Measuring Rental Price Changes for Prospective Tenants Using Rental Listings Microdata

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Abstract

Data from Canada and other countries show that new tenants have experienced higher rent growth compared to existing tenants in recent years. In Canada, the rent component in the Consumer Price Index (CPI) is calculated based on rents paid by all tenants. To better capture current market conditions, we develop an asking rent index for prospective tenants who are not yet renting using rental listings microdata. Hedonic regression is employed for quality adjustment, and rental price changes are estimated at selected census metropolitan areas (CMAs) and provinces. Our calculations show that, in general, average asking rents faced by prospective tenants in Canada exhibited a higher degree of volatility than average rents paid by all tenants since the onset of the pandemic. In addition, challenges and limitations associated with using rental listings microdata to measure rent changes are discussed. Particularly, we assess various outlier treatment tailored to right-skewed rent data, the impact of long-term listings, and the efficacy of manual editing.

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Keywords: rental price index, new tenants, rental listing microdata, hedonic regression

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1 Introduction

The rental housing market is a vital component of the economy, impacting housing affordability and economic stability. According to the 2021 Census, approximately 33% of Canadian households were renters, and over one-fifth (21%) of renter households were new tenants.[2] Various data show that new tenants in Canada have encountered increasing challenges in housing affordability in recent years. Census statistics unveil that the median monthly shelter cost for a two-bedroom dwelling in 2021 is significantly higher for new tenants than existing tenants across Canada. The Rental Market Report released by the Canada Mortgage and Housing Corporation (CMHC) further underscores this trend, showing that at the national level, the average rent growth for purpose-built, 2-bedroom units that turned over to a new tenant in 2022 was 18.3%, well above the 2.9% rent growth for units without turnover. Meanwhile, disparate trends in rental prices for new and all tenants were observed in various countries during the covid-19 pandemic. For instance, in the US and Australia, rent growth for new tenants outpaced the average rent growth for all tenants during 2021-2022 (Adams et al. 2022, ABS 2023). These observations highlight the importance of tracking the rental price movement separately for existing tenants and new tenants.

In Canada, the current rent component in the Consumer Price Index (CPI) is calculated based on rents paid by all tenants (both existing tenants and new tenants) from a sample of occupied rental units. As existing leases are subject to rent control in certain areas, some researchers (Ambrose et al. 2018, 2022; Adams et al. 2022) recommend monitoring changes in rents for new tenants as a more accurate reflection of current market conditions. In this paper, we explore a potential enhancement to Canadian housing statistics by developing a rent index based on rental properties newly advertised in the market. Specifically, we calculate asking rent growth for prospective tenants using rental listing microdata. Our focus is on monthly indexes for four selected Census Metropolitan Areas (CMAs)[3]: Vancouver, Calgary, Toronto, and Montreal, and their respective provinces: British Columbia, Alberta, Ontario, and Quebec.

Unlike the matched samples typically utilized to compile price indexes for most commodities,

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[2] New tenants are those who begin a new tenant lease within one year of the reference day. Households renting part of an owner-occupied dwelling are excluded. Source: [A tale of two renters: Housing affordability among recent and existing renters in Canada (statcan.gc.ca)]

[3] A CMA must have a total population of at least 100,000, of which 50,000 or more must live in the core. [Dictionary, Census of Population, 2021 – Census metropolitan area (CMA) and census agglomeration (CA) (statcan.gc.ca)]

the composition of rental market reflected from the rental listing data varies over time as the inventory of vacant rental units changes from month to month. The data we acquire include detailed information on housing characteristics, which allows us to apply hedonic quality adjustment in index computations. Results from various hedonic regression approaches reveal similar trends of rental price movement across CMAs and provinces in Canada: average asking rents for prospective tenants experienced a dramatic increase since mid-2021. These findings are in line with the rent trends observed in the U.S. and Australia.

When compared to the CPI rent index, the asking price index for prospective tenants exhibits larger fluctuations. The disparate trends in rental prices for prospective tenants and all tenants became more pronounced since mid-2021 when rental market began to recover gradually. The rebound in rental demand following two years of global pandemic led to an unprecedented shift in the asking rent index for prospective tenants. In contrast, the rent index for all tenants showed a relatively modest increase, largely due to various rent control policies. These findings align with Yardi's rental market reports,[4] which indicates that year-over-year rent growth for new leases significantly outpaced growth for all leases during 2022-2023.

In addition to comparing various hedonic approaches and discussing the selection of regressors and splicing method, we discuss the challenges and limitations associated with using rental listings microdata to measure rent changes. Specifically, our discussion encompasses outlier treatment tailored to right-skewed rent data, concerns surrounding long-term listings, and the efficacy of manual editing. Through comparing rent indexes calculated from data employing different outlier detection methods, we find that rent index is not very sensitive to the choice of outlier method when the sample is large enough. Furthermore, by examining rent indexes under varying restrictions on active listing durations, we observe that the presence of long-term listings tends to mitigate rent growth faced by prospective tenants. Lastly, we evaluate the impact of manual data editing and conclude that its influence is negligible.

With the emergence of new rental data sources in recent years, including both survey data and administrative data, statistical agencies worldwide have adopted diverse methodologies to calculate rent indexes specifically for new tenants. For instance, the US Bureau of Labor Statistics (BLS) utilizes pairs of observed rents for the same housing unit sampled in the BLS Housing Survey to compute a weighted new-tenant repeat-rent (NTRR) index on a quarterly basis (Adams

[4] Yardi Canada | Multifamily Market Reports

et al. 2022). Meanwhile, in Australia, monthly rent indexes for new tenants are computed based on administrative data collected through a widely used rental property management software (ABS 2023). Both of their indexes display a similar trend to that observed in Canada that new tenants have experienced a larger rent growth since mid-2021. Furthermore, the US study (Adams et al. 2022) reveals that rent inflation for new tenants leads the official BLS all-tenant rent inflation by four quarters.

The rest of this paper proceeds as follows. In Section 2, we describe rental listing microdata utilized in this study in detail. Various hedonic approaches employed to construct rental price indexes for prospective tenants are explored in Section 3. Section 4 presents rental price changes for selected provinces and CMAs in Canada in recent years. This section also includes a comparative examination of indexes constructed through different hedonic approaches and splicing methods, alongside discussions on the selection of regressors. In Section 5, we address the challenges and limitations in utilizing rental listing microdata to develop rental price indexes. Here, we conduct a series of sensitivity tests to assess various outlier detection methods, examine the impact of long-term listings, and evaluate the efficacy of manual data editing. Finally, we offer concluding thoughts in Section 6.

2 Rental Listing Microdata

For this study, we construct a price index for asking rent using the rental listing microdata from January 2019 to October 2023. The data were collected from the *Rentals.ca* network of online rental listing services. Observations include the address of rental property, asking rent, dwelling type, the numbers of bedrooms and bathrooms, types of utilities included, the square footage[5], and a few unit features and building amenities. This rich information on housing characteristics allows us to apply hedonic quality adjustment in index computations.

The data encompasses both primary and secondary rental markets across Canada. We exclude hotels, retirement homes, and vacation rentals from our analysis due to the diverse range of services typically included in their rental rates. Co-op housing and Rent-Geared-to-Income housing are also excluded as these housing programs may receive government subsidies, grants,

[5] However, the large number of missing values for square footage limits our ability to incorporate this variable into the regression analysis.

or low-interest loans to support their development and operation and subject to affordability guidelines that keep rents below market rates for individuals and families with limited financial resources.

The addresses of rental properties serve two primary purposes. Firstly, they are used to locate the rental properties. To address inaccuracies and missing elements resulting from user input of addresses, we utilize both Google Maps Geocoding API and our proprietary geocoding services to geocode addresses. This process assigns geographic classifications such as Forward Sortation Areas (FSAs),[6] CMAs, and Census Subdivisions (CSDs) to each address, enabling us to control for neighborhood effects in our regression analyses and compute indexes at CMA level. Secondly, addresses are utilized for grouping purposes. Due to the varied usage of street suffixes or their abbreviations by landlords when inputting addresses, we implement an address standardization process. This standardization helps facilitate the extraction of building addresses, and subsequently, based on groupings by building address, we impute missing information on building-level characteristics.

Considering landlords may cross post their rental units on multiple online listing platforms, it is essential to remove duplicate listings during the data cleaning process. we identify duplicate listings by comparing various attributes such as address, number of bedrooms and bathrooms, advertised rents, unit number, and unit size in square feet if available. If two listings share the same values for these attributes, they are flagged as duplicates and one of them will be subsequently removed.

We calculate rental price index for potential tenants using asking rents. The rent used in index computation is the latest rent recorded each month provided the landlord has updated it. Our data cleaning process based on the rent information involves three steps. Firstly, to remove inaccurate rent information provided by landlords, we drop observations with rents below 300 Canadian dollars or exceeding 10,000 dollars. This step results in the removal of 0.19% of observations. Secondly, for rental units with more than one bedroom, we calculate the rent per room by dividing the advertised rent by the number of bedrooms. If the rent per room is below 300 dollars, we assume that the rent advertised is for one bedroom only. Consequently, we adjust the number of bedrooms to one for that observation and categorize the dwelling type as shared accommodations

[6] The Forward Sortation Area (FSA) is the first three characters of the postal code, designating a postal delivery area within Canada. [Dictionary, Census of Population, 2021 – Forward sortation area (FSA)© (statcan.gc.ca)]

if it was not initially indicated. Thirdly, we employ a specific method to identify and remove outliers. In Section 5.1, we delve into various techniques of outlier detection tailored to right-skewed data.

To perform quality adjustment, our regression analysis controls for a host of housing characteristic variables. We control for dwelling types by categorizing the rental property as (1) single houses, (2) multi-unit homes encompassing row houses, townhouses, duplexes, triplexes, and fourplexes, (3) shared accommodations, (4) apartments, and (5) condominiums. We also account for property size by controlling for the number of bedrooms and bathrooms. To allow for the marginal effect on rents of adding one more room to vary with the number of existing rooms, we categorize rental units into five groups based on the number of bedrooms: studio, one bedroom, two bedrooms (including one bedroom plus den), three bedrooms (including two bedrooms plus den), and four bedrooms (including 3 bedrooms plus den, as well as units with more than four bedrooms. We similarly group the number of bathrooms into three categories: one bathroom, two bathrooms, and three or more bathrooms. Additional housing characteristics information are provided by indicator variables for utilities included (electricity, heat, water, internet, cable), unit features (furnished status; availability of appliances like fridge, stove, microwave, dishwasher, and in-suite laundry; presence of a balcony), and building amenities (proximity to shopping center, public transit, and sports complexes). Finally, we include FSA in the regression to control for unobserved neighborhood heterogeneity.

