The Effect of the COVID-19 Pandemic on Urban Decentralization Across High, Medium, and Low Population Density Cities

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Abstract

In this paper, we examined how the COVID-19 pandemic has reshaped the real estate market by causing a shift in property demand from urban to suburban areas, a concept referred to as urban decentralization. We hypothesize that such an effect is more obvious in higher density cities like San Francisco than in lower density cities like Irvine. Our analysis shows that pre-pandemic, the high and medium density cities had much hotter markets than low density cities in both the urban area and suburbs. Post-pandemic, urban San Francisco is the coolest market while urban San Diego is the hottest. Moreover, both urban and suburban areas of low density cities were hotter than those of high density cities. We didn't find hotness difference between pre-pandemic and pandemic periods, although, we observed post-pandemic hotness being higher than that of the pre-pandemic time. We also found the following two factors to have no influence on market hotness: (1) location type - whether properties are located in urban or suburban areas and (2) the interaction between the location type and region's population density. On the other hand, the following sets of factors influence the market hotness significantly: (1) The main effects of time phases and region density, and (2) interaction between time and region density, time and location type, and time and both region density and location type.

1. Introduction

The COVID-19 pandemic has significantly impacted the real estate market and has changed the behaviors of home buyers. Whether it is because more companies went remote during COVID shutdowns or the fact that people could not enjoy the cities as much during the pandemic, there has been a significant trend in spatial movement away from major cities. Since the outburst of COVID-19, there has been a strong urban decentralization effect, referring to a shift in people's home buying preferences from urban to suburban areas. A lot of studies have been performed to examine the immediate effects of the COVID-19 pandemic on the real estate market trends and the growth of the city decentralization phenomenon. Now that most people have come back to normal post-pandemic life, is the decentralization of cities still a major trend in the real estate market? How has the pandemic changed the home-buying decisions over time? Using some predefined “hotness” indicators, we saw that during the pandemic, some suburbs were relatively “hotter” than urban areas. In our definition “hotness” is a measure that describes the popularity of properties within specific areas of interest. If we observe that over a period of time, the hotness of urban regions has declined more than that of suburban areas, or, put another way, that suburban areas are relatively hotter than urban areas, we then consider it as an indication of a decentralization. We want to see how the phenomenon of spatial movement away from the cities is varying within 3 different timelines: pre-pandemic, pandemic, and post-pandemic. We are interested in the magnitude of this phenomenon across cities that significantly vary in their population density. In order to study this behavior, we decided to classify cities into 3 different categories that are defined by population density (high, medium, low population density cities) and chose 3 cities in California for each category. We hypothesize that the urban decentralization effect is more obvious in high density cities (in our case, San Francisco) than in medium and low density ones (using San Diego and Irvine as examples, respectively).

2. Literature review & prior research

In this section, we would like to describe related research work that has inspired us to approach our research questions and provide further insights into these research topics. We have used these studies as a reference for our work and process of studying the effect of the COVID-19 pandemic on the phenomenon of decentralization of cities and the behaviors of the real estate market.

The first author that inspired our research, Sitian Liu et al. (2021), were interested in the effect of the COVID-19 pandemic on housing demand in different geographical areas of dense neighborhoods and central cities versus suburbs and low density neighborhoods. In order to answer their research question, they studied trends and fluctuations in rent prices and home inventory in pre-pandemic time and right after the pandemic started. They found that there was more demand for housing in areas with previously lower population densities as compared to the densely populated areas and cities after the pandemic started. Home inventory growth was higher in cities than in the suburbs and at the same time, these areas experienced reduced home and rental prices. This, the authors suggest, led to a movement in demand for housing in suburban areas. They hypothesized that the migration out of the densely populated areas is due to the fact that people no longer need to live near offices and workplaces; there are fewer visits to consumption facilities like restaurants, which attracted people to dense neighborhoods; and they see no value in paying the high housing prices in cities which were caused by low housing supply. However, the researchers conclude that there is a smaller divergence in home price growth as compared to rent and inventory growth between central cities and suburbs. They suggest this means that this migration is temporary and the demand in cities will rebound. This is a pattern of interest in our hypothesis regarding how the pandemic influenced people’s living and investment preferences. We wanted to further explore the effect of the COVID-19 pandemic on the real estate market and provide more insights on its behavior post-pandemic as well. We were interested in comparing the behaviors across a larger timeline and studying the significance of the pandemic on the real estate market long term instead of focusing on its short term effect. We also wanted to analyze this phenomenon across cities with various population densities and provide a clear definition of city classifications to determine whether this phenomenon persists across all city types.

