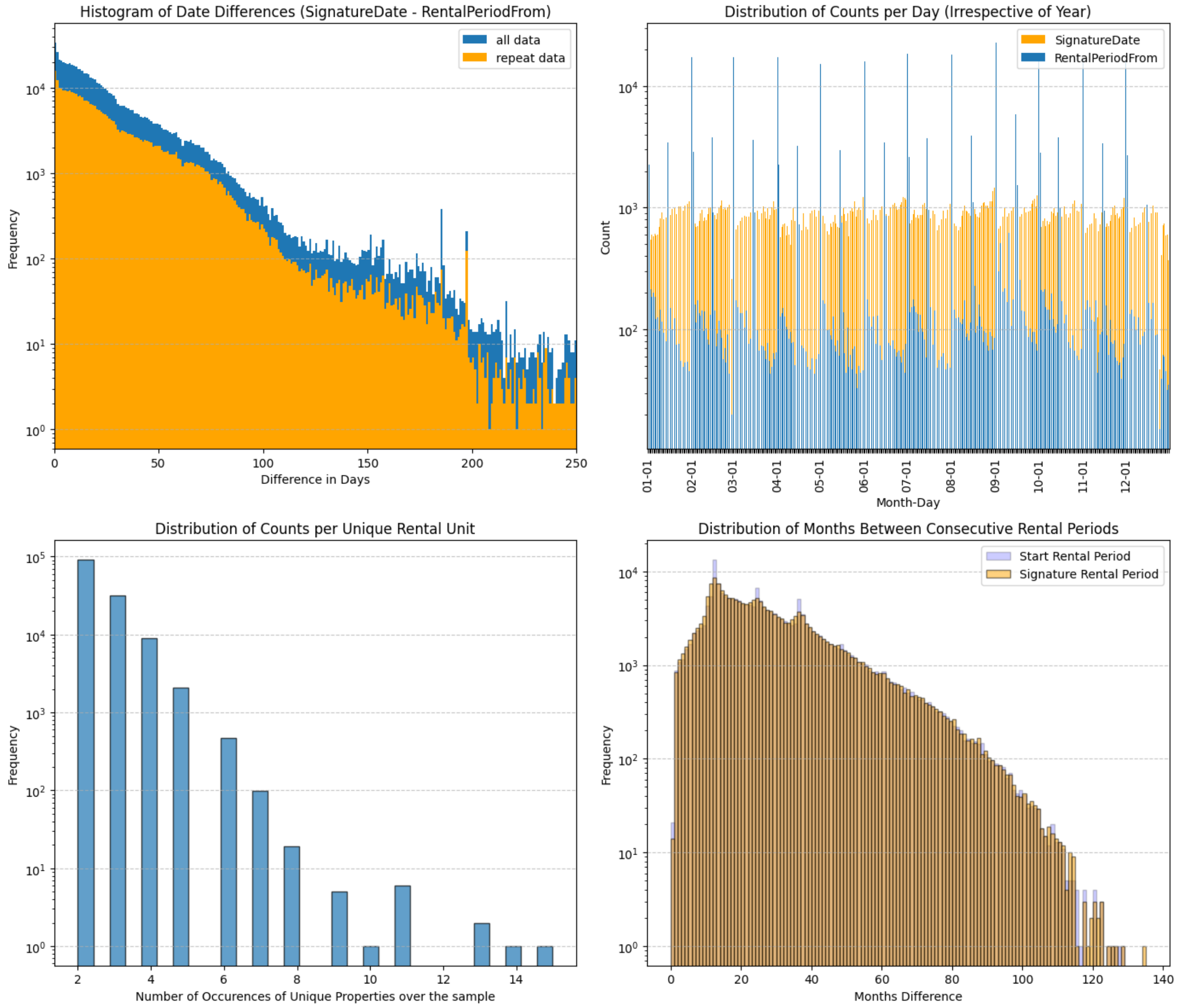
time tracking of developments in the rental market, while start-date indices better reflect the evolving conditions experienced by the broader population of current tenants. Differences between indices constructed on either temporal marker have been observed, but beyond Ambrose et al. (2015) and Adams et al. (2024), the impact of those differences on repeat rent indices has received little attention.