Our study focuses on the four most populous province in Canada: British Columbia (BC), Alberta (AB), Ontario (ON), and Quebec (QC). According to the 2021 Census, these four provinces account for 86.47% of Canada's total population. Within each province, we explore the rental price change in the largest rental markets at the CMA level, namely Vancouver, Calgary, Toronto, and Montreal. Descriptive statistics by selected province and CMAs are provided in Table 1 and Table 2, respectively.

Comparisons of average asking rents across years reveal notable trends during 2019 – 2023. In Calgary and Toronto, average asking rents initially experienced a slight decrease in the first two years of the pandemic, followed by a dramatic increase in 2022 and 2023. By contrast, average asking rents in Vancouver remained relatively stable in 2020 and 2021 but exhibited a similar upward trend as Calgary and Toronto two years after. Montreal, on the other hand, saw consistent rent increases over the years, making it a unique case. These trends are further reflected at the provincial level, although the extent of rent fluctuations varies. For example, Ontario saw a comparatively modest decline in rents in 2020, contrasting with the more pronounced changes observed in Toronto. This indicates the inconsistency in rent patterns across different regions within the province.

The rental market composition across various dwelling types reflected by our data is roughly aligned with census data, implying that our data is a reasonable representative of dwelling type composition in the general rental market at CMA and provincial levels. In Vancouver, Toronto, and Montreal, as well as their respective provinces, apartments and condominiums comprise approximately 90% of rental properties listed. In contrast, in Alberta and its leading rental market, Calgary, this proportion is no more than 60%. In Calgary, single detached houses, and multi-family homes each account for 15% and 14% of the rental market, respectively, while shared accommodations make up 20% of rental listings. Notably, Montreal has the lowest share of single detached houses among four CMAs.

The most common rental properties in the four selected provinces and CMAs are one-bedroom units and two-bedroom units, comprising at least 70% of all rental units. Among the four CMAs, Calgary has the highest share of rental units with three or more bedrooms and lowest share of studios. This aligns with the observation that Calgary has a relative higher share of single houses and multi-units houses in its rental market.

The popularity of *Rentals.ca*'s rental listing services varies across provinces, with the highest number of observations per FSA in Alberta, followed by Ontario. On average, we have approximately 9,000 observations per month for Calgary and 6,000 observations per month for Toronto. The numbers for Montreal and Vancouver are 2,500 and 1,400, respectively. The distribution of listings by province does not consistent with the renter distribution across Canada suggested by Census data. This indicates the need to construct weights when calculating overall rent growth at the national level, although this is beyond the scope of the paper. Further discussion on the challenges and limitations associated with using rental listings microdata to measure rent changes is provided in Section 5 and 6.

Table 1: Sample Descriptive Statistics, by Province (Jan 2019 – Oct 2023)

	British Columbia (BC)	Alberta (AB)	Ontario (ON)	Quebec (QC)
Monthly rent				
2019	1,769.92 (1,035.48)	1,422.94 (661.92)	1,955.80 (896.44)	1,425.75 (668.86)
2020	1,863.50 (926.46)	1,393.89 (618.18)	1,951.80 (762.77)	1,649.49 (695.12)
2021	1,891.51 (928.23)	1,373.37 (611.38)	1,885.65 (652.69)	1,651.68 (691.98)
2022	2,463.09 (1,361.20)	1,523.51 (728.73)	2,240.72 (835.63)	1,773.36 (735.43)
2023	2,802.26 (1,579.56)	1,751.30 (877.52)	2,502.60 (901.86)	1,921.40 (746.34)
# of bedroom				
Studio	0.07	0.03	0.07	0.12
One bedroom	0.41	0.30	0.39	0.39
Two bedrooms	0.39	0.40	0.39	0.37
Three bedrooms	0.11	0.20	0.12	0.11
four bedrooms	0.02	0.08	0.02	0.01
# of bathroom				
One bathroom	0.73	0.60	0.75	0.81
Two bathrooms	0.23	0.25	0.22	0.18
Three bathrooms	0.04	0.15	0.04	0.01
Dwelling type				
Single house	0.05	0.13	0.06	0.01
Multi-units	0.04	0.13	0.04	0.01
Shared ACCOM	0.02	0.15	0.04	0.01
Apartment	0.76	0.39	0.63	0.81
Condo	0.12	0.20	0.24	0.16
Utility included				
Electricity	0.11 (0.31)	0.13 (0.34)	0.10 (0.30)	0.08 (0.28)
Heat	0.21 (0.41)	0.26 (0.44)	0.20 (0.40)	0.17 (0.37)
Water	0.23 (0.42)	0.28 (0.45)	0.22 (0.41)	0.18 (0.38)
Internet	0.06 (0.24)	0.07 (0.26)	0.06 (0.23)	0.05 (0.21)
Cable	0.03 (0.18)	0.04 (0.19)	0.03 (0.17)	0.02 (0.15)
Features & amenities				
Furnished	0.08 (0.28)	0.11 (0.32)	0.07 (0.26)	0.09 (0.29)
Fridge	0.82 (0.38)	0.88 (0.32)	0.82 (0.39)	0.82 (0.38)
Stove	0.80 (0.40)	0.86 (0.34)	0.79 (0.41)	0.80 (0.40)
Microwave	0.40 (0.49)	0.45 (0.50)	0.46 (0.50)	0.36 (0.48)
Dishwasher	0.59 (0.49)	0.63 (0.48)	0.62 (0.49)	0.59 (0.49)
In-suite laundry	0.51 (0.50)	0.55 (0.50)	0.53 (0.50)	0.52 (0.50)
Balcony	0.48 (0.50)	0.47 (0.50)	0.47 (0.50)	0.54 (0.50)
Shopping center	0.65 (0.48)	0.73 (0.44)	0.66 (0.47)	0.70 (0.46)
Public transit	0.64 (0.48)	0.74 (0.44)	0.68 (0.47)	0.72 (0.45)
Sport complex	0.35 (0.48)	0.47 (0.50)	0.32 (0.47)	0.26 (0.44)
# of FSAs	177	154	458	187
# of observations	131,835	1,015,700	569,907	163,165

Note: Table reports means with standard deviations in parentheses for all variables except for share of bedroom and bathroom categories, share of dwelling types, and number of FSAs. Multi-unit homes encompassing row houses, townhouses, duplexes, triplexes, and fourplexes.

Table 2: Sample Descriptive Statistics, by CMA (Jan 2019 – Oct 2023)

	Vancouver, BC	Calgary, AB	Toronto, ON	Montreal, QC
Monthly rent				
2019	2,024.59 (1,114.59)	1,507.67 (745.32)	2,301.36 (912.85)	1,482.15 (685.92)
2020	2,088.86 (973.91)	1,480.94 (699.78)	2,188.07 (781.63)	1,694.13 (697.16)
2021	2,038.48 (966.06)	1,474.77 (693.19)	2,029.56 (643.80)	1,684.45 (695.90)
2022	2,777.73 (1,432.19)	1,735.35 (847.99)	2,419.32 (889.55)	1,799.31 (743.46)
2023	3,289.80 (1,709.10)	2,055.24 (976.00)	2,848.74 (943.79)	1,945.73 (749.30)
# of bedroom				
Studio	0.07	0.01	0.08	0.12
One bedroom	0.43	0.30	0.40	0.39
Two bedrooms	0.37	0.40	0.38	0.37
Three bedrooms	0.11	0.19	0.12	0.10
four bedrooms	0.03	0.10	0.02	0.01
# of bathroom				
One bathroom	0.72	0.56	0.74	0.81
Two bathrooms	0.24	0.26	0.23	0.18
Three bathrooms	0.04	0.18	0.03	0.01
Dwelling type				
Single house	0.05	0.15	0.05	0.01
Multi-units	0.04	0.14	0.02	0.01
Shared ACCOM	0.03	0.20	0.03	0.01
Apartment	0.73	0.27	0.54	0.80
Condo	0.16	0.25	0.36	0.17
Utility included				
Electricity	0.11 (0.31)	0.14 (0.35)	0.11 (0.31)	0.08 (0.27)
Heat	0.22 (0.41)	0.29 (0.45)	0.21 (0.41)	0.16 (0.37)
Water	0.24 (0.43)	0.30 (0.46)	0.22 (0.42)	0.18 (0.38)
Internet	0.06 (0.24)	0.08 (0.28)	0.06 (0.24)	0.04 (0.21)
Cable	0.03 (0.18)	0.04 (0.20)	0.03 (0.17)	0.02 (0.15)
Features & Amenities				
Furnished	0.09 (0.29)	0.15 (0.35)	0.08 (0.27)	0.10 (0.30)
Fridge	0.83 (0.37)	0.89 (0.31)	0.82 (0.39)	0.83 (0.38)
Stove	0.81 (0.39)	0.87 (0.34)	0.79 (0.41)	0.81 (0.39)
Microwave	0.41 (0.49)	0.49 (0.50)	0.48 (0.50)	0.36 (0.48)
Dishwasher	0.60 (0.49)	0.66 (0.48)	0.64 (0.48)	0.59 (0.49)
In-suite laundry	0.52 (0.50)	0.58 (0.49)	0.55 (0.50)	0.52 (0.50)
Balcony	0.47 (0.50)	0.46 (0.50)	0.48 (0.50)	0.55 (0.50)
Shopping center	0.67 (0.47)	0.76 (0.43)	0.67 (0.47)	0.70 (0.46)
Public transit	0.67 (0.47)	0.76 (0.43)	0.69 (0.46)	0.72 (0.45)
Sport complex	0.37 (0.48)	0.52 (0.50)	0.33 (0.47)	0.25 (0.43)
# of FSAs	93	45	177	138
# of observations	83,638	523,228	349,751	149,588

Note: Table reports means with standard deviations in parentheses for all variables except share of bedroom and bathroom categories, share of dwelling types, and number of FSAs. Multi-unit homes encompassing row houses, townhouses, duplexes, triplexes, and fourplexes.

