Online Listing Keywords and Housing Market Dynamics: A Focus on the COVID-19 Shock and Housing Demand Change

Jieun Lee and Kwan Ok Lee*

April 2022

Abstract
This paper is the first to consider the keywords of online listings to reveal a dynamic change in consumer preferences and to apply these keywords to model housing price premiums. Deeming the COVID-19 outbreak as a natural shock that brought a significant change in Singapore with increasing trends of working-from-home, we match the database of more than 70,000 listings scraped from the major online platform with the actual transaction database of resale public housing. Our text analysis results suggest the online listing keywords capture the change in housing demand that could not be detected from the conventional database. Listings highlighted a larger interior space and nice view more frequently while words related to accessibility or location appeared less. Next, using the triple Difference-in-Difference model, we find the 2.09% higher price premiums paid for housing units advertised with keywords highlighting the "view" after COVID-19, relative to units located in the same block and similar floor levels but have not been advertised with such keywords. This suggests that consumers would be willing to pay higher premiums for unobserved, unique features that are increasingly popular. It also emphasizes the role of agents to quickly capture and highlight popular features in the dynamic market.

Keywords: Online Listings; Keywords; PropTech; Agents; Housing Demand; COVID-19

Jieun Lee is the postdoctoral research fellow at the National University of Singapore. Kwan Ok Lee is the Dean's Chair Associate Professor of Real Estate at the National University of Singapore (email: kwan.lee@nus.edu.sg). Financial support from the National University of Singapore is gratefully acknowledged (R-297-000-146-115)

1. Introduction

While the real estate sector has traditionally lacked the digitalization process, emergence of big data and internet of things has recently led to a boom in technological advancement, called Property Technology (PropTech). In particular, online listing platforms have been widely used by potential home purchasers for searching and real estate agents for marketing. To get more attention of consumers in these platforms, keywords used to advertise the home listing should be carefully selected (Delmelle and Nilsson, 2021). These keywords are likely to quickly reflect changing demand in the local housing market, if there is a significant shock to the market. In particular, how the keywords effectively advertise the housing features that are increasingly popular to consumers would play a significant role in attracting more consumers and their payment of the premium to such an advertised housing unit relative to other similar units (Shen and Ross, 2021).

In this paper, we attempt to analyze dynamic interrelationships between keywords used for online advertisement and local housing markets. We use the COVID-19 outbreak as a natural shock to the local housing market in Singapore. As the COVID-19 has limited public mobility and transformed the work arrangement, and in turn, the consumer preferences for their homes, this provides a good opportunity for us to explore how quickly keywords of online listings have captured a change in these preferences. For example, we would expect increasing popularity for more spacious homes with a nice view while accessibility to public transportation would be a less important factor for homebuying decisions in the post-COVID-19 period. By connecting the online listing information to the actual transaction database, therefore, we attempt to estimate the price premiums paid for housing units advertised with keywords highlighting increasingly popular attributes, relative to units that have similar attributes but have not been advertised with such keywords.

In doing so, we use more than 70,000 public housing resale listings for the period of 2019 to 2021, scraped from the major online listing company, PropertyGuru, which has 84% of the market share regarding agent subscription revenue in Singapore (Business Wire, 2022). We then match them with the actual transaction databased of resale public housing provided by the Housing and Development Board (HDB) by precise location and housing unit characteristics such as the number of rooms and the floor level. To explore the keyword trend of online listings, we perform an exploratory text analysis on keywords that mainly describe the physical features of housing units (e.g. room, view, floor level, space, etc.) and their location (e.g. accessibility to the station, neighborhood amenities, etc.). To estimate the price premiums associated with these features, we use the triple Difference-in-Difference modeling approach that account for temporal variation (before vs. after COVID-19) as well as variations in advertised keywords (e.g. including vs. not including increasingly popular features like "view") and actual housing attributes related to these keywords (e.g. above vs. below tenth floor).

To our knowledge, this is the first paper to consider the keywords of the online listing platform as a mean to reveal a dynamic change in consumer preferences and to apply these keywords to model housing price premiums. Our paper contributes to the thin literature on the effects of PropTech, especially online listing platforms, on housing market outcomes. Our focus on keywords builds upon the existing research that similarly uses the descriptions of online listings. Shen and Ross (2021) use these descriptions to measure the uniqueness of housing properties while Delmelle and Nilsson (2021) use them to identify neighborhood characteristics. Our paper is similar to several papers that estimate hedonic models of housing prices or evaluate the performance of listings (i.e. success rates in sales and performance of real estate agents) with housing attributes characterized by the machine learning techniques

(Lindenthal, 2017; Aburey et al., 2019; Shen and Ross, 2021; Sing and Zou, 2021). Different from these papers, however, our focus is on the dynamic change in housing demand with the COVID-19 shock which can suggest the broader role of PropTech. Because keywords of online listings highlight the housing features that are not captured in the standard housing transaction database but becomes more popular in the market (e.g. view, renovation), housing price models including them provide a better understanding of the market trend. Furthermore, as the online listings capture housing demand change a lot faster than ex-post transaction data, using the information from these platforms could help the earlier market forecast.

Next, in suggesting the underlying mechanisms through which the keywords of online listings are able to capture consumer preference changes ahead of time and may influence price premiums, we borrow ideas from the classic real estate literature focusing on marketing and brokerage. Real estate agents spend a significant amount of time and effort to attract listings as they get commission generally based on the amount they sold (Munneke and Yavas, 2001; Jud and Frew, 1986; Yavas, 1994). Therefore, on the one hand, agents try to capture a change in consumer preferences as quickly as possible and use keywords that could effectively reflect this change. On the other hand, the unobserved, qualitative information on properties matters for search behaviors of potential homebuyers and their interpretation of the information influences transaction prices (Goodwin et al., 2018). In particular, in dynamically changing markets after the COVID-19 shock, properties uniquely positioned with unobserved features that are increasingly popular (e.g. nice view and larger interior space) could have greater market power (Bayer et al., 2007; Wong, 2013).

Finally, our paper adds insights into how a rising incidence of working-from-home (WFH) influences housing demand changes. A series of research suggest that the COVID-19 pandemic has influenced household housing demand especially with the substantial increase in WFH along with reduced mobility because of the restricted measures and infection concerns (e.g. Di Renzo et al., 2020; Muhyi and Adianto, 2021; Zarrabi et al., 2021; Bottero et al., 2021). In particular, researchers report that residential demand has increased in neighborhoods with lower density and crowdedness (Liu and Su, 2021; Baleimi et al., 2021) and in housing units with more interior and outdoor space like the home office and terrace (Boesel et al., 2021; Zarrabi et al., 2021). Based on existing evidence, we encompass both physical and locational features of housing units for our analysis on local housing demand change in Singapore. One advantage of using the resale public housing data in Singapore is that because units are quite homogeneous in terms of design and community facilities (Lee, 2021), it is simpler to disentangle the price premium effect of specific features like unblock view with the higher floor level or accessibility to the subway station. Our research features the Singapore's unique context for residential choices in only one city that differs from most other countries that have more than one metropolitan area with urban and suburban locations. Also, unlike existing research, we focus on demand for multifamily housing units in the high-density environment. We attempt to test external validity of existing evidence from other countries and report how this uniqueness leads to similar or different results.

The rest of this paper is organized as follows. The next section provides brief scholarly and institutional backgrounds for our research followed by the section that describes data and methodology. Next, the main results of this research are presented with the exploratory text analysis that shows how keywords in online listing platforms reflect actual demand change as well as with the triple DID regression results that suggests premiums paid for advertised keywords. Finally, we conclude and provide policy implications.