Rosenthal et al. (2021) also provided valuable insights into the behavior of the real estate market before and during the pandemic. Their research work was focused on finding spatial patterns of the commercial leasing market using 68,000 leases in 89 US cities. They compared the rent using pre-COVID and COVID data from Jan 2019 to Oct 2020. The pre-COVID data shows a 2.3% drop in rent per mile away from the city's center. With the COVID data, the authors found a significant reduction in long-term rent in cities that rely heavily on public transportation, defined as "transit cities" that represent urban areas. The rent gradient falls around 15% in such cities, whereas in cities where commuters primarily commute with cars, defined as "car cities," such effect is much weaker, with a rent gradient of 0.9%. Another crucial finding by the authors is the relationship between local density and rent elasticity. Before COVID-19, the rent increased on average 8.4% with twice local density. The COVID data shows such elasticity is flattened in both types of cities for about 2%. Lastly, the authors showed a decreased rent gradient concerning transit proximity in urban areas, which implies in the pandemic world, the proximity to public transportation in cities may be less critical in terms of property values than it was before. These findings provide us with more insights into the behavior of the real estate market within the rental domain, which also contributes important information to the phenomenon of decentralization and the reasons behind its occurrence. We hypothesized the investment shifting effect to be more prominent in high population density city markets such as San Francisco than in lower population density markets. Rosenthal et al. brought an interesting perspective about the potential reason why this is the case. While we were not planning on studying rental patterns, this study helped us understand the effect of the COVID-19 pandemic on the behavior in the real estate market that is highly related to home investment decision making. It also shed light on the potential factors and confounds, such as the public transportation networks, that might contribute to the phenomenon of city decentralization.

Regarding our interest in people's investment preference shifting and spatial movement away from the cities, D'Lima et al. (2020) conducted an insightful study showing a correlation between property values and population density under the impact of COVID-19. The authors focused on the residential market that suffered from government-enforced shutdowns and analyzed more than two million residential transactions between January 2019 and December 2020. The result showed around a 1.4% price drop in dense regions. Contrastingly, less-dense areas showed an upward trend of around 1.5% of price growth. The price drop was as significant as three standard deviations above the mean in zipcodes of denser regions, such as Manhattan. Besides pricing v.s population density, the authors also investigated the relation between prices and property types. They found that properties of different sizes and structures tend to show an extra level of influence. For instance, properties with fewer bedrooms tend to suffer more price fluctuations than bigger units. Following the shutdown orders, people preferred houses with yards and were willing to pay more for the former. These findings are closely related to our interest and suggest a sound track of investigation. We wanted to further study the behavior of the real estate market and the effect of city decentralization beyond the timeline of December 2020 as well. We wanted to study the effect of the COVID-19 pandemic on decentralization and its significance across different population density type cities. A major difference is, however, that instead of exploring the property pricing vs. population density directly, we took a step back with a broader view to investigate the relationship between the population density and market hotness in a more general sense.

3. Data collection & pre-processing

3.1 Dataset overview

The dataset of our choice is a comprehensive public dataset that is available on the Realtor.com website. This dataset includes US property data that is organized by zip code and includes multiple variables that are aggregated over a monthly basis. There were over 20 pieces of information in our dataset from which we found the following four to be the most valuable for our analysis:

- Hotness Score - a composite metric of supply and demand scores of a specific zip code area
- Hotness Rank - the rank a zip code area receives using its hotness score compared with that of all other areas nationwide
- Supply Score - metric that represents median days spent on the market ranking of a specific zip code area compared to other zip code areas
- Demand Score - metric that represents listing page views per property ranking of a specific zip code area compared to other zip code areas

The timeline over which this data was collected and aggregated spans a period of approximately 5 years: starting in August 2017 and ending in January 2022. We wanted this data to give us insights into the pre-pandemic, pandemic, and post-pandemic movement so that we can effectively study the impact of the COVID-19 pandemic on the phenomenon of city decentralization. We extracted portions of the data and split it into equal length periods of time that involved data collected between February and November for pre-pandemic, pandemic, and post-pandemic years of 2019, 2020, and 2021, respectively. We decided to divide our data in this manner due to the fact that different months display different real estate behaviors and there are constant fluctuations in the real estate market over the course of a calendar year. This way, our dataset had a consistent timeline over the years and was independent of disparities in the behaviors of a real estate market over different months.

3.2 Data classification

We wanted to focus on three different types of cities and study the effect of COVID 19 on their decentralization. The cities of interest were classified by population density. The population density was calculated over the top half of most population-dense zip codes and defined for us 3 distinct density groups for cities:

- high population density cities have a population density of over 10000 people per square mile
- medium population density cities have population density between 5000-10000 people per square mile
- low population density cities have population density below 5000 people per square mile

Due to the high volume of data, we decided to narrow down our area of interest. Instead of working with all possible cities in the United States, we decided to work with 3 cities of our choice in the state of California: San Francisco, San Diego, and Irvine. We calculated their population densities by our population density definition described above and obtained the following results:

- San Francisco - 30535.81769 people per square mile (high population density city category)
- San Diego - 8564.052667 people per square mile (medium population density category)
- Irvine - 4951.4625 people per square mile (low population density category)

In order to calculate the above population densities, we used a public data set from a website called zipatlas.com, which included information on all city zip codes and their respective population densities for our cities of choice.