3 Index Estimation

To compile a rental index with constant quality it is necessary to control the quality of rental units, which is represented by number of bedrooms, number of bathrooms and other characteristics associated with the units. Because of the vast variety of available rental units over time, it is difficult to compile the rental index based on a precisely matched model. A natural choice for adjusting the quality of rental units is to apply hedonic models. To identify the most appropriate hedonic model that fits our purpose, we assess different hedonic methods, including the pooled time dummy method, the rolling window time dummy method, and the characteristics imputation hedonic method. The features included in these hedonic models are the number of bedrooms, number of bathrooms, type of rental units, FSA, utilities[7] included in rents, and selected available amenities.[8]

3.1 Pooled Time Dummy Variable Regression Model

The pooled time dummy (PTD) method runs a single regression on both characteristics and time dummy variables for all the time periods under consideration. It is very simple and straightforward to apply in practice. The price index can be obtained directly from the estimated regression equation. The dependent variable is the logarithm of the asking rents, and the overall price indexes are obtained by taking the exponential of the estimated coefficients of time dummies. The regression model is as follows:

$$\ln p_i^t = \beta_0 + \sum_{k=1}^{K} \beta_k x_{ik}^t + \sum_{m=1}^{M} \beta_m FSA_{im}^t + \sum_{t=1}^{T} \delta^t D_i^t + \varepsilon_i^t$$

where $\ln p_i^t$ denotes the logarithm of the asking rents for rental unit *i* at period *t*, x_{ik}^t is the value of the k^{th} characteristics for rental unit *i* at period *t*, FSA_{im}^t is the m^{th} location dummy for rental unit *i* at period *t*, and D_i^t is a time dummy for period *t*. ε_i^t is the error term.

Based on the regression model, the rent index going from period *0* to period *t*, $I_{0,t}$, can be derived based on the following equation:

[7] Utilities in this analysis are electricity, water, heating, cable, and internet.
[8] Amenity variables included in the regression are dummies for furnished units, balcony, fridge, dishwasher, microwave, in-suite laundry, shopping center nearby, public transit nearby, and sport complex nearby. Note that the proximity to amenities is self-reported by the lessor.

$$I_{0,t} = \exp\left(\hat{\delta}^t\right)$$

Using pooled time dummy hedonic regression model, we implicitly assume that tenants' tastes or preferences are constant over the examined period. This is a very strong assumption that is normally not true for a long period. Another issue associated with this hedonic method in regular index production is reassessment of the parameters when more recent data become available. The derived price index might vary with time when more recent data are added, making the old indexes not robust to revision.

3.2 Rolling Window Time Dummy Variable Regression Model

The rolling window time dummy (RWTD) method is a simple solution to the problems discussed in the above section. It resembles the pooled time dummy method, with the difference in the number of time dummy variables included, which is determined by the window length. The rolling window method runs a sequence of hedonic regressions for a fixed number of time periods, such as a year. The model is moved forward one period in each regression, enabling the price indexes to continuously update as new data for subsequent periods become available, and no need to revise indexes for previous periods. Guerreiro, Weinand and Konijn (2023) suggests that the window should be sufficiently long to cover two successive in-season periods for seasonal products. Ivancic, Diewert and Fox (2011) points out that the length of a 13-month window is a natural choice as it allows strong seasonal commodities to be compared. Based on these findings in the literature, we apply a rolling window procedure with a 13-month window length in this study, as we believe that a year is long enough to capture seasonal variations in rents. Another advantage of this method is that it allows for gradual changes in consumer tastes or preferences over time.

When applying this approach, it is necessary to choose a link period for chaining together the price indexes estimated from previous windows. Theoretically speaking, for a window length of $w+1$ periods, all the periods except for the first period in the previous window could be a potential linking period.[9] The choice of linking period has impact on the resultant price indexes. The magnitude of the impact depends on the variation in asking rents within each window. Three approaches to linking the rental indexes with non-revisable or published indexes compiled from earlier periods are tested in this paper, including:

[9] For more discussion on the methods of selecting linking period, please refer to Diewert and Fox (2017, 2022).

- Option 1: Linking to the second month in the previous window or the first month in the current window. This method is also called the window splice method and is suggested by Krsinich (2016).
- Option 2: Linking to the last month in the previous window, suggested by Ivancic, Diewert and Fox (2009), also called the movement splice method.
- Option 3: Applying the mean splice method, which links to all the months of the previous window and takes geomean of these indexes, suggested by Diewert and Fox (2017).

A drastic rent change in the selected linking month might result in chain drift in the rent indexes. The last option, which can reduce possible chain drift, is probably the "safest strategy" suggested by Consumer Price Index Theory (2020)[10] and has been used by Australian Bureau of Statistics. We would like to recommend it in the production of rental index. The comparison of rental indexes based on different linking methods will be presented in Section 4.

3.3 Characteristics Prices and Imputation Method

In this paper we also test the hedonic imputation approach, in which a separate hedonic regression on characteristics variables is run for each period. In general, a set of fixed values of characteristics of a standard or matched model should be chosen to impute the rents for "pseudo matched" rental units using the estimated coefficients from the hedonic regression model. For instance, the parameters estimated using the period $t+1$ hedonic regression could be taken to evaluate all the rental units that appeared in period t. This generates predicted period $t+1$ "rents" for the period t units. Therefore, the characteristics price imputation method is useful for maintaining constant quality of rental units over time.

As we know, in the housing context, it is impossible to find precisely matched samples across periods. Depreciation and renovation activity, as well as availability, mean that rental units might not be comparable over time. For instance, the composition of rental units for each location might vary with time, and in particular, some FSAs might lack enough data for certain periods. Also, some dwelling type might be unavailable in some months. To ensure comparability of indexes over time, we drop observations with characteristics that are not common in both periods from the index

[10] Refer to Diewert (2020a) or Chapter 7, "The Chain Drift Problem and Multilateral Indexes", in "Consumer Price Index Theory", 2023. Available at [Update of the Consumer Price Index Manual (imf.org)](). The "safest strategy" is from the viewpoint of statistics; if we have multiple indexes that measure the same thing, then it is "best" to take the mean of these measures.

estimation process. In each reference period, we run separate regressions for two adjacent periods, and the ratio of predicted values based on the selected quantities of common characteristics is used to link with the price index in the previous periods. The regression model is as follows:

$$\ln p_i^t = \beta_0^t + \sum_{k=1}^{K} \beta_k^t x_{ik}^t + \sum_{m=1}^{M} \beta_m^t FSA_{im}^t + \varepsilon_i^t$$

where $\ln p_i^t$ is the logarithm of the asking rents for rental unit *i* at period *t*, x_{ik}^t is the value of the k^{th} characteristics for rental unit *i* at period *t*, and FSA_{im}^t is the m^{th} location dummy for rental unit *i* at period *t*.

In each period, we run separate regressions for both period *t* and $t-1$. In this regression, the function is the log transformation of the following equation:

$$p_i^t = \exp\left(\beta_0^t + \sum\nolimits_{k=1}^{K} \beta_k^t x_{ik}^t + \sum\nolimits_{m=1}^{M} \beta_m^t FSA_{im}^t + \varepsilon_i^t\right)$$

When we use ordinary least squares (OLS) to estimate the log-transformed function, we obtain predicted log of prices based on the estimated hedonic coefficients. To exponentiate to form the predicted price, we need to account for the expectation of $\exp\left(\varepsilon_i^t\right)$, which under this assumption is $\exp\left(0.5\hat{\sigma}_t^2\right)$, where $\hat{\sigma}_t^2$ is the estimated variance of error terms. Applying this correction, we implicitly assume that the disturbance in the log form is independently and identically distributed normal, which is a very strong assumption.[11] Then the predicted price at reference period *t* evaluated using quantities of characteristics of period τ, denoted as $\hat{p}_{t,\tau}$, is derived based on the following equation:

$$\hat{p}_{t,\tau} = \mathrm{e}^{\left(\hat{\beta}^t x^\tau + 0.5\hat{\sigma}_t^2\right)}$$

where $\hat{\beta}^t$ are estimated hedonic coefficients, x^τ are quantities of characteristics at period τ.

In the above model, the estimated coefficients $\hat{\beta}$ vary from period to period, allowing for tenants to have different preferences over the selected characteristics across time. Based on which period the fixed characteristics belong to, the Laspeyres, Paasche and Fisher imputation indexes can be estimated for each period.[12] We compile the Fisher imputation indexes in this study.

[11] We compared the resultant indexes with and without correction and found that the correction does not really matter for our data.
[12] For more details on Characteristics prices method refer to *Handbook on Residential Property Prices Indices* by Eurostat (2013) page 53-55.

The period-to-period index is then linked with the previous price index to form a chained index:

$$I_{0,t} = I_{0,t-1} \times I_{t-1,t}$$

where $I_{0,t}$ is the price index going from period *0* to reference period *t*, and $I_{t-1,t}$ is the price index for period t going from $t-1$.

A problem associated with the characteristics prices approach is that some areas lacking data in every period might be eliminated from the regression, and thus the resultant rent index might not be representative for those areas. Moreover, uneven distribution of different factor variables in the regression might result in undefined models for some periods. One way to avoid this problem is to use continuous variables. For instance, instead of grouping the number of bedrooms to form a categorical variable, we can use it directly as a continuous variable. A big advantage of the hedonic imputation method is that it allows us to compile a rent index which eliminates included utilities by setting the indicator variables for their inclusion to zero. In addition, this approach allows for changes in tenants' preferences over time.

In the following section, we present preliminary rental indexes for prospective tenants derived from the currently available data applying various hedonic regression models. Additionally, a comparative analysis is conducted with other published rent changes to illustrate different trends in rent changes for various segments of the rental market.