2. Background

2.1. COVID-19 Outbreak as a Shock to Housing Markets

The COVID-19 pandemic has influenced household housing demand especially with the dramatic increase in working-from-home (WFH) along with reduced mobility because of the restrictions and infection concerns (Di Renzo et al., 2020; Muhyi and Adianto, 2021; Lee and Lee; 2021; Zarrabi et al., 2021; Bottero et al., 2021). On the one hand, the COVID-19 shock has influenced on a change in preferences for residential locations. Decline in demand was reported to be stronger in more densely populated neighborhoods and central cities (Liu and Su, 2021). In the pre-COVID-19 period, homes in densely populated areas in cities have been valued for their access to amenities such as shopping malls and railway stations as well as proximity to workplaces. However, after the COVID-19 outbreak, visitors to and the expenditures at crowded places such as shops, restaurants, and gyms have decreased (Allcott et al., 2020), thus these amenities have been less attractive to potential homebuyers (Liu and Su, 2021). Also, perceived risk for virus infection tends to be higher in high-density areas, and in turn, lower housing demand in these areas (Baleimi et al., 2021).

On the other hand, research has reported a shift in consumer demands for larger space, both in the home's interior and exterior (Boesel et al., 2021). National lockdowns and social distancing measures have required people to conduct daily activities at home, to fight against the COVID-19 pandemic which (Kim, 2021). Hence, homes with larger interior living space and a larger lot have experienced a higher increase in their housing prices. This is to accommodate the increased demand for separate spaces for working individuals who need a home office and school-age children who take in-home classes (Boesel et al., 2021). Also evident is that consumer demand has increased for homes with natural light, visibility, the acoustics of interior spaces, and the open or semi-open space (terrace), which is associated with efforts to prevent potential psychological damage caused by staying at home (Zarrabi et al., 2021).

2.2. The Singapore Context

In response to the pandemic, Singapore government's measure included strict border controls, contact tracing, home isolation with closure of schools, universities, and workplaces, social distancing and permission of opening only essential businesses such as grocery stores and banks. Singapore government announced the beginning of lockdown on April 3rd in 2020, mandating unprecedented restriction of social gatherings in offices and schools. The Circuit breaker lockdown lasted until 1st June. After that time, the measure Phase 1 was started and offices re-opened, but with tele-commuting adopted to the maximum extent. After that, Singapore government announced work-from-home as a default and group size of gatherings was restricted to 5 people as Phase 2, which lasted from June 18 and Dec 27th. From Dec 28th until 2021 July, Singapore government changed their restrictions according to the domestic COVID-19 confirmed case situations. Those restrictions ranged from work-from-home as a default, sometimes requiring 50% or 75% could work at offices. In consequence, the effects of the COVID-19 pandemic on Singapore society, economy, and lives of the individuals within have undoubtedly been influential.

A number of Singaporeans started to work from home, virtually attended to schools, while large gatherings were suspended from June in 2020. These behavioral changes resulted in a sharp decrease of mobility and increase in the willingness to pay for preferred housing choice of Singapore. As the whole family members spent most of their time at home, households wanted larger spaces (Lin, 2021). A number of households decided to move away from central area to the cheaper area for more space. Since these changes were unprecedented and lasted for a couple of years, the changed lifestyle has come to such an extent that cannot go back to square one. In fact, quoting to a survey conducted in Singapore, 90.7% of people think that WFH is going to be a long-term trend in Singapore (Deng, 2020). Also, 53.7% of people responded they are willing to spend more cost on commuting if they can move to more preferred area after the pandemic occurred. Therefore, we can expect that people are still going to be willing to pay more for their homes even if it involves being further away from their offices in the future.

Against the backdrop, we focus on the change in public housing demand after the COVID-19 outbreak in Singapore. Public housing in Singapore is developed and sold by the government agency called the Housing and Development Board (HDB). While foreigners are able to purchase private housing and drive its market trends, public housing units could be purchased only by Singapore citizens or permanent residents. The purchaser gets the public housing unit at a subsidized price when directly buying from the HDB. After a 5-year minimum occupation period, homeowners of public housing can sell their units in a free and open market, called resale market, and there is no price control in the transaction process. The listing and transaction database used for all analyses in this paper are resale public housing. Hence, the changes in keywords for online listings and price premiums observed for public housing transactions will be able to fully capture housing demand in the local markets.

3. Data and Methodology

3.1. Data

HDB resale transaction Data

The analysis was performed with data from two separate sources: HDB and PropertyGuru. Our main data source is from Housing and Development Board (HDB) to perform DID regressions with public housings' resale price and various characteristics of each housing property. With the resale transaction price as a dependent variable, DID regressions to verify the price premium of the characteristic variables of interest are performed. We controlled the residential building's age, housing unit size, floor level, street name, time, and proximity to several amenities. Since proximity features to these facilities have been considered as important factors in the process of searching a house to purchase, we wanted to evaluate changes of their price premiums. We prepared location-based dummy variables indicating whether the distances to MRT (subway) station, CBD, or malls are within certain level through GIS proximity analysis.

Table 1 provides descriptive statistics of the HDB resale transactions from 2017 to the end of 2021. We used this long-term HDB resale transaction data to test price premiums occurred after pandemic in relation to certain features of interests in the first part of our empirical modelling. On the other hand, at the last part of our empirical analysis, we used HDB transaction data ranged from 2019 to match up the time range because PropertyGuru listing data ranges from 2019 through 2021. The summary statistics of the matching data is presented in Table 5.

PropertyGuru listing Data

The second data source is *propertyguru.com.sg*, the biggest on-line housing transaction platform in Singapore. To detect the trend of property promotions and preferences, we collected more than 70,000 HDB sale listings after excluding duplicate listings spanning the 2019 through 2021 time period with python-based web-scraping tool. This data has information of listed asking price, floor area, location (latitude and longitude), house age, description of the house for sale, and so on. Especially, we used description text data and performed natural language processing (NLP) such as word cloud analysis, unigram, and bigram analysis to detect the changes in their advertisements. For the description texts, we exclusively analyse the first 15 words of descriptions to only include parts that agents wanted to display where it's the most visible or deemed those descriptions will appeal to potential customers the most, and to exclude the effect of the description's length.

Apart from text data illustrated above, our PropertyGuru dataset includes variables of housing such as the number of rooms, locations, and its belonged neighbourhoods. Including all available features, we scraped PropertyGuru listing data from 2019-10-28 until 2021-07-19, at 10 discrete time points[1]. Among all listings, we extracted only HDB flat type apartment so other types of houses like condominiums, terraced or detached houses were excluded. Also, we included in our analysis only housing units completed its construction at least one year earlier from the listing date to exclude newly-built (initial sale) housing properties.

3.2. Methodology

Econometric Modelling of HDB Resale Transaction Data

Firstly, to investigate which key features became popular after the COVID-19 through resale transaction price, difference-in-differences (DID) is employed with transaction price per square meter as a dependent variable $\mathrm{y_{it.}}$ In the model equation below, D_i indicates whether the observation has certain housing feature (e.g. high floor, spaciousness, proximity to key facilities) or not, while T_i indicates whether the data is belonged to post-pandemic period. The coefficient estimates of the interaction term (D_iT_i) of these two variables, β reflects additional price premium of each certain feature we are interested after pandemic. $\boldsymbol{X}_i$ is the vector of other housing characteristics that need to be controlled. $\boldsymbol{F}_{tj}$ is the vector of fixed effect terms regarding both geographical and temporal variations aiming to maximize the exogeneity of treatment effect.

$$\mathrm{y_{it}} = \alpha + \delta D_i + \gamma T_i + \beta D_i T_i + \theta \boldsymbol{X}_i + \varphi \boldsymbol{F}_{tj} + e_i \qquad (1)$$

Next, based on the findings revealed from equation (1), we conducted triple interactions by multiplying the housing unit's spaciousness dummy to the prior interaction term to reveal its price premium change in regards to the substitute relationship between superior location and spaciousness. At this stage, key estimates are three-way interaction terms ($D_iT_iS_i$) between post-pandemic period dummy, locational proximity dummy, and the binary indicator of housing unit size. Through the analysis, we discover homebuyers' decisions made in between the locational benefits and the eager to ampler space after pandemic started.

$$\mathrm{y_{it}} = \alpha + \beta D_i T_i S_i + \varphi D_i T_i + \chi T_i S_i + \psi D_i S_i + \delta D_i + \gamma T_i + \rho S_i + \theta \boldsymbol{X}_i + \varphi \boldsymbol{F}_{tj} + e_i \qquad (2)$$

Text Analysis of PropertyGuru Listings for HDB sales

We performed word-cloud, unigram, and bigram analysis to grasp the trend in advertising housing features with the description texts obtained from PropertyGuru listings. In the pre-

[1] Data scraping dates are as follows: 2019-10-28, 2020-09-29, 2020-11-02, 2020-12-04, 2021-01-14, 2021-02-21, 2021-03-26, 2021-03-29, 2021-05-27, 2021-07-19

processing stage of the texts, prepositions, articles, the verb ‘be’ were removed to capture only meaningful unit of words following the conventional pre-processing methods.