In the first part of this section, we assess the extent to which changing the temporal basis of the index affects our results and whether the main findings remain robust under this alternative specification. The second part of the section addresses the sensitivity of our results to the choice of the Huber loss parameter (θ). In our main analysis (Section 4), we follow Bourassa et al. (2013) and set the Huber tuning parameter to 1.345. Here, we evaluate how varying theta influences the robustness of our findings.

5.1 Repeat Rent Indices on Start Dates and the Impact on the Main Results.

We start with summarizing the key characteristics of both the repeat rent dataset and the full sample (Table 1) with an emphasis on differences between signature and rental lease starting dates in Figure 4. The top-left panel shows the lag between contract signature and start-dates. In both datasets, this lag frequently exceeds 1-2 months, underscoring the importance of the choice between signature and start date-based dating in index construction. The top-right panel groups signature and start dates of repeat contracts within the calendar year. Start dates cluster at the beginning, middle, and end of months, whereas signature dates are more uniformly distributed, exhibiting a zig-zag pattern of increasing lease signings as the month progresses. The lower-left panel reports the distribution of property-level repeat occurrences over the 10-year span of the sample: most properties appear exactly twice, the minimum threshold for inclusion in a repeat rent index, after which the number falls rapidly. The lower-right panel presents the distribution of months between successive contracts, separately for signature and start dates. For start dates, pronounced spikes appear at 12, 24 and 36 months, reflecting standard lease durations. Since a repeat rent index has its historical values revised whenever new rent pairs are added, this distribution provides a proxy for revision risk. The majority of pairs occur within 3 years, after which the likelihood of further substantial revisions diminishes rapidly.

Figure 4. Repeat Rent Indices based on Signature vs. Start Date: Timing Differences



Top left: the distribution of the gap between contract signature and start date for the full dataset and the repeat sample. Top right: the difference in clustering between signature date and contract start date for all data mapped to the dates on the yearly calendar. Bottom left: the number of occurrences of the same unique property in the repeat rent dataset over the entire 10-year span. Bottom right: the distribution of months between repeat rents in the repeat rent dataset based upon signature or contract start dates.

The construction of our repeat rent indices on starting dates remains similar to section 3.4. Repeat rent units are again identified the moment a second rental contract becomes available. Note that the signature date of a lease cannot precede the database entry date, the start date however can be any given number of periods in the future (Figure 4). To establish a consistent comparison between indices built on signature (RCPI) and start date, 'future' datapoints due to signed leases with 'far out' starting dates are omitted (which would inflate the volatility of those indices). The constructed indices are restricted to the end of the 'present' month, aligned with the objective of providing an estimate at the end of the 'current' month.

Table 5 displays the results regarding mean growth rates (log diff.) and volatility of indices constructed on start dates over signature dates (section 4). The BMN, TPD and BMN-H indices are constructed on start dates, RCPI is however only constructed and distributed on signature dates. The full tables similar to section 4 are available in Appendix B. The impact of constructing the monthly repeat rent indices with a Huber loss over an OLS estimation procedure remain largely unaltered from Section 4.2; the BMN-H indices do not indicate to produce significantly different mean growth rates (the null is never rejected at any significance level). The results with respect to equality of mean growth rates for the TPD-RCPI columns in which the former is constructed on start dates, and the latter (also based on an TPD-OLS estimation) on signature dates are in line with the expectations for the nationally based indices, resulting in the same mean growth rates. For the low sample density provinces (e.g. Brabant Wallon and Brussels) we see the start date-based indices to have substantially higher growth mean grow rates, which is attributed to the concentration of rent contract start dates at certain months.