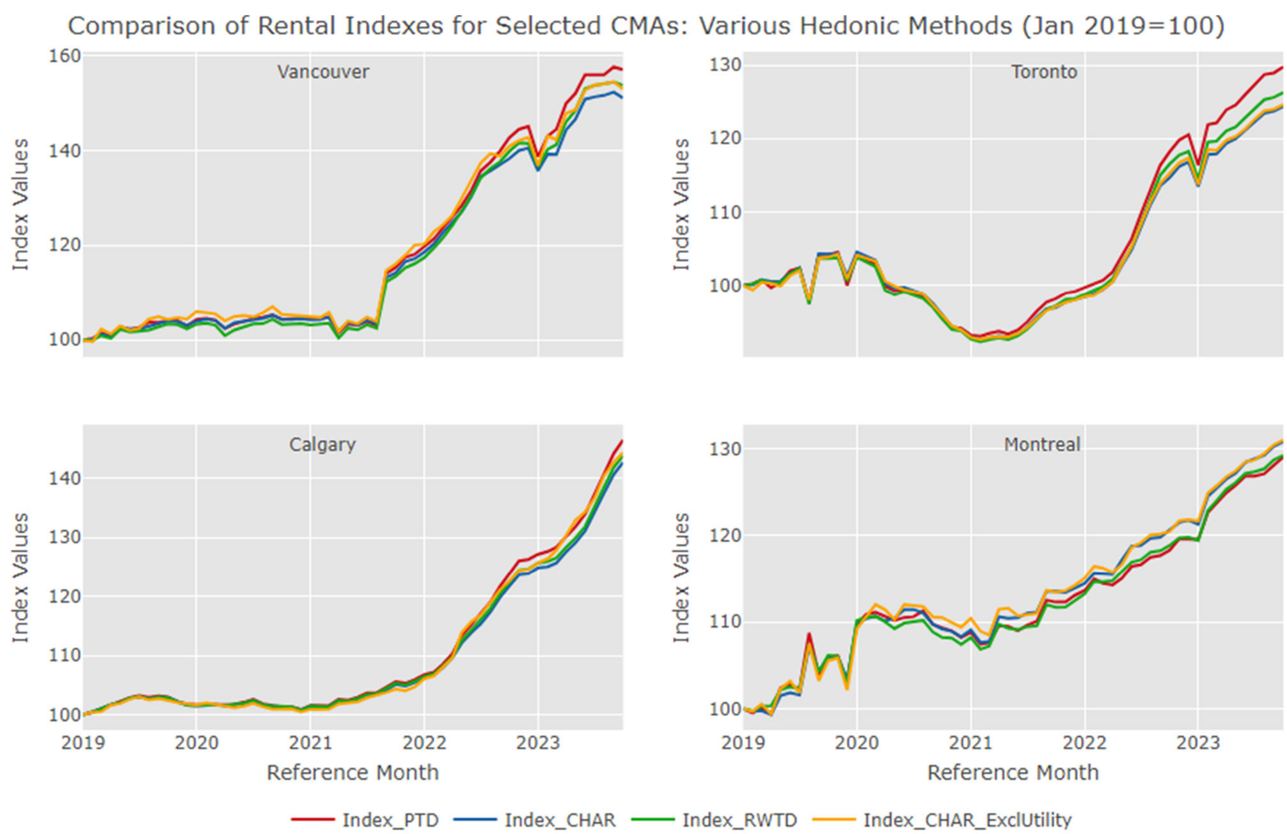
4 Preliminary Rental Indexes for Prospective Tenants

Using *Rentals.ca* data, we compile rental indexes for the potential tenants for selected CMAs and provinces in Canada. In the first part of this section, the preliminary rental indexes are reported for four CMAs in Canada, including Vancouver, Calgary, Toronto, and Montreal. In addition, we show rental indexes for British Columbia, Alberta, Ontario, and Quebec.

4.1 Preliminary rental index for selected CMAs and provinces

To identify the most appropriate method that fits the data and satisfies our purpose of compiling rental index of unfurnished rental units, we test different hedonic models. The rental indexes compiled using different hedonic regression models for the four CMAs are shown in Figure 1. From this figure, we can see that the general trends of rent movement are similar across hedonic regression models. Divergence among rental indexes compiled based on different approaches varies with CMAs. It gets greater for those CMAs with larger rent fluctuations, such as Montreal. Moreover, the spread of different indexes increases towards the end of the examination period. This might suggest the existence of chain drift. Comparing the rental trends across four CMAs, we can see that the movements in asking rents in these CMAs differ from each during the COVID-19 period. The fluctuation in Vancouver and Calgary is moderate compared with Montreal. A noticeable decrease in rents is observed in Toronto in the early stage of the pandemic. From the second half of 2021, all four CMAs witnessed substantial increases in the price indexes of asking rent.

Figure 1

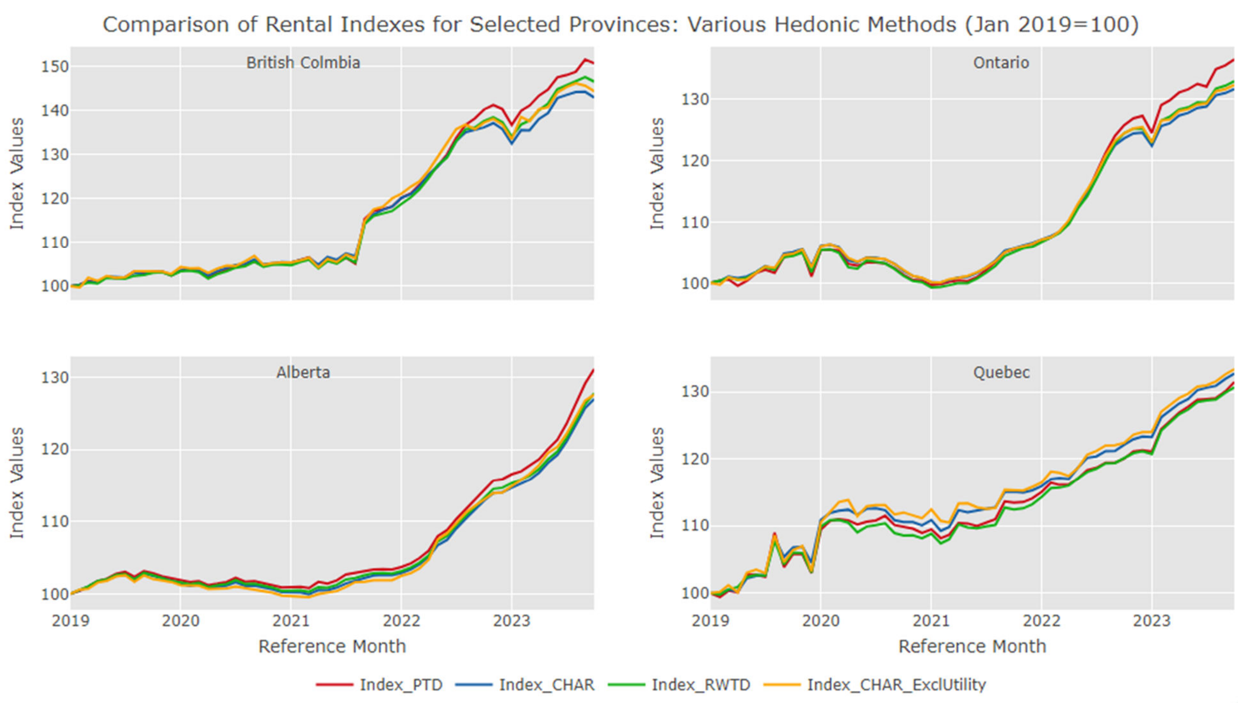


Notes: Index_PTD: rental indexes estimated using pooled time dummy method; Index_CHAR: rental indexes estimated using characteristics imputation method; Index_RWTD: rental indexes estimated using rolling window time dummy method; and Index_CHAR_ExclUtility: rent indexes estimated excluding "utilities included" and using characteristics imputation method.

In Figure 1, we also compare price indexes of rents including and excluding utilities, compiled using the characteristics imputation method (the blue and orange lines in the charts). The differences between these index series are ignorable, except for Vancouver. This might imply that the landlord could implicitly adjust the rents by modifying what have been included in the rents.

Figure 2 compares rental indexes based on different hedonic methods for four selected provinces. The price indexes are estimated directly from hedonic regressions at the provincial level.

Figure 2



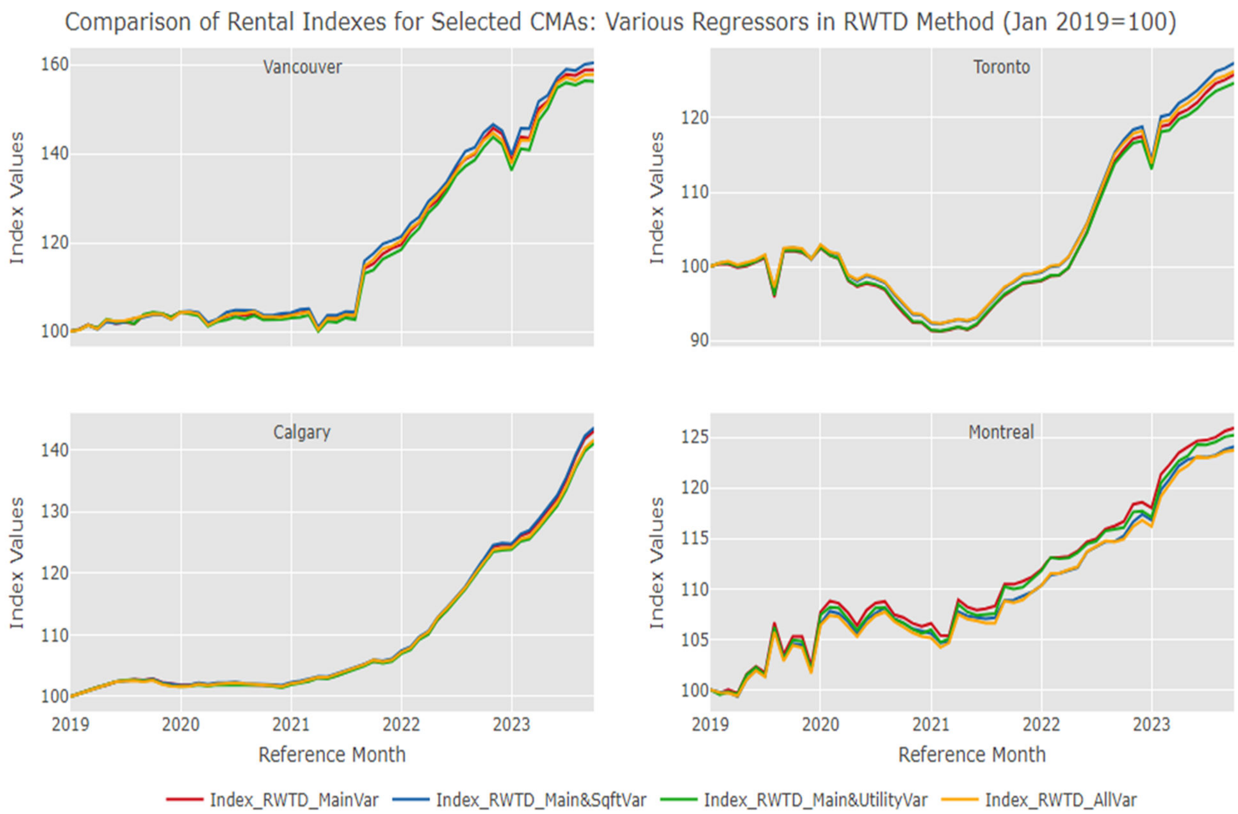
Notes: Index_PTD: rental indexes estimated using pooled time dummy method; Index_CHAR: rental indexes estimated using characteristics imputation method; Index_RWTD: rental indexes estimated using rolling window time dummy method; and Index_CHAR_ExclUtility: rent indexes estimated excluding "utilities included" and using characteristics imputation method.