In the word-cloud analysis, we compare each year’s word-clouds and explore a comprehensive set of words that are frequently used in description headlines of HDB sale listings. Next, we performed unigram analysis to numerically verify each word’s trend change in a way that sorting and selecting the top 1,000 most frequently appeared words by year and calculated the probability of occurrence for each word ($\mathrm{p_{it}}$) out of the total sum of their frequency.

$$\mathrm{p_{it}} = \frac{count\ of\ word_i\ in\ year\ of\ t}{\sum_{i=1}^{1,000} count\ of\ word_i\ at\ rank\ i\ in\ year\ of\ t} \tag{3}$$

Based on that, the rate of percent changes ($\mathrm{c_{(i,\ t_0,t_1)}}$) of the appearance probability of each word in the year of 2020 and 2021 compared to 2019 were calculated to highlight their uptrends and downtrends. Also, we performed the same analysis in a same manner but with pair of words, called bigrams. Discovered trend from the percent changes are presented in Figure 2 and 3.

$$\mathrm{c_{(i,\ t_0,t_1)}} = (\mathrm{p_{it_1}} - \mathrm{p_{it_0}})/\ \mathrm{p_{it_0}} \tag{4}$$

Our Big-data approach sets aside this study at the point that we use not only conventional econometric models, but also try to employ unstructured data recently have become available. Big-data paradigm tries to intuitively derive implications that has not been discovered before, through descriptive results or correlations rather than proving a causal relationship. Our text analysis such as word-cloud, unigram, and bigram include this strand of efforts.

Econometric Modelling of Matched HDB transaction data with listing description info

In the last part of our econometric modelling, we employ the DID and triple DID models again, but with a binary indicator of the listings description whether the same-featured-listings had been advertised with certain keywords of our interests. To do this, listing descriptions’ characteristics from PropertyGuru data are matched with HDB resale transaction data. In doing so, we connected PropertyGuru listings’ certain keyword advertisement emphasis information to HDB resale transaction data based on its homogeneity bringing the data in concordance with the combination of location, floor level, house size, and timing.

To be specific, as a common variable connecting the two dataset, property feature set ID (hereafter, we call this as PID) was created with the combination of the latitude and longitude, number of rooms whether it has four or more rooms[2] or not, floor level category such as high floor, middle floor, and low floor, and the timing of observations. Then, by each PID, the probability of the keywords’ usage on online listings was calculated based on whether the description contained a keyword related to certain feature group[3]. Then, we

[2] Same meaning as whether it has three or more bedrooms

[3] View-related keywords include the set of these words: unblocked, river, lake, view, and highfloor while location-related keywords’ include the following words: MRT, near, nearby, nearest, location, walk, minute, mins, short, distance, amenities, station, central, school, shop, street, bus, opposite, centre, surround, interchange, go, accessible, supermarket, bank, and connectivity.

created and used the binary variable indicating whether the probability of each keyword category is included in the top tertile in our empirical models.

In this way, the additional premium given to the HDB housing units that were advertised with certain features through listing headlines could be tested. This model specification can be expressed as following equation where A_i denotes the binary indicator if the property group is the case of top tertile group that are highlighted with certain keyword groups in the listing descriptions, and A_iT_i refers its additional impact on transaction price premium after the pandemic started.

$$\mathrm{y_{it}} = \alpha + \beta A_iT_i + \delta A_i + \gamma T_i + \beta A_iT_i + \theta \boldsymbol{X}_i + \varphi \boldsymbol{F}_{tj} + e_i \quad (5)$$

To further test the relationship between the role of on-line listings, housing units' condition, and the role of headlined descriptions, we employ another triple DID model to assess price premium changes occurred from highlighting with certain keywords in relation to actual condition of the housing units. Equation (6) represents its specification including the triple DID interaction term ($T_iD_iE_i$) when T_i indicates post-pandemic dummy, C_i indicates whether the unit equips certain condition such as high floor, near MRT, or either near CBD, and E_i flags whether certain keywords are used in online listings. For the dependent variable, we tested not only with price per square meters, but also with Log of price for its robustness check and the ease of interpretation.

$$\mathrm{y_{it}} = \alpha + \beta T_iD_iE_i + \varphi T_iD_i + \chi T_iE_i + \psi D_iE_i + \delta D_i + \gamma T_i + \rho E_i + \theta \boldsymbol{X}_i + \varphi \boldsymbol{F}_{tj} + e_i \quad (6)$$

4. Results

4.1 Regression Results with HDB Resale Transaction Data

Table 2 displays estimates of the Difference-in-Difference (DID) model presented in equation (1). The results from this specification show average price premium difference of certain features (high floor, spaciousness, proximity to MRT, proximity to CBD) between the pre-pandemic and post-pandemic. The significant price premium increase in high floor housing units and spacious units after pandemic are found. As shown in Appendix 1 table, regardless of the breaking point defining 'high floor', the interaction term of post-pandemic and dummy variable indicating the flat's high floor level consistently showed positive effects. We also find that large units having four or more rooms have had higher price premium after pandemic. In Singapore, HDB flats with 4 or more rooms are deemed as 'big flat' while a living room is counted as one room. The model (2) at Table 2 shows the coefficient estimates regarding the spaciousness feature. The price premium of spaciousness was significantly increased after pandemic. The significant positive estimates of the interaction terms between post-pandemic and high-floor dummies in Table 2 indicate the risen popularity of a high floor feature. High floor unit provides more superior view compared to middle- or low- floor units, allowing people the sense of openness in residential space. We can also infer that strictly-restricted outdoor activities boosted eager to feel the openness through higher premium not only to the high floor units but also its spaciousness in the HDB resale market as well.

On the other hand, proximity to MRT and CBD showed significant decrease of its price premium after pandemic in model (3) and (4), implying that preventive measures such as working from home or restrictions of social gathering affected Singaporean potential homebuyers in a way underscoring the value of locational features. The coefficients on other housing features showed consistent results with previous studies. However, this might not due to people's non-preference to the accessibility to amenities, rather it happened in pursuit of more spacious units considering the fact that there are substitution effects between superior location and spaciousness. Therefore, we proceeded to reveal how the price premium changed after the pandemic according to the proximity to key facilities in relation to the housing unit size with three-way interaction regressions.

Table 3 shows the three-way interaction terms between post-pandemic dummy, proximity to MRT, CBD, malls, and parks each, and house size whether it has 4 or more rooms. After the pandemic, the importance of location according to the proximity to MRT stations decreased while the price premium for large-sized houses increased its premium even more as shown in model (1). Also, although the interaction terms between post-pandemic and CBD proximity showed negative significant changes, in case of large houses close to the CBD, their price premium according to location has risen after pandemic (model (2)). This means that the magnitude of the influence of housing unit size was greater than whether it was located nearby CBD or not. Similarly, in regards to proximity to malls, the price premium of large houses located near malls has risen while small houses nearby the malls experienced its decrease in price premiums of its proximity to the malls (model (3)).