Table 5. Start Date-Based Indices: Growth Rates and Volatility

Region	Mean Monthly Log Diff. ($\times 10^{-3}$)			p-Value Newey-West t-Test			HAC-Standard Errors Log Diff. ($\times 10^{-3}$)			p-Value Variance Ratio Test	
	BMN	BMN-H	TPD	TPD -RCPI	BMN -TPD	BMN-H -BMN	BMN	BMN-H	TPD	BMN-H -BMN	TPD -RCPI
Belgium	2.51	2.23	2.41	0.808	0.134	0.208	0.38	0.30	0.41	0.011	0.129
Antwerpen	2.92	2.46	2.93	0.785	0.983	0.409	0.69	0.33	0.73	0.000	0.999
Brabant Wallon	6.14	5.90	6.09	0.947	0.909	0.909	4.22	3.68	1.82	0.103	1.000
Brussels	2.98	2.73	2.73	0.533	0.591	0.841	1.84	0.79	1.94	0.000	1.000
Hainaut	1.82	1.68	1.74	0.420	0.722	0.818	0.81	0.38	0.60	0.000	0.960
Limburg	2.65	2.20	2.49	0.993	0.421	0.467	0.75	0.42	0.83	0.000	1.000
Liège	2.01	2.05	1.97	0.486	0.879	0.971	1.44	0.69	1.72	0.000	1.000
Luxembourg	3.08	2.82	3.33	0.882	0.590	0.815	1.77	1.10	1.49	0.000	1.000
Namur	4.20	3.72	3.97	0.771	0.634	0.741	2.79	1.85	2.23	0.000	1.000
Oost-Vlaanderen	2.37	2.13	2.30	0.458	0.588	0.433	0.46	0.33	0.50	0.002	0.657
Vlaams-Brabant	2.59	2.36	2.40	0.999	0.395	0.704	0.82	0.46	1.00	0.000	1.000
West-Vlaanderen	2.23	2.14	2.13	0.599	0.477	0.827	0.50	0.33	0.62	0.000	0.980

Results are shown for the data spanning January 2020 - March 2025 when compared to the RCPI method, otherwise the data spans January 2018 – March 2025. BMN-H indicates the index is built with Huber loss (BMN is built on standard OLS). All indices (except RCPI) are constructed on lease start date time index (starting date). The mean monthly log differences are displayed in the first column. The second column displays the *p*-values of a two-sided Newey-West t-test, with HAC-covariance matrices (lags selected via AIC (Akaike Information Criterium), restricted to 12 months. The Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors with one quarter (3 months) lags are reported in the third column. The result of the one side *F*-test for equal Index variance is reported in the last column (*p*-value).

In section 4.2 we concluded the M-estimator to reduce the volatility of the monthly indices constructed on lease signature date. We find a similar results when constructing our monthly repeat rent indices on start dates. However, when constructing the national (Belgium) TPD index on start dates, the increased volatility from the lower presence of lease start dates in certain months (e.g. December and January (Figure 4 top right)) results in a more volatile index. The null of larger or equal variance in growth rates between the TPD and RCPI cannot be rejected anymore at 5 or 10% significance level.

Table 6 reports the revision variability (RV) for the start date-based indices. The first columns present the revision variability (6) for both the Huber loss (BMN-H) and OLS (BMN) estimated indices across the different revision horizons. The subsequent columns report the one-sided Diebold–Mariano (Diebold–M.) test statistics with HAC errors on the mean squared error between the end of month rent growth estimate and the update *n*-years later. Across all revision horizons the null is strongly rejected in favor of BMN-H, indicating that the Huber–loss-based index exhibits systematically smaller revision errors than the OLS-based BMN index, consistent with the findings in Section 4.3.

Table 6. Revision Volatility of Start Date-Based Indices.