The divergences in provincial rental indexes based on different hedonic models mirror those observed in the CMA indexes. This is because the selected CMAs count a relatively large portion of the rental markets in their provinces.[13]

[13] The *Rentals.ca* data show that the observations in Vancouver, Calgary, Toronto, and Montreal account for roughly 63%, 51%, 61%, and 92% in their provinces, respectively.

To identify most relevant variables for explaining the changes in the asking rents, we also conduct comparative analysis on the selection of predictor variables in the hedonic models. The following charts in Figure 3 compare rental indexes using rolling window time dummy method with mean splice approach, where various explanatory variables are included.

Figure 3

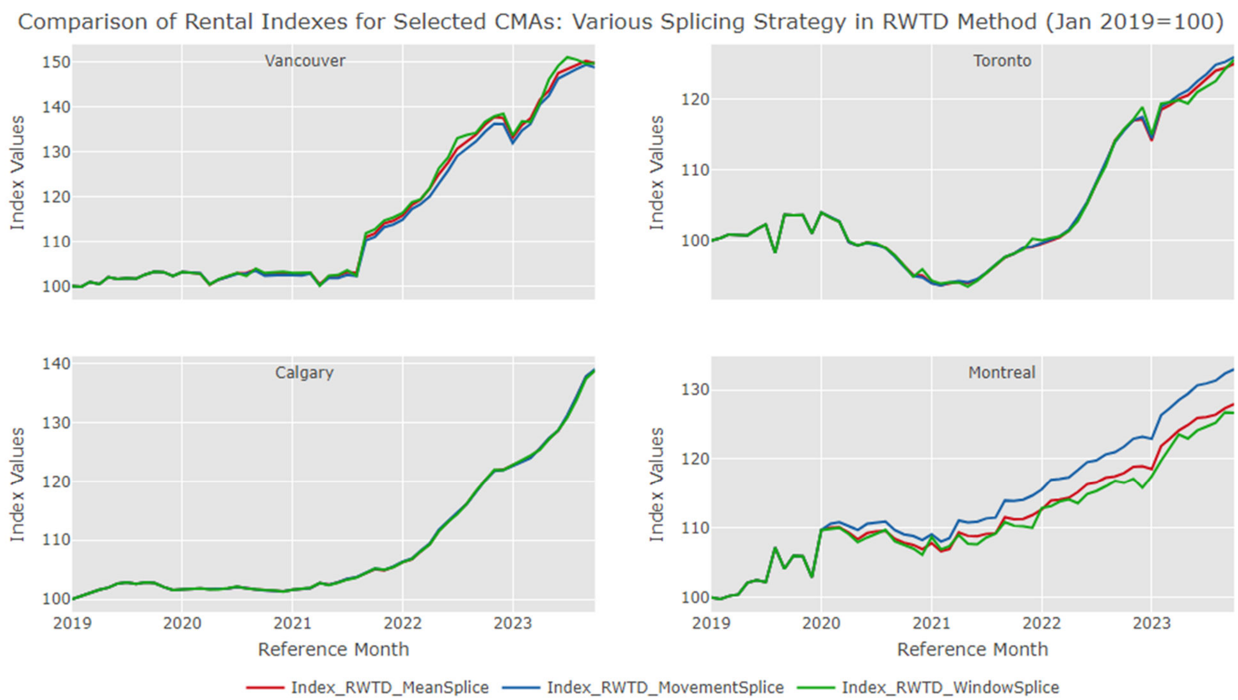


Notes: "MainVar": regressors include bedrooms, bathrooms, dwelling type, and FSA. "Manin&SqfVar": regressors include bedrooms, bathrooms, dwelling type, FSA, and square feet of living area. "Main&UtilityVar": regressors include bedrooms, bathrooms, dwelling type, FSA, and dummies for furnished, utility and amenities. "AllVar": regressors include bedrooms, bathrooms, dwelling type, FSA, square feet of living area, and dummies for furnished, utility and amenities.

The differences among these rental indexes are relatively small. This suggests that the impact of adding additional explanatory variables on the improvement of index estimation is limited. Comparing the movement in the indexes with and without square feet in the regression model, we noticed that the difference is not negligible for some CMAs. However, since the missing data in the living area of rental units account for almost 15% of the total observations, to avoid shrinking the sample size, it is recommended to incorporate square footage in the regression model only when the quality of the variable reaches a satisfactory level.

Considering both efficiency of index production and simplicity of regression model, as well as the need of compiling rental indexes for smaller CMAs, the preference is given to the rolling window time dummy method. As we have discussed before, the choice of the link month to chain indexes estimated from different windows is critical to the resultant indexes. To understand the impact of various splicing strategies on the final indexes, we test mean splice, movement splice and window splice method in this paper. The comparison of the rental indexes resulting from different splicing approaches for four CMAs is shown in Figure 4.

Figure 4



Notes: Index_RWTD_MeanSplice: rental indexes estimated using rolling window time dummy method with mean splice approach; Index_RWTD_MovementSplice: rental indexes estimated using rolling window time dummy method with movement splice approach; Index_RWTD_WindowSplice: rental indexes estimated using rolling window time dummy method with window splice approach.

By comparison, we observed that the impacts of splicing approach on the rental indexes vary with the monthly fluctuations in the asking rents, irrespective of the regressors included in the regression models. The indexes using mean splice are smoother than those generated based on the other splice methods. The discrepancies in the rental indexes with different splicing methods are larger for the CMAs with relatively greater fluctuations in the rent, such as Montreal and

Vancouver. We follow the recommendation of Consumer Price Index Theory (2020) and propose to use the mean splice approach.

In summary, the rolling window time dummy method with mean splice is our finalized model based on the status of the current historical data, including type of bedroom, type of bathrooms room, dwelling type, FSA, dummies for furnished units, utilities included and selected amenities as explanatory variables.

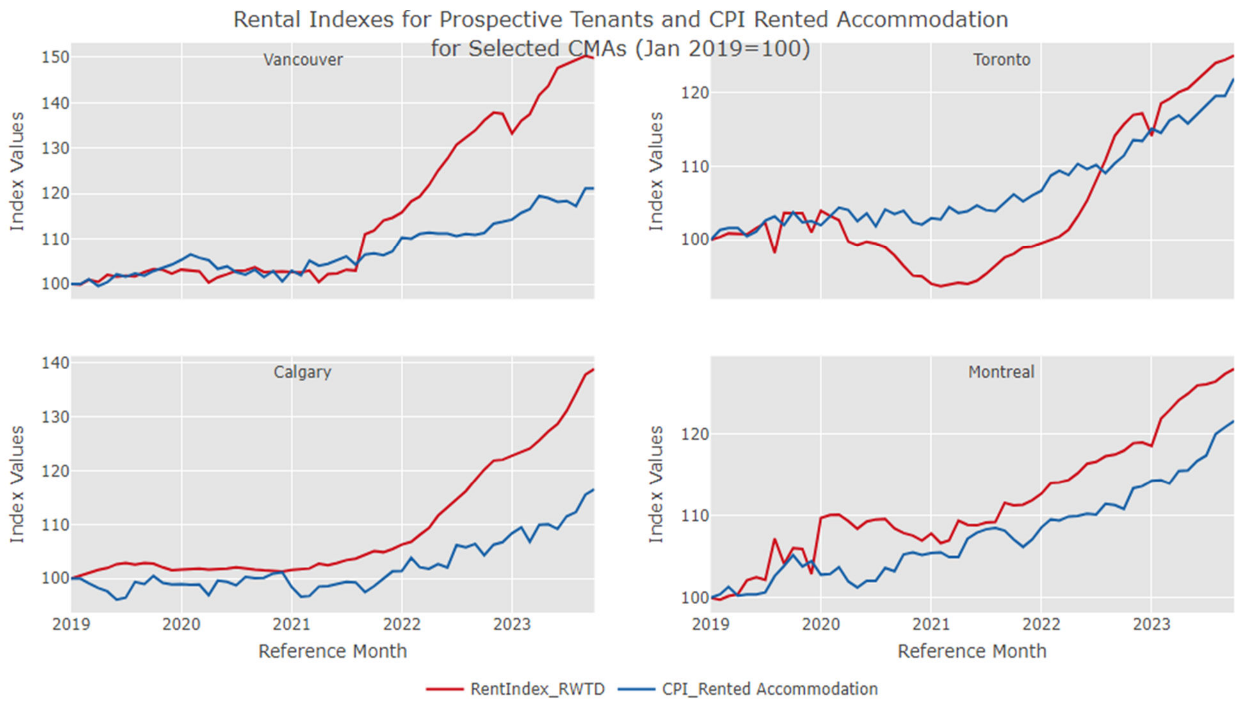
4.2 Comparison with other rent series

Using *Rentals.ca* data, we compile a new rental index for prospective tenants, which can reflect changes in the market rent. To verify if this rental index exhibits different trend in the movement, we compare it with the CPI series for rented accommodation for four CMAs, shown in Figure 5. The CPI is an official measure of pure consumer price change over time. It "is often used to adjust incomes, wages or other payments to maintain previous purchasing power in the face of changing consumer prices."[14] The scope of CPI rented accommodation differs from the residential rental price index (RRPI) compiled in this paper, as it includes Tenants' insurance premiums and of Tenants' maintenance, repairs, and other expenses. The indexes are compiled based on real transaction prices, reflecting changes in rents and other expenses paid by both existing and new tenants. Because of the large contribution of rent index in the CPI rented accommodation, this comparison can still give us some idea on how the movements in the two types of rent indexes might differ from each other. It is obvious that the pattern of rent movement reflected in the two types of rental indexes are quite different. Overall, we observe a greater increase in the rental index for potential tenants than in those for all tenants. In addition, the fluctuations in the CPI rented accommodation are relatively smaller than those reflected in the rental index for prospective tenants. Moreover, the decrease in rents in Toronto during the pandemic period is not prominent in the CPI rented accommodation, since it reflects changes in the rents paid by all tenants, and new tenants only account for a small portion. We also observe that the gap between CPI index series and rental indexes for potential tenants varies across four CMAs. Although "multiple factors help explain these regional variations, such as differences in rent control policies or the size and quality

[14] Please refer to "The Canadian Consumer Price Index Paper" (2023), Statistics Canada. Catalogue no. 62-553-X, page 17.

of available rental units," the key factor is the different rent control policies.[15] In Ontario and British Columbia, rental control policies limit rent increases for existing tenants, while Quebec's policies limit rent increases for all rented units, which can partially explain why the rent increase for potential tenants in Montreal are smaller than the other three CMAs.