Whether it is located near a park or a large house, both has had powerful price premiums for decades. However, we found that large houses had an increased park proximity premium after the pandemic, but small houses have not experienced significant increase in park accessibility premium throughout the pandemic (model (4)). These results consistently imply that even though good accessibility to amenities has been and still considered as an advantageous feature, recent trend preferring more space and policy measures forced people to value ample space much higher than proximity.

4.2 Text Analysis Results with PropertyGuru listing descriptions

In this section, we illustrate text analysis results in pursuit of additional discoveries from online listings that have not found in the prior analysis. Our main interest lies on finding undiscovered trends that hard to be found in a numerical manner by comparing headline descriptions written in 2019 contrasting with the results of post-pandemic seasons'.

Word-Clouds

Firstly, word clouds were drawn with HDB listing data in 2019, 2020, and 2021 respectively for exploratory purpose. As shown in Figure 1, keywords such as 'high floor', 'minute walk', 'walk MRT', 'unblock view', and 'mid floor' are most frequently included in the headline of PropertyGuru listing descriptions[4]. Although the set of keywords used in the headlines of the housing sale listings doesn't seem to have changed that much in the aggregated form of

[4] The reason why some of the phrases look awkward is as because in the process of pre-processing of natural language, every English words were converted into simple form of the language and lower case, and prepositions and articles were removed to fully consider the only meaningful words. For example, original description written as 'unblocked' was converted into 'unblock', 'well maintained' into 'well maintain', 'walk to mrt' into 'walk mrt', and so on. This is to unify the format of same-meaning phrase to simple or present format from passive form, present progressive, past tense, and so on.

clouds, still we can detect some of the changes from the word-clouds. As highlighted with rectangle-shape boxes, some phrases appeared more frequently in the post-pandemic seasons and some did less. Considering the fact that each word-cloud image sizes are same, you can see which words were used relatively more frequently in the year by looking at the change in the size of specific phrases. Compared to 2019, the proportion of mentioning well-maintain (highlighted with yellow box) and 4room flat (green box) have increased, while 'walk mrt' and 'near mrt' showed its decrease in relative frequency of occurrence. Although these word clouds show us popular group of words that appear in the description headlines throughout the past three years, it is difficult to capture each of the words' up and downtrends, so unigram and bigram text analysis were conducted.

Unigram Analysis

Figure 2 shows the unigram analysis results grouped by similar category features. Each bar graph shows the percent change of appearance on the PropertyGuru listing description headlines between 2019 and 2020, and 2019 and 2021. Firstly, Nature-scenery related words such as river, seaside, beach, greenery, garden, nature, and lake appeared more frequently after pandemic (Figure 2-A). These words are generally used with 'view' such as 'river view', 'seaside view', and so on in the descriptions. In the second panel in Figure 2 (2-B), the group of words which implies its possibility of enjoying good views such as 'top', 'unblock', and 'balcony' also showed its increase in probability to appear in the listing descriptions after pandemic.

Regarding the indoor-environment, unigrams which explicitly present the number of rooms showed its change in a different way depending on the size of the units. It is noticeable that unigrams indicating 5 or 4 rooms increased its percent change of appearance after pandemic, while 2-room units showed its decrease of it. 3-room showed slight decrease of probability in 2020 and little increase of probability in 2021 compared to 2019.

Also, the unigrams showing the quality of indoor area displayed increase in their appearance. Unigrams like 'well-maintained', 'renovated', 'décor', and 'interior' are examples of those. Features favourable to people working from home such as 'quiet' and 'work' also increased its appearance in description headlines.

On the other hand, location-related words such as 'minutes', 'near', 'opposite', 'supermarket', 'central', 'mall', 'shop', 'bank', 'school', 'interchange', 'bus', 'mrt', and 'station' showed noticeable decrease in its appearance after pandemic. These unigram analysis outputs are not only supporting the resale transaction price premium hedonic regression models' results, but also allowing us to understand more dimensional picture of trends that could not be able to discover in the resale price premium models.

Bigram Analysis

Bigram analysis shows consistent results as shown in Figure 3. Based on the similarities of the themes, we categorized bigrams into several groups. Looking at the floor-related features group (3-A), the "top floor" bigram's percent change rate has been increased by over 30 percent, while the low floor, ground floor, and mid floor appeared less likely after pandemic. Considering the fact that top floor allows nice views, this indicate that people's preference toward high floor has been strengthened in the post-pandemic season which made people quarantined[5]. Similarly, most of the bigram related to the view – river view, seaside view, greenery view, open view, beautiful view, garden view, superb view, park view, nice view, and unblocked view – commonly showed high growth rates (3-B).

Besides, bigrams presenting its indoor environment regarding study room availability or quality of renovation showed positive percent change rate in its appearance after pandemic (3-C). For example, 'plus study' and 'study room' can be seen as a signal of nice environment for working from home or more functionally separable space for home-schooling, teleworking, and so on. Also, the preference of renovated property has been reflected with more frequent mentioning in description headlines as the shown in bigram cases related to renovated units – 'renovated 5room', 'renovated 4room', 'renovated 3room', 'tastefully renovated', 'fully renovated', 'renovated home', 'renovated bedroom', 'newly renovated', 'beautifully renovated', and 'well renovated'.

Although convenient and accessible locations have always been an important feature among the housing features, it seems to have changed as post-pandemic lifestyle was set in Singapore (3-D in Figure 3). Regarding the proximity to amenities like parks, schools, MRT stations, or malls, we discovered declining trend of its appearance. Those downtrend bigrams are generally related to its locational features, such as 'near park', 'near school', 'near mrt', and 'shopping mall'. For example, it was interesting to discover that the bigram 'near park' decreased by 20 percent points, while the bigram "park view" increased by similar absolute level of percent points. We may interpret these findings as a process of adaptation to changing housing demand expressed by the local agents who always communicate at the front-end of housing market. These text analysis results not only support our previous DID regression results, but also provide more plenty information that could not have been demonstrated in transaction data.

When we see the supply side through the PropertyGuru listings, the distribution of listings' floor level categories and the average flat size has remained at almost same levels as shown in Figure 4. Therefore, with the results, it can be concluded that the preference toward higher floors and larger units increased during the pandemic, meaning this trend comes from the demand side, not the supply side.

Besides, as shown in Table 4, we could find many examples showing the description changes between the two units having the same address, floor level category, and house unit size and brought some of those typical example pairs. In case of the first example pair, a listing posted in October 2019 promotes its convenient location, but the same building's same-sized unit in a same floor level category is emphasizing its spaciousness, renovated condition, and the number of rooms with exact housing unit size. The other pairs also show similar description trend change, in a way emphasizing high floor, unblocked, great view, or many number of rooms after pandemic while housing units with the same set of condition had promoted their proximity to MRT subway station or convenient location before pandemic.

4.3. Regression results with resale transaction price after matching listing feature columns

The last part of our analysis shows the additional price premium change for the housing units where certain characteristics are advertised on on-line listings. Data matching was processed by PID which defined as combination of location, floor level, house size, and timing as illustrated in methodology section and Figure 5. Table 6 shows estimates of DID model presented in equation (5). Results demonstrate that usage of keywords regarding the view

[5] The bigram 'high floor' also showed positive percent change but its magnitude was less than 0.1%, resulting its bar length was not visible on the figure. Therefore, 'high floor' category was excluded in this figure.

boosted housing unit's price premium after pandemic (model (1) and (2) in Table 6). Before pandemic, top tertile units promoted with view-related keywords had significant negative coefficients (about -28 SGD), but after pandemic, its premium became positive to substantial extent (over +30 SGD).

On the other hand, as shown in model (3) and (4), using location-related keywords in descriptions of online listings had positive impact on price per square meters before pandemic (about 2 SGD), but the impact decreased after pandemic by making its effect to be significantly negative although the magnitude is not very substantial. The results were consistent controlling its time-variants with 'year and month' or 'year and quarter'.