Region	1Y Revision Horizon			2Y Revision Horizon			3Y Revision Horizon			4Y Revision Horizon		
	RV ($\times 10^{-3}$)		Diebold–M.	RV ($\times 10^{-3}$)		Diebold–M.	RV ($\times 10^{-3}$)		Diebold–M.	RV ($\times 10^{-3}$)		Diebold–M.
	BMN	BMN-H	BMN-H -BMN	BMN	BMN-H	BMN-H -BMN	BMN	BMN-H	BMN-H -BMN	BMN	BMN-H	BMN-H -BMN
Belgium	0.08†	1.50†	-2.10**	0.14†	1.84†	-2.68***	0.15†	2.04†	-3.37***	0.15†	2.08†	-3.58***
Antwerpen	0.01	0.07	-4.84***	0.01	0.13	-4.26***	0.01	0.19	-4.92***	0.01	0.10	-5.52***
Brabant Wallon	2.46	4.20	-2.68***	3.26	6.02	-2.53***	3.79	6.38	-2.08**	4.92	8.36	-2.13**
Brussels	0.21	0.86	-4.94***	0.18	1.14	-4.45***	0.22	1.47	-4.01***	0.22	1.41	-3.25***
Hainaut	0.02	0.18	-4.45***	0.02	0.25	-5.41***	0.02	0.25	-4.44***	0.03	0.21	-3.83***
Limburg	0.02	0.19	-3.29***	0.01	0.16	-3.61***	0.02	0.23	-4.18***	0.02	0.22	-3.56***
Liège	0.18	0.62	-3.99***	0.12	0.68	-4.73***	0.16	1.14	-3.22***	0.15	1.27	-2.78***
Luxembourg	0.23	0.85	-4.28***	0.12	1.06	-5.15***	0.12	1.01	-4.32***	0.13	1.23	-4.96***
Namur	0.67	2.18	-2.67***	0.66	1.91	-3.04***	0.72	1.79	-2.67***	0.93	2.32	-2.31**
Oost-Vlaanderen	0.01	0.04	-3.53***	0.01	0.06	-4.45***	0.01	0.07	-4.99***	0.01	0.09	-5.09***
Vlaams-Brabant	0.06	0.28	-4.29***	0.06	0.35	-4.62***	0.07	0.33	-3.74***	0.05	0.31	-3.64***
West-Vlaanderen	0.00	0.03	-3.42***	0.01	0.10	-3.99***	0.01	0.07	-4.80***	0.01	0.06	-4.59***

The first two sub-columns indicate performance with respect to the revision horizon in terms of revision variability[11] for the BMN (Bailey, Muth & Nourse, OLS estimated) and BMN-H (BMN-Huber Loss estimated) indices. The subsequent sub-column displays Diebold-Mariano (Diebold-M.) test values given with the standard * on 10, 5 and 1% significance level. For the 1-year horizon, the original vintages span from January 2018 to March 2024 allowing for a full 1-year update window. The procedure for longer revision horizons is similar, leading to shorter windows

We conclude our main findings of volatility reduction and reduced revision variability are highly robust to the choice of time index (signature or start) for monthly repeat rent total cost of tenancy indices.

5.2 Impact of the Huber Loss Parameter on the Monthly Repeat Rent Indices

The Huber loss parameter θ, influencing how many datapoints are treated as outliers (5), has been kept at the default value of 1.345 in our previous analysis. Under normally distributed errors, this choice yields approximately 95% of the statistical efficiency of ordinary least squares (the Huber estimator's variance is only about 5% larger than the OLS variance) while providing substantially greater robustness to outliers. A natural question arises if our results in section 4 (Main Findings) are robust to a different setting of θ. In Table 7 we reconstruct our BMN-H indices over the discrete set of Huber loss parameter values on the national level as in section 4. Decreasing θ results in 'penalizing' (downweighting) more datapoints, increasing θ results in the opposite effect. The results in Table 7 indicate changing the Huber loss parameter θ significantly from the default value (1.345) does not alter our main findings.

Table 7. Impact of the Huber-loss Parameter on Monthly Repeat Rent Indices.