Figure 5

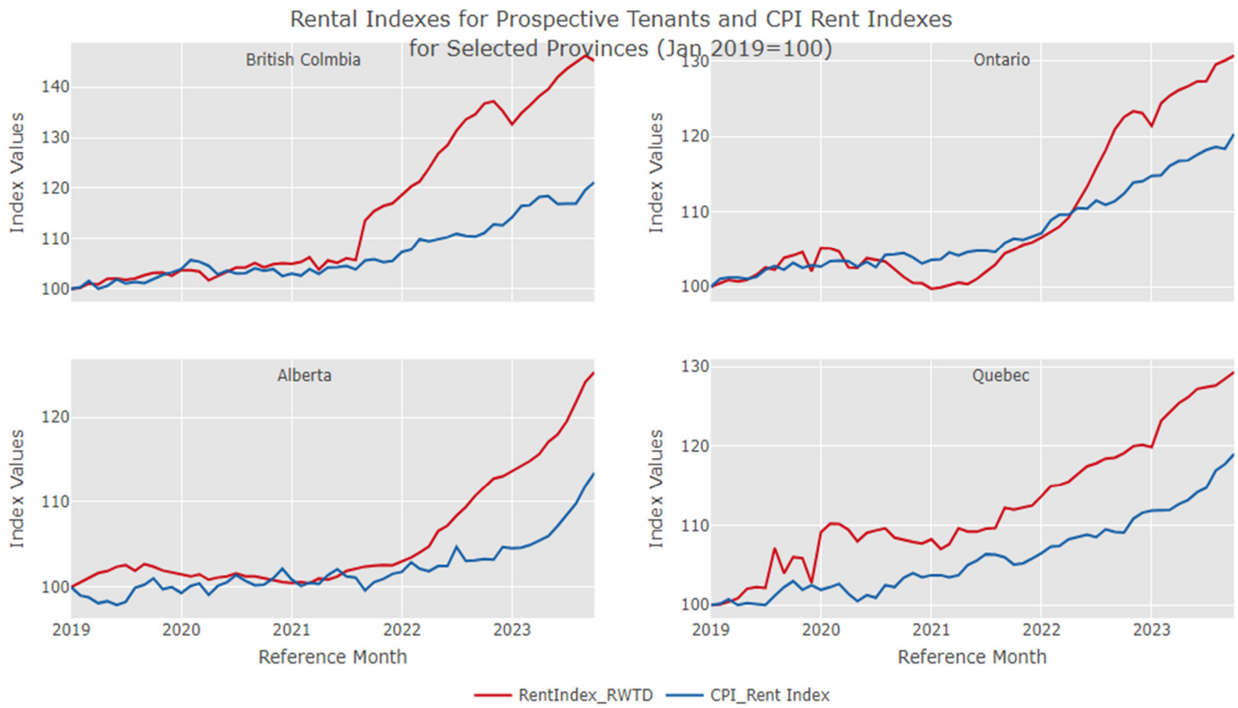


Source: CPI Rented accommodation, Statistics Canada. Table 18-10-0004-01 Consumer Price Index, monthly, not seasonally adjusted.

The following charts in Figure 6 show the different rental indexes for prospective tenants and CPI rent index at provincial level. Again, similar differences are observed in these indexes. CPI rent indexes are generally flatter than rental indexes reflecting changes in the market rents.

[15] For more detail discussion, please refer to "A tale of two renters: Housing affordability among recent and existing renters in Canada (statcan.gc.ca)", released by Statistics Canada, Oct 2023.

Figure 6

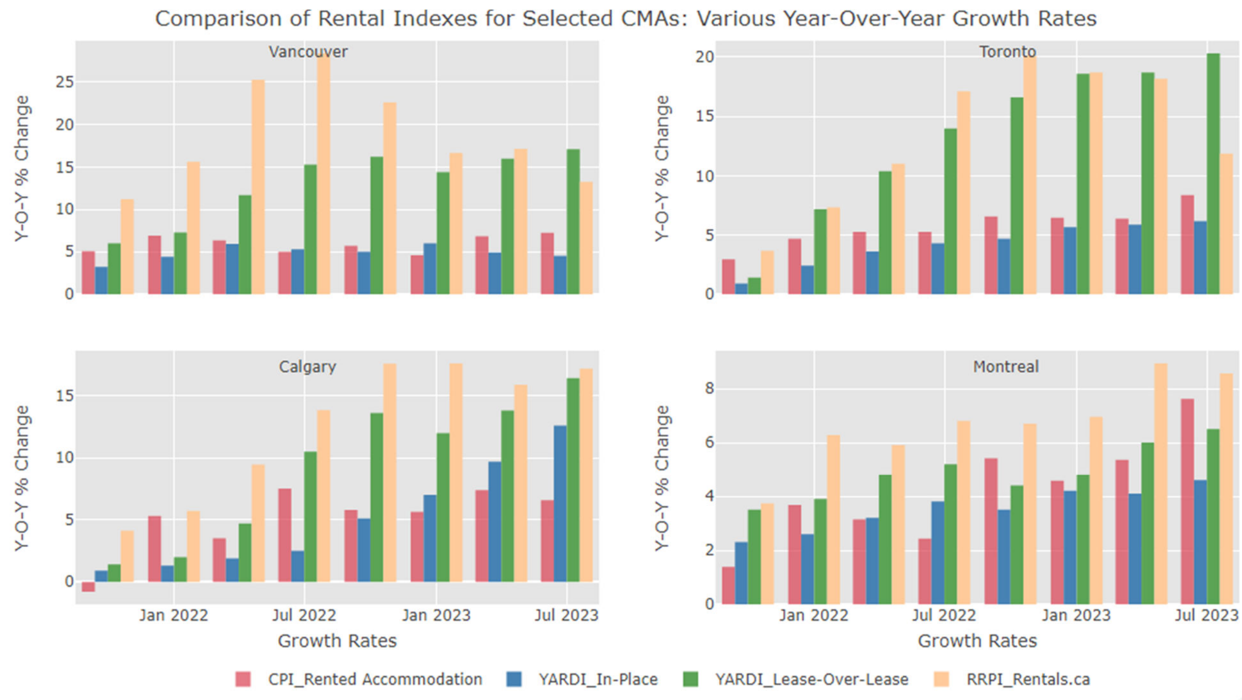


Source: CPI Rented accommodation, Statistics Canada. [Table 18-10-0004-01 Consumer Price Index, monthly, not seasonally adjusted].

In Canada, there are various rent reports published by different entities. Among those, the quarterly "Canadian National Multifamily Report" published by Yardi[16] contains comprehensive information on changes in the average in-place rent[17] and lease-over-lease rent[18] over time. Figure 7 compares year-over-year growth rates of the rent indexes for prospective tenants with two Yardi's year-over-year growth rates and those of the CPI rented accommodation.

[16] Yardi is a company providing property management software. The data in Yardi's report encompasses 5,100 properties that represent more than 464,000 private rental units across Canada.
[17] Based on the definition in Yardi's report, the in-place rent is monthly rent per unit for all leases, including new lease rents, renewal lease rents and existing leases.
[18] Lease-Over-Lease Rent Growth is the percentage change in monthly rent between a new lease and the previous lease for the same unit.

Figure 7



Source: CPI Rented accommodation, Statistics Canada. Table 18-10-0004-01 Consumer Price Index, monthly, not seasonally adjusted; Yardi, Canadian National Multifamily Report, October 2023.

For most periods the quarterly year-over-year growth rates of the CPI rent series are slightly higher than those of Yardi's in-place rents in Vancouver, Toronto, and Montreal. Although both growth rates reflect changes in the rents paid by all the tenants. Yardi focuses on the primary rental market and the growth rates are calculated based on the average rents without controlling the quality changes of rental units over time, while the CPI reflects the pure rent change. The growth rates of rental index for prospective tenants are closer to those of Yardi's lease-over-lease rents. From these charts, we observed divergence in the year-over-year growth rates across different segments of the rental market. To fully reflect changes in the rents paid by different tenants, it is beneficial to release disaggregate rental indexes for reflecting changes in rents of different rental markets. Compiling a rental index for potential tenants will indeed fill in this data gap and increase the relevance of rent index statistics.

5 Sensitivity Studies

As we have mentioned in section 2, the rent listing data from *Rentals.ca* is a type of administrative data. To develop an efficient and cost-effective data cleaning and editing procedure for regular monthly production, we conduct a series of sensitivity studies. The following part of this section reports our findings from some of these studies.

5.1 Sensitivity to the approach of outlier treatment

Outliers in the rent data might distort the representativeness of rental indexes. For instance, the inclusion of the luxury and large rental units in the index estimation might result in bias in the rental indexes. In addition, potential outliers might be erroneous observations. For example, the rent for a room is misclassified as the rent for a house. Failed to identify the outliers and potential errors might dampen the quality of the indexes. The importance of outlier treatment on the regression model depends on the data quality, data variations and the sample size. To determine the most efficient method for detecting and handling outliers, we assess the sensitivity of rental indexes by employing various approaches and criteria to remove outliers. Based on the sample size of the rent data, we simply remove outliers from regression. To detect outliers, we test median absolute deviation (MAD) method, interquartile range (IQR) method, simple trimming method and Cook's distance method.[19] Using first three methods, any value that falls outside a certain threshold[20] can be considered an outlier.