The matching models' DID result also supports the prior findings from other analysis by allowing us to confirm that HDB flats which likely to be referred with these keywords actually experienced their price premium changes throughout the pandemic season. The results can be interpreted also in a way that agents started to emphasize the features that housing seekers are looking for. At this point, the role of property agents who upload the online listings can be highlighted.

Table 7 and Table 8 present the triple DID regression results of equation (6) with different form of dependent variable to robustly assess the effect of referring the keywords about popular features on online listing description headlines in relation to the period of post-pandemic and actual house conditions. Table 7 shows the estimates with price per square meters and Table 8 with the log of real price. The results suggest that housing units advertised with view-related keywords enjoyed 2.09% higher price premiums after pandemic, relative to housing units having mostly same features in its address, floor level, and size but have not been referred such keywords in the online listings.

From the positive coefficients of near MRT, near CBD, and top tertile keywords related to location, we can infer that convenient locations providing good access to amenity facilities still work as booster of price premiums. However, its effect experienced a slight diminution after the pandemic as the interaction term between the post-pandemic time flag and top tertile keywords related to location show about 2% lower price premiums (-2.13% in model (2) and -2.4% in model (3)) after pandemic. This implies that referring location-related keywords have worked as a good strategy to advertise housing units but its effect has recently diminished throughout the pandemic. In sum, the triple DID results with description matching models confirm that advertising with view-related keywords served as a catalyst to increase the housing unit's price premium whereas locational keywords' effectiveness had been less effective.

5. Conclusions

In this study, we find the online listing keywords quickly capture the change in housing demand. Listings have highlighted a larger interior space and nice view more frequently in the post-COVID-19 period while words related with accessibility or location appeared less. Next, using the triple Difference-in-Difference model, we find the 2.09% higher price premiums paid for housing units advertised with keywords highlighting the "view" after COVID-19, relative to units that are located in the same block and similar floor level but have not been advertised with such keywords. This suggests that consumers would be willing to pay higher premiums for unobserved, unique features that are increasingly popular.

These findings have important implications on public policies and real estate industry. On the one hand, the big data from PropTech could be utilized to forecast changes in household housing demand and to evaluate the dynamic trend of real estate markets. These data could be acquired and analyzed a lot faster than administrative data that government agencies collect. Housing policy measures adopted in emergent situations such as the COVID-19 pandemic could gather some useful information from such data analyses. On the other hand, our findings suggest the great marketing potential of keywords of online listings. Potential consumers appear to pay attention to keywords that reflect their emerging desire and be willing to pay higher premium for products advertised with these keywords. The capacity of real estate agents to quickly capture and highlight these features is likely to play an important role to their performance in the dynamic market.

References

Arndt, A., D.M. Harrison, M.A. Lane, M.J. Seiler, and V.L. Seiler. (2013) Can Agents Influence Property Perceptions Through Their Appearance and Use of Pathos? Housing Studies, 28:8, 1105–16.

Balemi, N., Füss, R. & Weigand, A. (2021). COVID-19's impact on real estate markets: review and outlook. Financ Mark Portf Manag 35, 495–513. https://doi-org.libproxy1.nus.edu.sg/10.1007/s11408-021-00384-6

Boesel, M., Chen, S. & Nothaft, F.E. (2021) Housing preferences during the pandemic: effect on home price, rent, and inflation measurement. Bus Econ 56, 200–211. https://doi-org.libproxy1.nus.edu.sg/10.1057/s11369-021-00241-4

Boozer, R.W., D.C. Wyld, and J. Grant. (1990) Using Metaphor to Create More Effective Sales Messages. Journal of Services Marketing, 4:3, 63–71.

Bottero, M., Bravi, M., Caprioli, C., Dell'Anna, F., Dell'Ovo, M., Oppio, A. (2021). New Housing Preferences in the COVID-19 Era: A Best-to-Worst Scaling Experiment. In: , et al. Computational Science and Its Applications – ICCSA 2021. ICCSA 2021. Lecture Notes in Computer Science(), vol 12954. Springer, Cham. https://doi-org.libproxy1.nus.edu.sg/10.1007/978-3-030-86979-3_9

Business Wire (2022) PropertyGuru Delivers over S$100m Revenue in 2021, Beats Full Year Forecast. https://www.businesswire.com/news/home/20220228005408/en/PropertyGuru-Delivers-over-S100m-Revenue-in-2021-Beats-Full-Year-Forecast#:~:text=Singapore%3A%20PropertyGuru's%20year%2Dend%202021,by%2015%25%20in%20November%202021.

Cheung KS, Yiu CY, Xiong C. (2021) Housing Market in the Time of Pandemic: A Price Gradient Analysis from the COVID-19 Epicentre in China. Journal of Risk and Financial Management. 14(3):108. https://doi.org/10.3390/jrfm14030108

Cunningham, C., Gerardi, K., and Shen, Lily (2022). The Good, the Bad and the Ordinary: Estimating Agency Value-Added using Real Estate Transactions. Preliminary Draft.

Condon, P. M. (2010). Seven rules for sustainable communities: Design strategies for the post-carbon world. Island Press.

Dabholkar, P.A. and Overby, J.W. (2005), "Linking process and outcome to service quality and customer satisfaction evaluations: An investigation of real estate agent service", International Journal of Service Industry Management, Vol. 16 No. 1, pp. 10-27. https://doi-org-ssl.access.yonsei.ac.kr:8443/10.1108/09564230510587131

Del Giudice V, De Paola P, Del Giudice FP. (2020) COVID-19 Infects Real Estate Markets: Short and Mid-Run Effects on Housing Prices in Campania Region (Italy). Social Sciences. 9(7):114. https://doi.org/10.3390/socsci9070114

Di Renzo, L., Gualtieri, P., Pivari, F. et al. (2020) Eating habits and lifestyle changes during COVID-19 lockdown: an Italian survey. J Transl Med 18, 229. https://doi.org/10.1186/s12967-020-02399-5

Deng Jieying. (2020). Will the New Normal Alter People's Housing Choices? Evidence from Singapore. Department of Real Estate National University of Singapore B.Sc.

Goodwin, K. R., Waller B.D., and Weeks H.S. (2018). Connotation and Textual Analysis in Real Estate Listings. Journal of Housing Research 27(2): 93-106.

Haag, J.T., R.C. Rutherford, and T.A. Thomson. (2000). Real Estate Agent Remarks: Help or Hype? Journal of Real Estate Research, 20, 205–15.

Huang CL, Wang YM, Li XW, Ren LL, Zhao JP, Hu Y et al. (2020) Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. Lancet. doi: 10.1016/S0140-6736(20)30183-5.

Jud, G. D. and Frew, J. 1986. Real Estate Brokers, Housing Prices, and the Demand for Housing. Urban Studies, 23(1), 21-31. https://www.jstor.org/stable/43083063

Kim, I. (2021). Has the COVID-19 Pandemic Changed People’s Attitude about Where to Live? Some Preliminary Answers from a Study of the Atlanta Housing Market. http://hdl.handle.net/1853/64677

Lin, C. (2021) Going big on space: Buyers eye larger homes amid pandemic. Channel News Asia. 03 May 2021. https://www.channelnewsasia.com/business/singapore-wfh-bigger-space-new-homes-hdb-condo-sales-1338181

Muhyi, Mahdaniar Maulidini and Adianto, Joko (2021) "Literature Review: The Effects of Covid-19 Pandemic-Driven Home Behavior in Housing Preference," Smart City: Vol. 1: Iss. 1 , Article 2. Available at: https://scholarhub.ui.ac.id/smartcity/vol1/iss1/2

Munneke, H. J., & Yavas, A. (2001). Incentives and performance in real estate brokerage. The Journal of Real Estate Finance and Economics, 22(1), 5-21. https://doi.org/10.1023/A:1007879109026

PropertyGuru Group (2021) PropertyGuru launches ‘Green Score’ to guide Singaporeans to sustainable homes. 02-Sep 2021. https://www.propertygurugroup.com/newsroom/propertyguru-launches-green-score-to-guide-singaporeans-to-sustainable-homes/

Sitian Liu, Yichen Su (2021). The impact of the COVID-19 pandemic on the demand for density: Evidence from the U.S. housing market, Economics Letters, Volume 207. 110010, ISSN 0165-1765, https://doi.org/10.1016/j.econlet.2021.110010

World Health Organisation (2021). WHO-convened Global Study of Origins of SARS-CoV-2: China Part Joint WHO-China Study 14 January-10 February 2021 Joint Report

World Health Organisation (2022) Singapore: WHO Coronavirus (COVID-19) Disease Dashboard https://covid19.who.int/region/wpro/country/sg

World Health Organisation (2022) WHO Coronavirus (COVID-19) Disease Dashboard https://covid19.who.int/

Xianhang Qian, Shanyun Qiu, Guangli Zhang. (2021), The impact of COVID-19 on housing price: Evidence from China, Finance Research Letters, Volume 43, 101944, ISSN 1544-6123,https://doi.org/10.1016/j.frl.2021.101944.