θ	Mean M. Log Diff.	p-Value Newey-West t-Test		HAC-SE. Log Diff.	p-Value Variance Ratio Test		1Y Revision		2Y Revision		3Y Revision	
	BMN-H	BMN-H -RCPI	BMN-H -BMN	BMN-H	BMN-H -BMN	BMN-H -RCPI	RV	D.–M.	RV	D.–M.	RV	D.–M.
1.0	2.200	0.586	0.336	0.299	0.000	0.000	0.754	-5.02***	1.141	-4.94***	1.207	-4.93***
1.345	2.225	0.616	0.382	0.296	0.000	0.000	0.806	-5.07***	1.239	-4.94***	1.403	-4.87***
3.0	2.314	0.828	0.577	0.300	0.000	0.000	1.398	-5.01***	2.115	-4.70***	2.433	-4.48***

We display for different values of θ $(1, 1.345, 3)$ the results of section 4 on the national level (Belgium) in a condensed format. Results are shown for the data spanning January 2020 - March 2025 when compared to the RCPI method, otherwise the data spans January 2018 – March 2025. The mean monthly log differences are displayed in the first column. The second column displays the *p*-values of a two-sided Newey-West t-test, with HAC-covariance matrices (lags selected via AIC (Akaike Information Criterium), restricted to 12 months. The Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors of mean growth rates with one quarter (3 months) lags are reported in the third column. The result of the one side F-test for equal Index variance is reported in the fourth column (*p*-value). The right column (Diebold-Mariano) depicts end of month rent growth estimate given a (1 to 3)-year (12 to 36 months) revision horizon. For the 1-year horizon, the original vintages span from January 2018 to March 2024 allowing for a full 1-year update window. The procedure for longer revision horizons is similar, leading to shorter windows. Test values are given with the standard * on 10, 5 and 1% significance.

[11] Values on the national (Belgium) level (indicated with †) indicate multiplication with 10^{-5} instead of 10^{-3}.

We conclude the findings from section 4 (the indices based on our dataset capturing the same rental market dynamics as the national RCPI index and applying the M-estimator leads to reduced index-volatility and revision variability over the standard OLS-estimator) to be robust to a change of the time index (signature vs start date) for monthly repeat rent indices. We conclude the same with respect to changing the Huber loss estimator parameter (θ) beyond the default value (1.345). Most notably, in terms of revision variability of end of month growth in the total cost of private tenancy vis a vis 1-to-4-year revision updates, the M-estimator (Huber loss) consistently outperforms the OLS based implementation.

6. Conclusion

In an ideal setting, a monthly repeat rent index would accurately capture the underlying evolution of rental prices for dwellings whose characteristics remain unchanged throughout the observation period. In practice, however, rental contracts are not observed at monthly intervals, and a nontrivial minority of dwellings undergo substantial updates that modify their quality. These features generate outliers and introduce considerable revision variability into the estimation process, thereby complicating the goal of producing a stable and reliable index.

To address these challenges, this paper advocates the use of robust M-estimators as an alternative to conventional OLS-estimation methods. Robust M-estimators limit the influence of atypical observations and help reduce the volatility of subsequent index revisions. Our empirical analysis demonstrates the practical advantages of this approach and underscores its potential to improve the accuracy and stability of repeat rent indices used in economic analysis and policy measurement.

The empirical application is based on a newly constructed dataset of more than 660,000 individual signed rental contracts. After extensive data cleaning and a detailed matching procedure with the national building register, approximately 330,000 of these contracts are identified as repeat rental observations. Using this dataset, we implement and compare two variants of the Bailey, Muth, and Nourse (1963) repeat rent framework at both the national and provincial levels: a standard ordinary least squares specification and a robust M-estimator based on the Huber loss function.

Our findings show that repeat rent indices estimated with a robust M-estimator are substantially less volatile than those derived from a conventional OLS estimator, while still capturing the same underlying movements in the rental market. Robust estimation also yields end-of-month measures of month-over-month rent growth that are markedly less volatile and less prone to revision. These advantages hold whether repeat rent indices are constructed using lease signature dates or lease start dates, and they persist across a wide range of Huber loss function parameterizations. Because monthly rent inflation feeds directly and unrevised into the CPI, overstating volatility from outliers can distort this key measure. We therefore advise statistical agencies to adopt robust estimators, such as the M-estimator with Huber loss, when constructing monthly repeat rent indices.