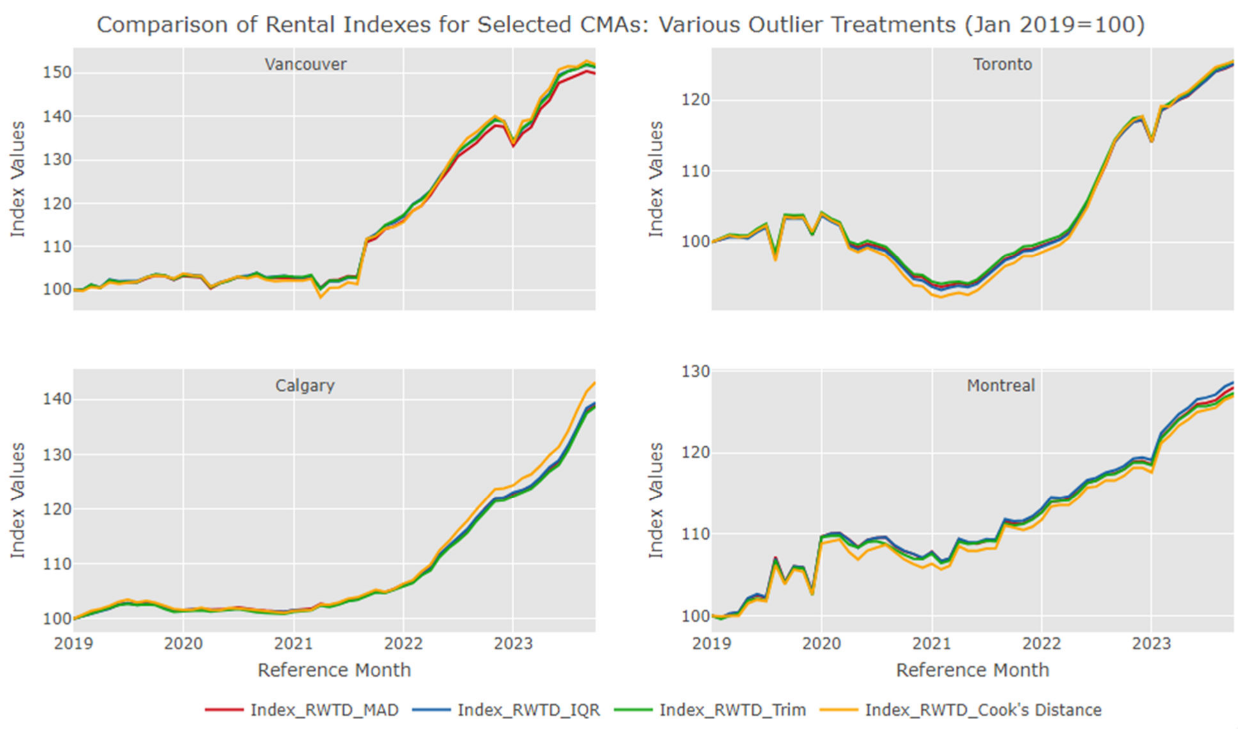
To identify outliers in the data, we check the skewness measure for the distribution of rents for the four CMAs. On average, the skewness values for Vancouver, Calgary, Montreal, and Toronto are 4, 3.529, 2.66, and 3.43, respectively, which indicate that the distribution of the rents in these CMAs are highly right skewed. As a result, asymmetric trimming is used and observations with rent in the top 3% and bottom 1% of the distribution are removed when applying simple trimming method. We also test different upper and lower multipliers when using MAD and IQR method.

[19] Cook's distance shows the influence of each observation on the fitted values, which is useful for identifying outliers in observations of independent variables of a regression. An observation with Cook's distance greater than a certain threshold might be an outlier. We apply a typical value, 4/n, where n is the sample size, in this paper.

[20] In this paper, observations that lie 1.5 times IQR above Q_3 and below Q_1 are considered outliers when using IQR. For MAD method, the median plus and minus 2.5 times MAD are used as upper bound and lower bound, respectively.

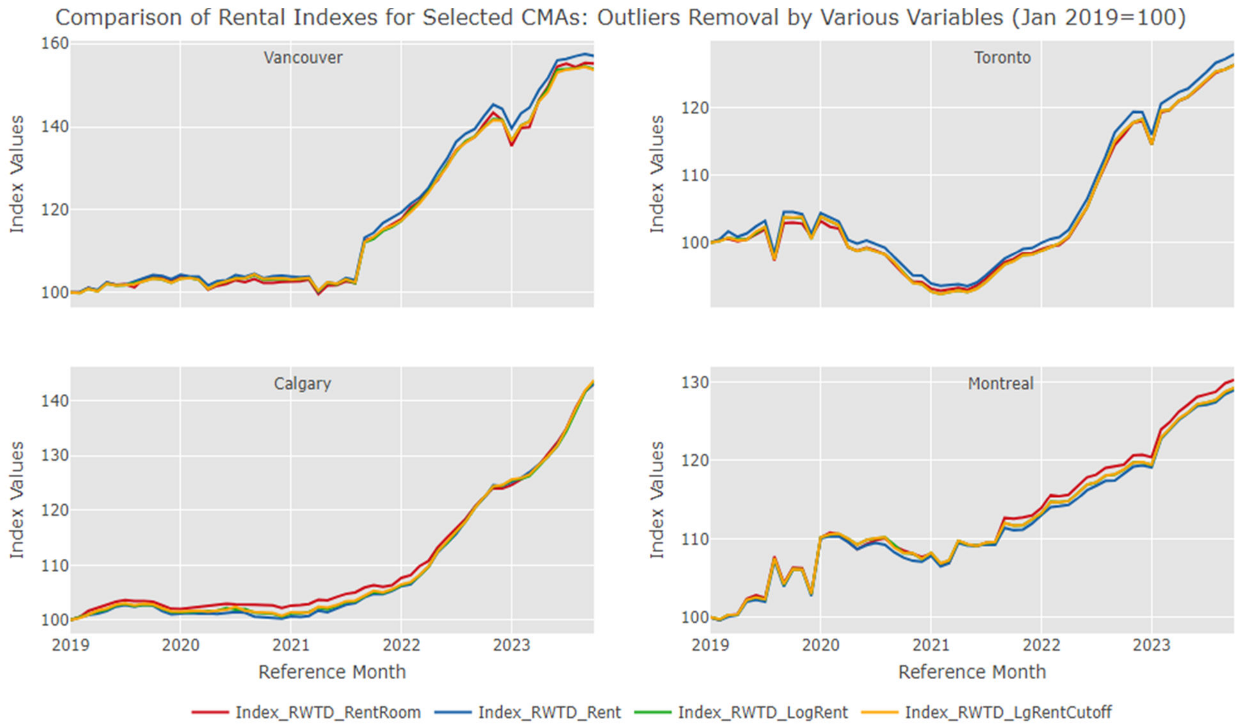
The following charts in Figure 8 compare the rental indexes estimated from the rolling window time dummy method with various approaches to eliminating outliers, where threshold values are determined based on the logarithm of the rent. The outliers are removed within each regression window. The rental indexes for Calgary compiled with outliers removed using Cook's distance method show an upward drift after May 2022. Overall, the disparity among indexes estimated from data using different outlier removal methods is minimal. This supports our expectation that the indexes are not every sensitive to the methods of outlier detection when sample size is sufficiently large.

Figure 8



To identify an effective method to detect outliers, we also investigate the impact of using different variables to determine threshold on the rental indexes, where rent per room, rent and logarithm transformation of rent are used to determine the threshold. In Figure 9, the outliers are detected by applying the MAD method and removed by reference month. Utilizing the fourth option illustrated by the orange line in the figure, we remove outliers for both right- and left-hand side variables of a regression. The rental units with bedrooms greater than five and bathrooms greater than four are dropped from the regression.

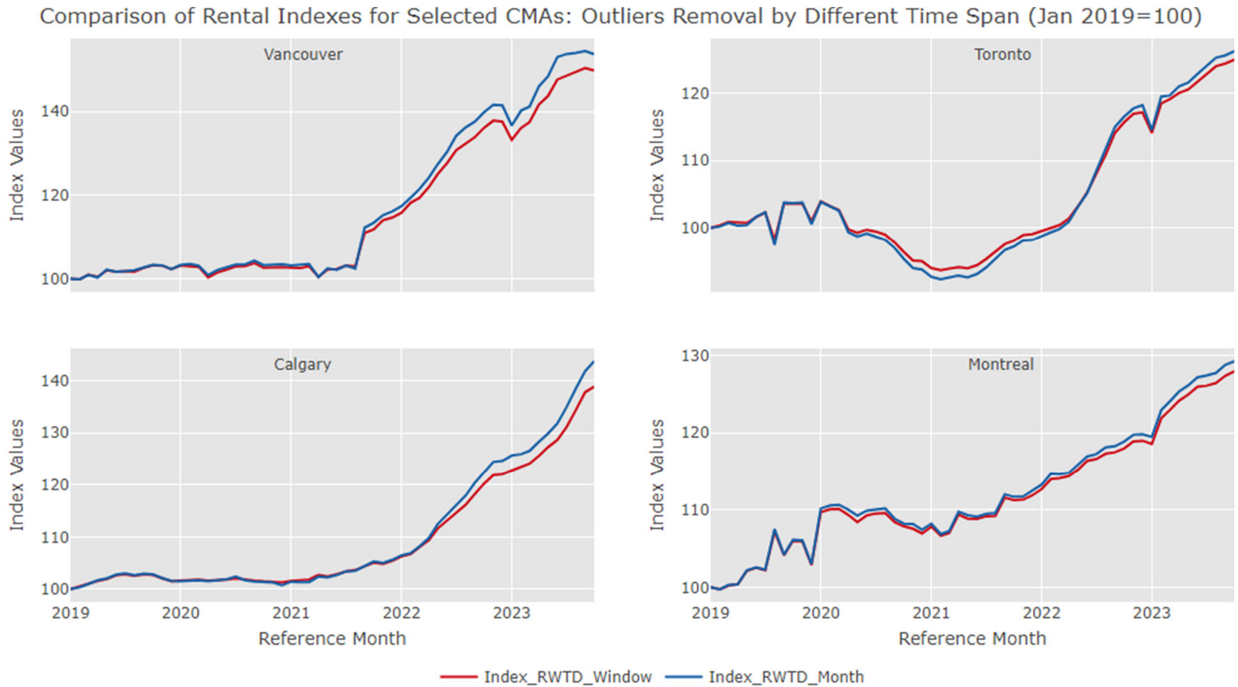
Figure 9



Through comparison, we found that the rental indexes are not very sensitive to the choice of variables used to determine the threshold. The rental indexes for Montreal are more sensitive than the other CMAs, which might be caused by the relatively small sample size in Montreal. The skewness in the raw data varying from month to month might also result in the differences for some period. The measures of skewness suggest that the rent data are right skewed for all four CMAs. An effective way to reduce the impact of skewness on outlier detection is to use the logarithm transformation of the data.

Additionally, we discovered that the time span over which outliers are removed also impacts the index estimation. Figure 10 compares the rental indexes when removing outliers by regression window and by reference month. Although the skewness varies from month to month, we believe it is more appropriate to remove outliers based on all the data used in each regression, as the indexes are estimated from the regression.

Figure 10



Notes: Index_RWTD_Window: rental indexes estimated using rolling window time dummy method where outliers are removed by regression window; Index_RWTD_Month: rental indexes estimated using rolling window time dummy method where outliers are removed by reference month.

5.2 Sensitivity to the length of listing

We notice that certain listings remain active for extended periods of time, sometimes up to six months or even over a year. It is plausible that the initially advertised vacant units have already been rented out, but property managers may choose to keep the listings active to continually promote available vacancies and maintain a pool of potential renters. This practice is particularly common for larger rental buildings. However, for these long-term listings that receive no updates, it becomes challenging to discern whether the long listing time is due to a slow rental market or overpricing, resulting in the unit remaining unrented, or just because the building managers do not update their listings in a timely manner.