Yavas, A. (1994). Economics of Brokerage: An Overview. Journal of Real Estate Literature, July, 2(2). 169-195. https://www.jstor.org/stable/44103270.

Zarrabi, M., Yazdanfar, S. A., & Hosseini, S. B. (2021). COVID-19 and healthy home preferences: The case of apartment residents in Tehran. Journal of Building Engineering, 35, 102021. https://doi.org/10.1016/j.jobe.2020.102021

Zhu, Y. (2013). Seven rules for sustainable communities: Design strategies for the post-carbon world. Taylor & Francis Group. https://doi.org/10.1080/13574809.2013.772850

Figure 1. Word Clouds with HDB listing descriptions for sale on PropertyGuru

Figure 1-A: year 2019

Figure 1-B: year 2020

Figure 1-C: Year 2021

Figure 2. Unigram Analysis Results

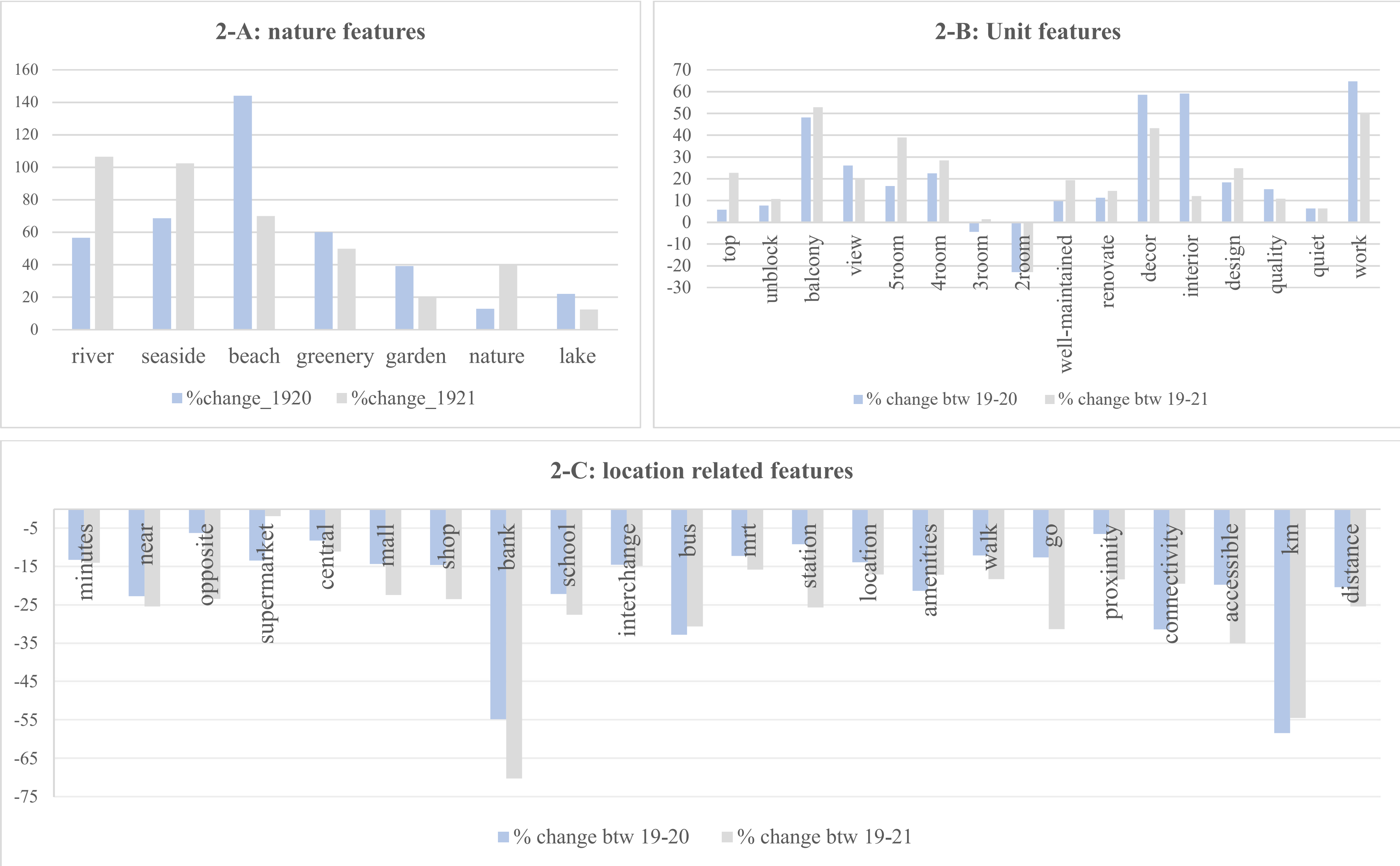
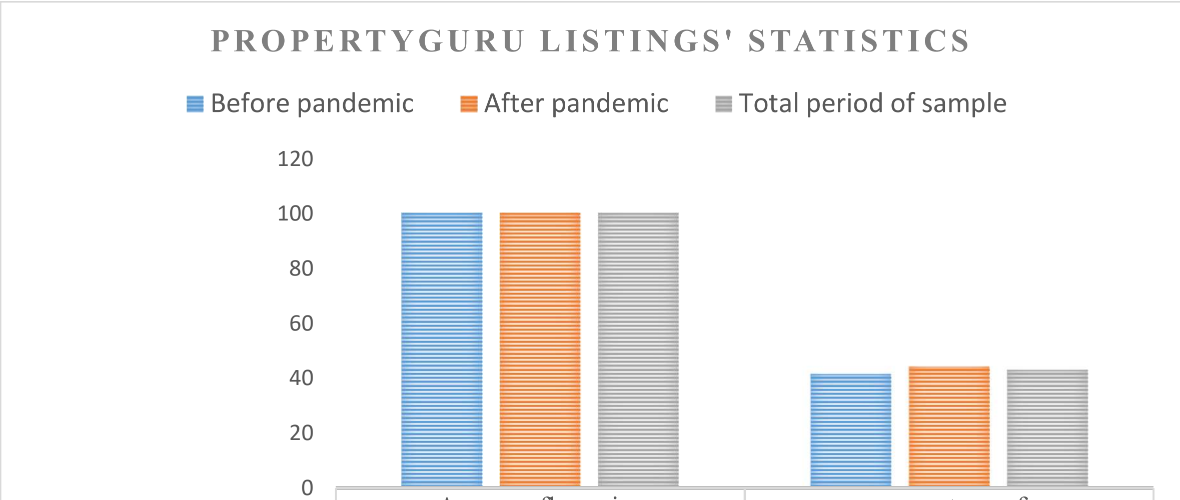