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References

Adams B., Loewenstein L., Montag H. & Verbrugge R. J. 2024. Disentangling Rent Index Differences: Data, Methods, and Scope. *American Economic Review: Insights* 6(2): 230-245.

Ambrose B., Coulson E., & Yoshida, J. 2015. The Repeat Rent Index. *The Review of Economics and Statistics* 97 (5): 939-950.

Bailey M. J., Muth R. F. & Nourse H. O. 1963. A Regression Method for Real Estate Price Index Construction. *Journal of the American Statistical Association* 58(304): 933-942.

Bourassa S. C., Cantoni E. & Hoesli M. 2013. Robust Repeat Sales Indexes. *Real Estate Economics* 41(3): 517-541.

Calhoun C. A. 1996. OFHEO House Price Indexes: HPI Technical Description. *Office of Federal Housing Enterprise Oversight.*

Case, K. E. & Shiller R. J. 1987. Prices of Single-Family Homes Since 1970: New Indexes for Four Cities. *New England Economic Review* Sept.: 45-56

Clapham E., Englund P., Quigley J. M. & Redfearn C. L. 2006. Revisiting the Past and Settling the Score: Index Revision for House Price Derivatives. *Real Estate Economics* 34(2): 275-302.

de Haan J. & van de Laar R. 2021. House Price Indexes: A Comparison of Repeat Sales and other Multilateral Methods. *Statistics Netherlands, Division of Data Services, Research and Innovation.*

Elliot G., Rothenberg T. J. & Stock J. S. 1996. Efficient Tests for an Autoregressive Unit Root. *Econometrica* 64(4): 813-836.

Goetzmann W. N. 1992. The Accuracy of Real Estate Indexes: Repeat Sales Estimators. *Journal of Real Estate Finance and Economics* 5: 5-53.

Huber P. J. 1964. Robust Estimation of a Location Parameter. *Annals of Mathematical Statistics* 35(1): 73-101.

Johansen S., & Juselius, K. 1990**.** Maximum likelihood estimation and inference on cointegration—with applications to the demand for money. *Oxford Bulletin of Economics and Statistics* 52(2): 169–210.

Nagaraja C. H., Brown L. D. & Wachter S. M. 2014. Repeat Sales House Price Index Methodology. *Journal of Real Estate Literature* 22(1): 23-46.

Reusens P., Vastmans F. & Damen S. 2023. A new framework to disentangle the impact of changes in dwelling characteristics on house price indices. *Economic Modelling* 123: 106252

Shiller R.J. 1991. Arithmetic Repeat Sales Price Estimators. *Journal of Housing Economics* 1: 110–126.