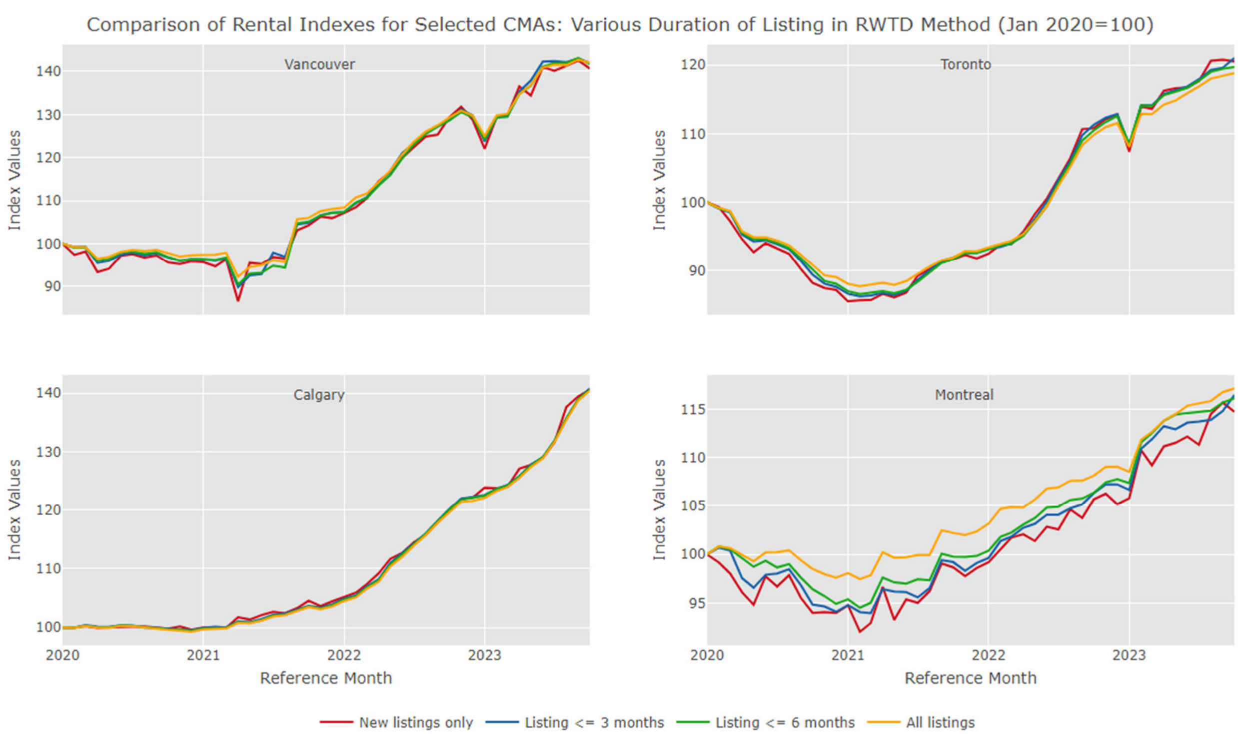
To assess the impact of these prolonged listings on estimated rent changes, we compare rent indexes calculated from datasets subject to varying listing duration restrictions. Specifically, we computed rent indexes using four different criteria: (1) new listings only; (2) listings active for up to 3 months; (3) listings active for up to 6 months; and (4) all listings regardless of their listing duration.

Table 3 presents the distribution of observations based on listing duration, and Figure 11 illustrates index comparisons. In Calgary, the proportion of new listings is notably higher, and we observe minimal discrepancies between methods, especially during periods of stable rents in 2000 and the early months of 2021. By contrast, Montreal has a higher proportion of longer-term listings, contributing to greater disparities between indexes. In general, rent indexes calculated solely from new listings display greater volatility, with fluctuations diminishing as longer-term listings are integrated into the sample. Furthermore, the presence of prolonged listings tends to dampen the rental growth experienced by prospective tenants.

Table 3: The distribution of observations by listing duration

share (%)	Vancouver, BC	Calgary, AB	Toronto, ON	Montreal, QC
New listings only	45.44	54.74	48.83	36.67
1 < listing duration <= 3	22.96	32.33	28.24	28.84
3 < listing duration <= 6	8.09	6.49	9.83	12.73
Listing duration > 6	23.51	6.44	13.10	21.75

Figure 11



5.3 Sensitivity to the level of manual editing

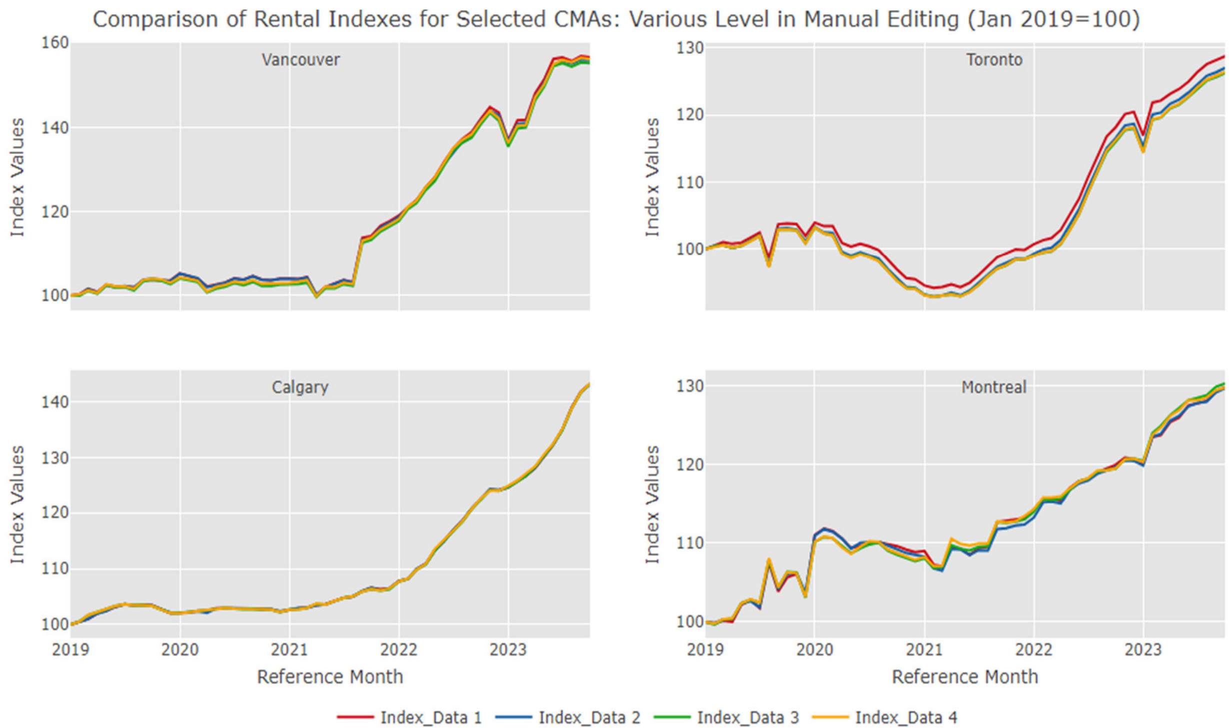
Data cleaning and editing is a necessary procedure for regular index production. With more involvement of manual work, the data quality and sample size can be improved. However, this process is time consuming and might result in additional human errors. Considering the time constraints of monthly production of rental index, we need to find an efficient approach to clean the data. To achieve this, we prepare various data sets involving different levels of manual editing, and then compare rental indexes estimated from these data sets applying rolling window time dummy method with a mean splice approach. Table 4 explains the differences in the manual involvement conducted for these data sets.

Table 4: Data sets involving various level of manual editing

		Data 1	Data 2	Data 3	Data 4
Steps of data editing	1. Standardizing addresses	No	Yes	Yes	Yes
	2. Imputing missing values based on the address and corresponding latitude and longitude.	Non-standardized addresses are used.	Standardized addresses are used.	Standardized addresses are used.	Standardized addresses are used.
	3. Validating data based on various platforms of rent listings.	No	No	Yes	Yes
	4. Further imputing missing values in the square footage of rental units based on the average size of similar rental units in the same area.	No	No	No	Yes
Sample size (Total)		1,890,700	1,941,345	2,011,341	2,046,370

The Rental indexes compiled with these data sets applying rolling window time dummy method with the mean splicing strategy are shown in Figure 12.

Figure 12



Examining the above charts, we found that the differences in the rental indexes compiled using these data sets could be ignored, especially for Vancouver and Calgary. Even though some discrepancies could be observed in Toronto and Montreal, the benefit from extensive data validation is marginal. This finding supports our expectation regarding the influence of data quality on the final indexes. When sample size is sufficiently large, it might be safe to simply remove problematic observations. Then it is crucial to establish an effective procedure for detecting errors and outliers.

6 Conclusion

Rental price indexes for new tenants offer a leading indicator of price trends, providing valuable insights for policymakers, economists, and stakeholders. Using rental listing microdata, we develop asking rent indexes for prospective tenants for selected CMAs and provinces. Our calculations show that new tenants experience larger rent growth compared to existing tenants during the inflation surge that began in mid-2021.

We also discuss the challenges and limitations associated with using rental listings microdata to measure rent changes, including outlier treatment, the impact of long-term listings, and the efficacy of manual editing. We find that the rental index is not very sensitive to the choice of outlier method when sample is large enough, the presence of long-term listings tends to mitigate rent growth faced by prospective tenants, and the influence of manual editing is negligible.

In the absence of transaction price, using advertised prices as a proxy for transaction price can provide some insights. However, due to changing market conditions and negotiation strategies, list prices may not always be consistent with the final transaction prices. A recent study of the Australian rental market (ABS 2023) shows that the index of actual rent declined further than advertised rent series during the early stage of the pandemic when the rental market was experiencing a downturn, and subsequently increased at a greater rate than advertised rent as rental market started to rebound. Therefore, rent indexes computed using list price just serve as a rough indicator of market trends. To address this concern, we are actively seeking new data sources that include transaction prices. Meanwhile, we are in discussions with our data provider to ensure that transaction prices are collected alongside list prices. Furthermore, recognizing the importance of location in the housing context, we would like to investigate the impact of incorporating proximity measures, such as walk scores, into the index estimation, and provide theoretical foundation for the future index production.

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