Figure 3. Bigram Analysis Results

Figure 4. PropertyGuru Listings' Statistics



	Average floor size (square meters)	percentage of High Floor Units (%)
Before pandemic	100.33	41.63
After pandemic	100.38	44.25
Total period of sample	100.36	43.11

Figure 5. Data Matching Criteria and its Process

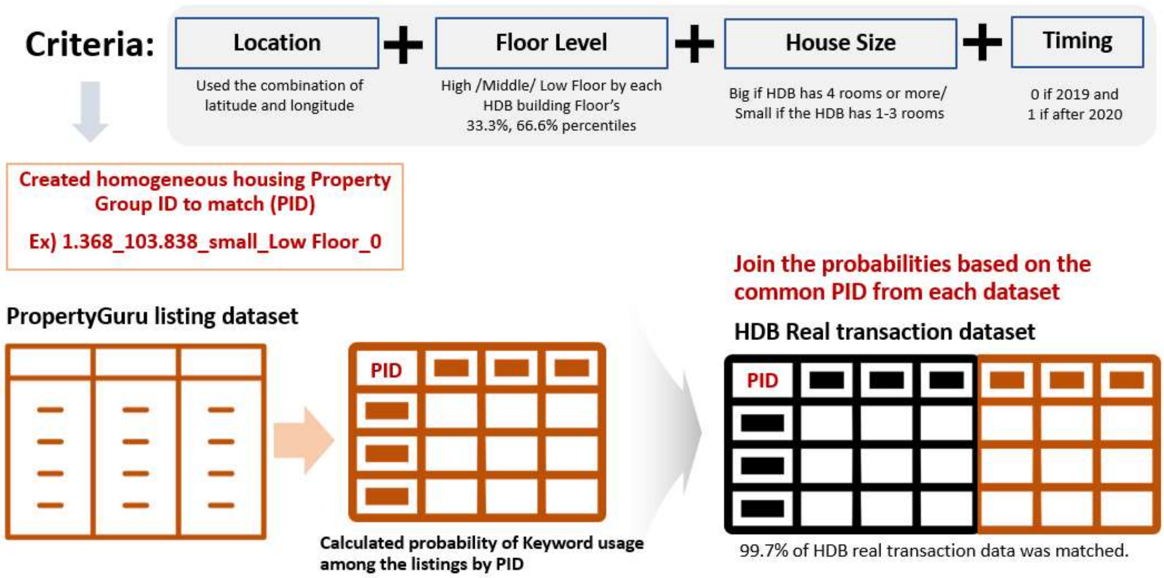


Table 1. Summary statistics of HDB resale transaction data

Variable	Mean	Std. Dev.	Min	Max
Unit characteristics				
Real price (S$)	463403.7	160716.6	140956.2	1408851
Log(real price)	12.991	0.331575	11.8562	14.15829
price per sqm	4771.383	1297.979	2103.824	13183.1
High Floor	0.382	0.4859731	0	1
Big-size unit	0.7514541	0.4321718	0	1
Floor area (sqm)	97.827	24.10001	31	249
House age	26.911	13.43385	3	56
Location characteristics				
Distance to the closest MRT station (m)	775.174	445.942	15.01512	3502.037
near MRT	0.194	0.396	0	1
Distance to CBD (m)	10403.85	4526.562	0	18877.03
near CBD	0.039	0.193	0	1
Distance to malls	625.667	360.560	0	3212.003
near malls	0.300	0.458	0	1
Distance to park	1319.936	686.817	81.839	3930.422
near parks	0.050	0.218	0	1
Temporal characteristics				
post-pandemic	0.450	0.497	0	1
year	2019.166	1.434	2017	2021
month	6.821	3.360	1	12
Number of observations	116397			

Note: All monetary values are in CPI-adjusted real terms (S$2017). S$1 = US$0.75 as of December 2017.

Table 2. Price per square meter Regressions: Spaciousness, Proximity to MRT and CBD

Dependent Variable: price per square meter

	(1) High floor	(2) Spaciousness	(3) Proximity to MRT	(4) Proximity to CBD
post-pandemic x High floor	295.64***			
post-pandemic x Big Size (≥4Rooms)		79.20***		
post-pandemic x near MRT			-52.14***	
post-pandemic x near CBD				-28.29*
post pandemic	325.12***	285.80***	355.98***	346.69***
high floor	361.91***	320.26***	319.80***	319.88***
Big Size (≥4Rooms)	-104.52***	-141.02***	-105.22***	-105.07***
near MRT	234.64***	234.60***	256.39***	234.46***
near CBD	62.33**	63.02**	63.55**	75.64***
near parks	156.28***	157.06***	156.85***	156.52***
near malls	66.92***	66.89***	67.27***	66.75***
house age	-63.53***	-63.60***	-63.58***	-63.58***
year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Street Name FE	Y	Y	Y	Y
_cons	4899.07***	4920.64***	4887.61***	4891.64***
N	116,397	116,397	116,397	116,397
adjusted-R^2	0.89	0.89	0.89	0.89

* p<0.05; ** p<0.01; *** p<0.001

Table 3. Three-way interaction Regressions btw post-pandemic, proximity, and unit size

Dependent Variable: price per square meter				
	(1) post-pandemic x MRT x big	(2) post-pandemic x CBD x big	(3) post-pandemic x mall x big	(4) post-pandemic x park x big
post-pandemic x near MRT x sizeBig	106.31***			
post-pandemic x near MRT	-127.11***			
near MRT x sizeBig	109.18***			
post-pandemic x near CBD x sizeBig		164.66***		
post-pandemic x near CBD		-118.81***		
near CBD x sizeBig		-40.33		
post-pandemic x near malls x sizeBig			91.25***	
post-pandemic x near malls			-35.41**	
near malls x sizeBig			-100.02***	
post-pandemic x near parks x sizeBig				55.66*
post-pandemic x near parks				7.25
near parks x sizeBig				183.78***
post-pandemic x sizeBig	56.35***	70.62***	53.48***	75.75***
post-pandemic	313.55***	293.07***	293.42***	286.25***
sizeBig	-159.00***	-138.42***	-116.40***	-150.53***
near MRT	173.06***	234.67***	234.64***	235.45***
near CBD	80.65***	96.59***	65.68***	58.76**
near malls	65.51***	66.95***	129.87***	68.84***
near parks	160.83***	156.81***	154.05***	4.92
house age	-63.36***	-63.60***	-63.64***	-63.63***
floor10above	320.33***	320.27***	320.03***	320.19***
year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Street Name FE	Y	Y	Y	Y
_cons	4918.01***	4918.28***	4909.31***	4930.56***
N	116397	116397	116397	116397
adjusted-R^2	0.89	0.89	0.89	0.89

* p<0.05; ** p<0.01; *** p<0.001

Table 4. Example cases showed a shifting trend of housing property listings on PropertyGuru.com

address	***Description headings,*** *listing date, floor area*	
	Before pandemic	**After pandemic**
335C Anchorvale Crescent	5rm corner designer decor **convenient location** mob Anchorvale Crescent blk 335c (2019-10-13) (1,205 sqft)	**spacious renovate 5rm premium unit** sale remain lease 93 years 112 sqm ns face high (2021-03-30) (1,205 sqft)
102 Jurong East Street 13	**mins walk jurong east MRT near** JEM JCube westgate MRT amenities (2019-10-24)(731 sqft)	3ng 68 sqm **high floor unblock** windy 21 years experience sell 2888 house (2020-11-27)(732 sqft)
80C Telok Blangah Street 31	corner 4rm unit **near MRT** amenities greater southern waterfront new list extremely rare nicely renovate (2019-09-30)(1,012 sqft)	**awesome unit great view** Telok Blangah tower new exclusive unit sale awesome rare home sale (2021-05-29) (1,001 sqft)
278 Bishan Street 24	rare unit **locate Bishan street** 24 rarely available pineapple block vicinity **convenient location** (2019-09-28)(1,163 sqft)	**high floor park view** open ethnic group citizenship rare **4 room flat** sale **high floor** (2020-12-02)(1,163 sqft)