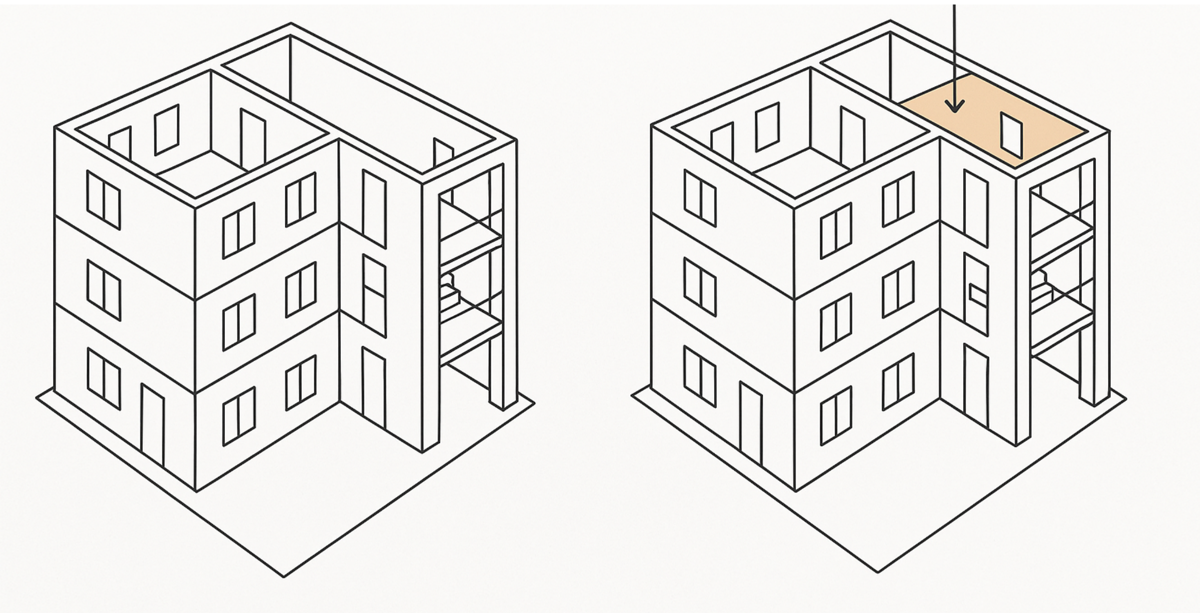
van de Minne A., Francke M., Geltner D. & White R. 2020. Using Revisions as a Measure of Price Index Quality in Repeat Sales Models. *Journal of Real Estate Finance and Economics* 60(4): 514-553

Vastmans F. & de Vries P. 2012. A rent index for the private rental sector in Flanders. *Journal of Housing and the Built Environment* 28: 435-449

Appendix

A: Example of Matching Data to the Level of Apartment Letterboxes

Figure 5. Apartment Buildings and Individual Rental Units.



On the left-hand side we display the matching of the data to the general building with the correct building number (Pater Damiaan Laan, 7B), on the right-hand side we show matching an individual apartment based on the letterbox (301).

Figure 5 displays the difference between matching data based on the street and house number basis (left hand side) and matching data on a letterbox basis. Although the example is trivial in this case, note that the diversity of street names / street numbers and box numbers combined with spelling/postal code errors and the absence of a standard on either level in the national building registry dramatically increases the computational complexity of mapping the correct raw database entry to the correct individual unit.

On the street level the data can be entered as e.g. Pater Damiaan, Pat. Damiaan, P/damiaan, p Damiaanstraat, P. Dmiaan etc. with possible faulty postal codes (highly prevalent in realtor data). The data regarding the street number and letterbox number is missing in many cases or entered as a single entry resulting in entries as e.g. 3.1, 30/1, 301B, B31, 3B1, 7/3.1B etc.). Apartment buildings do not necessarily have a standardized way of reporting the unit numbers so we must find a single form which can be applied to any unit for each specific building while minimizing the possibility of mapping distinct units to the same apartment (301 in this instance). It is this extended data matching procedure that allows us to achieve a substantial number of repeat rent pairs in our dataset, especially on the apartment level.

B: Full Tables with respect to Start Date-based Indices.

Table 7. Start-Based Growth Rates and Cointegration.