Table 5. Summary statistics of HDB resale transaction data matched with listing info

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Unit characteristics				
Real price (S$)	473944.5	163495.5	140956.2	1408851
Log(real price)	13.012	0.335	11.856	14.158
price per sqm	4885.222	1336.211	2103.824	13183.1
High Floor	0.384	0.486	0	1
Big-size unit	0.755	0.430	0	1
Floor area (sqm)	97.717	24.047	31	243
House age	24.412	14.047	2	55
Location characteristics				
Distance to the closest MRT station (m)	787.643	448.508	15.015	3502.037
near MRT	0.189	0.391	0	1
Distance to CBD (m)	10377.26	4452.669	0	18877.03
near CBD	0.038	0.191	0	1
Distance to malls	625.212	357.476	0	3212.003
near malls	0.298	0.457	0	1
Distance to park	1311.588	686.789	81.839	3930.422
near parks	0.052	0.221	0	1
Temporal characteristics				
post-pandemic	0.713	0.452	0	1
year	2020.155	0.877	2019	2022
month	6.658	3.531	1	12
others				
Top tertile keywords related to view	0.250	0.433	0	1
Top tertile keywords related to location	0.332	0.471	0	1
proportions of listings containing view related keywords by each matching ID	24.818	27.618	0	100
proportions of listings containing location related keywords by each matching ID	48.253	33.410	0	100
Number of observations		76,813		

Note: All monetary values are in CPI-adjusted real terms (S$2017). S$1 = US$0.75 as of December 2017.

Table 6. DID Regressions with listing's keywords and post-pandemic

dependent variable: price per square meters

	(1) post-pandemic x top tertile keywords related to view (year & month FE)	(2) post-pandemic x top tertile keywords related to view (year & quarter FE)	(3) post-pandemic x top tertile keywords related to location (year & month FE)	(4) post-pandemic x top tertile keywords related to location (year & quarter FE)
post-pandemic x top tertile keywords related to view	31.09**	32.43**		
top tertile keywords related to view	-28.49**	-28.76**		
post-pandemic x top tertile keywords related to location			-1.20***	-1.17***
top tertile keywords related to location			2.11***	2.09***
post-pandemic	1372.45***	1310.72***	1420.73***	1358.90***
Big Size (≥4Rooms)	96.33***	96.52***	95.49***	95.65***
high floor	369.83***	369.14***	377.66***	377.02***
house age	-64.24***	-64.27***	-64.53***	-64.55***
near MRT	462.63***	462.28***	441.17***	440.66***
near CBD	664.87***	667.68***	661.33***	664.14***
near malls	62.99***	62.74***	60.60***	60.34***
near parks	192.12***	192.62***	188.06***	188.63***
town FE	Y	Y	Y	Y
year FE	Y	Y	Y	Y
Month FE	Y	N	Y	N
quarter FE	N	Y	N	Y
_cons	6395.03***	6458.17***	6304.58***	6368.79***
N	76813	76813	76813	76813
adjusted-R^2	0.79	0.79	0.79	0.79

* p<0.05; ** p<0.01; *** p<0.001

Table 7. Triple DID Regressions between post-pandemic, preferred condition, and listing description emphasis with real price per square meters

Dependent variable: price per square meters	(1)	(2)	(3)
	post-pandemic x high floor x top tertile keywords related to view	post-pandemic x near MRT x top tertile keywords related to location	post-pandemic x near CBD x top tertile keywords related to location
post-pandemic x high floor x top tertile keywords related to view	51.66*		
post-pandemic x high floor	27.39*		
post-pandemic x top tertile keywords related to view	10.29		
high floor x top tertile keywords related to view	-74.43***		
top tertile keywords related to view	1.18		
post-pandemic	1362.02***	1421.84***	1423.86***
high floor	360.00***	373.86***	373.91***
top tertile keywords related to location		159.97***	143.97***
post-pandemic x top tertile keywords related to location		-84.41***	-91.85***
post-pandemic x near MRTx top tertile keywords related to location		-15.17	
post-pandemic x near CBDx top tertile keywords related to location			45.32
near MRT	463.35***	536.22***	445.59***
post-pandemic x near MRT		-15.94	
near MRT x top tertile keywords related to location		-149.93***	
near CBD	664.99***	654.96***	869.88***
post-pandemic x near CBD			-105.12**
near CBD x top tertile keywords related to location			-371.81***
house size big	-96.48***	-95.46***	-97.09***
house age	-64.23***	-64.41***	-64.31***
near malls	62.78***	63.37***	62.53***
near parks	192.44***	191.62***	190.71***
Year FE	Y	Y	Y
Month FE	Y	Y	Y
town FE	Y	Y	Y
_cons	6414.87***	6349.03***	6351.65***
N	76813	76813	76813
adjusted-R^2	0.79	0.79	0.79

* $p<0.05$; ** $p<0.01$; *** $p<0.001$

Table 8. Triple DID Regression result between post-pandemic, preferred condition, and listing description emphasis with Log(price)

Dependent Variable: Log(price)	(1)	(2)	(3)
	post-pandemic x high floor x top tertile keywords related to view	post-pandemic x near MRT x top tertile keywords related to location	post-pandemic x nearCBD x top tertile keywords related to location
post-pandemic	0.2848***	0.2945***	0.2920***
high floor	0.0835***	0.0694***	0.0695***
top tertile keywords related to view	-0.0042		
post-pandemic x top tertile keywords related to view	0.0054		
post-pandemic x high floor	-0.0207***		
high floor x top tertile keywords related to view	-0.0145*		
post-pandemic x high floor x top tertile keywords related to view	0.0209**		
top tertile keywords related to location		0.0326***	0.0294***
post-pandemic x top tertile keywords related to location		-0.0213***	-0.0240***
post-pandemic x near MRT x top tertile keywords related to location		0.0082	
post-pandemic x near CBD x top tertile keywords related to location			0.0023
near MRT	0.0846***	0.1221***	0.0820***
post-pandemic x near MRT		-0.0320***	
near MRT x top tertile keywords related to location		-0.0415***	
near CBD	0.1167***	0.1147***	0.1770***
post-pandemic x near CBD			-0.0502***
nearCBD x top tertile keywords related to location			-0.0666***
house is big	0.4581***	0.4582***	0.4579***
house age	-0.0088***	-0.0088***	-0.0088***
near malls	0.0113***	0.0116***	0.0112***
near parks	0.0348***	0.0347***	0.0344***
Year FE	Y	Y	Y
Month FE	Y	Y	Y
town FE	Y	Y	Y
_cons	12.8239***	12.8124***	12.8149***
N	76813	76813	76813
adjusted-R^2	0.6994	0.7002	0.7001

* $p<0.05$; ** $p<0.01$; *** $p<0.001$

[Appendix 1]

Table A-1. Price per square meter Regressions: High Floor features

Dependent Variable: price per square meter

Variable	(1) psm_floor7	(2) psm_floor10	(3) psm_floor13
post-pandemic x above floor 7	41.64***		
post-pandemic x above floor10		295.64***	
post-pandemic x above floor13			68.97***
above floor7	298.89***		
above floor10		361.91***	
above floor13			352.04***
post pandemic	323.15***	325.12***	330.13***
house age	-64.13***	-63.53***	-62.62***
Big Size (≥4Rooms)	-100.46***	-104.52***	-107.03***
near MRT	236.99***	234.64***	236.11***
near CBD	62.03**	62.33**	64.22**
near parks	158.15***	156.28***	161.50***
near malls	67.43***	66.92***	66.97***
year FE	Y	Y	Y
Month FE	Y	Y	Y
Street Name FE	Y	Y	Y
_cons	4840.01***	4899.07***	4937.25***
N	116397	116397	116397
adjusted-R^2	0.89	0.89	0.88

* p<0.05; ** p<0.01; *** p<0.001