Region	Mean Monthly Log Returns ($\times 10^{-3}$)			p-value Newey-West t-test			p-value DF-GLS			Trace Statistic Johansen-Juselius		
	BMN	BMN-H	TPD	TPD -RCPI	BMN -TPD	BMN-H -BMN	TPD	BMN	BMN-H	TPD -RCPI	BMN -TPD	BMN-H -BMN
Belgium	2.51	2.23	2.41	0.808	0.134	0.208	0.461	0.457	0.181	20.748**	21.076**	19.616**
Antwerpen	2.92	2.46	2.93	0.785	0.983	0.409	0.821	0.791	0.519	31.254***	26.499***	27.542***
Brabant Wallon	6.14	5.90	6.09	0.947	0.909	0.909	0.018	0.015	0.278	23.384***	74.709***	47.180***
Brussels	2.98	2.73	2.73	0.533	0.591	0.841	0.492	0.424	0.388	25.074***	43.712***	24.482***
Hainaut	1.82	1.68	1.74	0.420	0.722	0.818	0.989	0.993	0.735	16.168*	36.322***	36.857***
Limburg	2.65	2.20	2.49	0.993	0.421	0.467	0.923	0.911	0.787	21.231**	19.947**	22.074**
Liège	2.01	2.05	1.97	0.486	0.879	0.971	0.925	0.930	0.930	23.609***	23.951***	30.020***
Luxembourg	3.08	2.82	3.33	0.882	0.590	0.815	0.124	0.144	0.390	15.482	19.046**	45.830***
Namur	4.20	3.72	3.97	0.771	0.634	0.741	0.028	0.086	0.245	14.374	22.352**	18.130*
Oost-Vlaanderen	2.37	2.13	2.30	0.458	0.588	0.433	0.256	0.590	0.312	17.518*	37.012***	31.997***
Vlaams-Brabant	2.59	2.36	2.40	0.999	0.395	0.704	0.729	0.763	0.800	27.318***	24.240***	34.056***
West-Vlaanderen	2.23	2.14	2.13	0.599	0.477	0.827	0.854	0.903	0.876	23.880***	30.689***	19.584**

Results are shown for BMN (Bailey, Muth & Nourse, OLS estimated), BMN-H (BMN-Huber Loss estimated) and TPD (Time Product Dummy, OLS estimated) indices. Indices span January 2020 - March 2025 when compared to the RCPI (Rent Component of the National Monthly CPI estimate), otherwise the indices span January 2018 – March 2025. The Mean Monthly Log Differences are displayed in the first column. The second column displays the *p*-values of a two-sided Newey-West t-test, with HAC-covariance matrices (lags selected via AIC (Akaike Information Criterium), restricted to 12 months. The third column displays the *p*-values for an Elliott-Rothenberg-Stock (DF-GLS) unit root test. The last column shows the Trace test statistic for the Johansen-Juselius test for cointegration with the standard * on 10, 5 and 1% significance level.

Table 8. Volatility and Causality between Start Date-Based Indices.

Region	HAC-Standard Errors Log Diff. ($\times 10^{-3}$)			Variance Ratio		p-Value Variance Ratio Test	
	BMN	BMN-H	TPD	BMN-H / BMN	TPD / RCPI	BMN-H -BMN	TPD -RCPI
Belgium	0.38	0.30	0.41	0.61	0.75	0.011	0.129
Antwerpen	0.69	0.33	0.73	0.23	2.36	0.000	0.999
Brabant Wallon	4.22	3.68	1.82	0.76	14.44	0.103	1.000
Brussels	1.84	0.79	1.94	0.18	16.39	0.000	1.000
Hainaut	0.81	0.38	0.60	0.22	1.57	0.000	0.960
Limburg	0.75	0.42	0.83	0.31	3.04	0.000	1.000
Liège	1.44	0.69	1.72	0.23	12.99	0.000	1.000
Luxembourg	1.77	1.10	1.49	0.39	9.73	0.000	1.000
Namur	2.79	1.85	2.23	0.44	21.83	0.000	1.000
Oost-Vlaanderen	0.46	0.33	0.50	0.54	1.11	0.002	0.657
Vlaams-Brabant	0.82	0.46	1.00	0.31	4.36	0.000	1.000
West-Vlaanderen	0.50	0.33	0.62	0.44	1.70	0.000	0.980

Results are shown for BMN (Bailey, Muth & Nourse, OLS estimated), BMN-H (BMN-Huber Loss estimated) and TPD (Time Product Dummy, OLS estimated) indices. Indices span January 2020 - March 2025 when compared to the RCPI (Rent Component of the National Monthly CPI estimate), otherwise the indices span January 2018 – March 2025. The Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors with one quarter (3 months) lags are reported in the first column. The Variance Ratio column shows the ratio of HAC-adjusted variances. The result of the one side *F*-test for equal Index variance is reported in the third column (*p*-value).