We came up with a comprehensive list of zip codes for these cities and their suburbs. The pre-processing of our dataset included filtering out zip codes outside of our list. Our final datasets were labeled by city names of different population density categories and their location types. The "location type" refers to whether the area is urban or suburban. In the later part of this paper, when we use "high density region/city", it refers to San Francisco, "medium density region/city" refers to San Diego, and "low density region/city" to Irvine.

3.3 Generating population density

In order to calculate the population density for each zip code, we incorporated two additional datasets from the US Census Bureau:

(i) 2020 ACS 5-Year Estimation of Total Population (https://data.census.gov/cedsci/table?q=population%20by%20zip%20codes%20zcta&g=0400000US06%248600000&tid=ACSDT5Y2020.B01003)

This dataset provides us with an estimation of the population for each region. It includes granularity down to zip code level.

(ii) 2020 Census Gazzetter ZIP Code Tabulation Areas (https://www.census.gov/geographies/reference-files/time-series/geo/gazetteer-files.html)

This dataset contains various fields of land information to zip code level. We took the field of total land area for each zip code.

We took the field of population estimation from the ACS total population dataset and the total land area field from the Gazzetter dataset, joined the two tables, and then divided the former by the latter to get the population density for each zip code. We then filter only zip codes that are of our interest using the list of zip codes we had generated earlier.

Figure 1 shows the population density at zip code level using our calculation for each of the three cities.

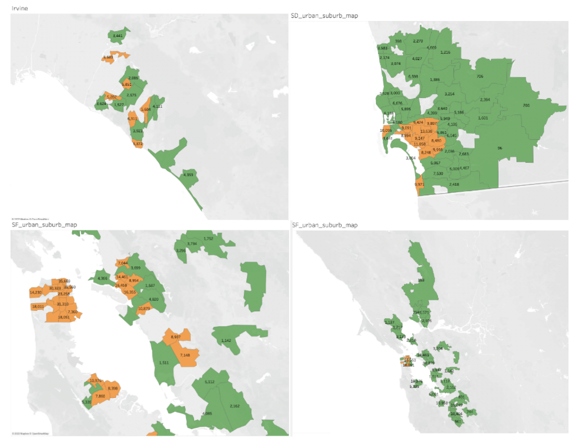

Figure 1: Population density at zip code level. Upper left: Irvine. Upper right: San Diego. Bottom left: San Francisco (north bay area). Bottom right: San Francisco (all bay area)

4. Methods

4.1 Procedure

We first conducted a series of pre-analysis using visualization and graphs to understand our data and to identify preliminarily whether or not our hypothesis is likely to be true. After we confirmed so, we then moved on to use statistical tools to verify our findings and hypothesis. The results will be described in the next section.

4.2 Pre-analysis

We first built interactive heat maps using the hotness score for each city to observe noticeable trends in terms of changes in hotness on maps. Darker colors represent higher hotness scores within that region. A drop-down list provides options of which month/year to observe. Figure 2 shows an example of San Francisco in July 2019 (pre-pandemic) and July 2020 (during the pandemic), respectively.

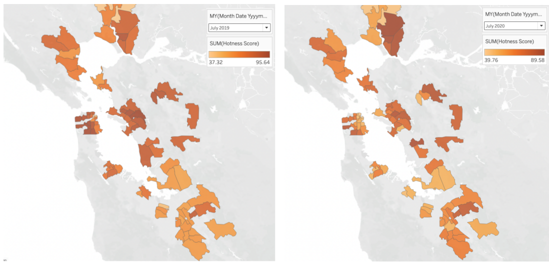

Figure 2: Heat maps to demonstrate shifts in hotness scores in San Francisco. Left: July 2019. Right: July 2020. Notice how hotness scores decrease in most zip codes in San Francisco, whereas some outskirt regions pick up the hotness relatively.

Using the interactive heat maps, we identified noticeable effects in hotness score changes that showed different patterns in urban and suburban areas in San Diego and San Francisco. Relying solely on the heat maps, we could not infer any significant changes for Irvine. This early observation corresponds to our hypothesis.

Next, we used line charts to observe the trends in different hotness variables over time. Among them, we focused on the hotness score and hotness rank, since they are the main indicators that directly reflect market hotness. Figure 3 shows the changes in hotness score in city and suburban areas for all three density regions. Through the charts, we found a sign which is in line with our hypothesis. During the pandemic period, the hotness in city and suburb Irvine mostly aligned with each other and did not show a visible difference in terms of trends. Whereas in San Diego, we see that pre-pandemic, city areas have a higher average hotness score, but declined right after the pandemic started. Suburb San Diego, while also declining, kept up relatively well and resulted in the overlap of the two lines. This implies that the suburb region in San Diego was relatively hotter during the pandemic period. Finally, in San Francisco, we saw similar effects but on an even larger scale. Much like in San Diego, the hotness score in the city region of San Francisco was mostly higher than that of the suburb. However, the former saw a very steep drop during the pandemic period that actually caused a crossing point of the two lines. The suburb of San Francisco has thus surpassed city areas in terms of hotness score and the effect has remained ever since.

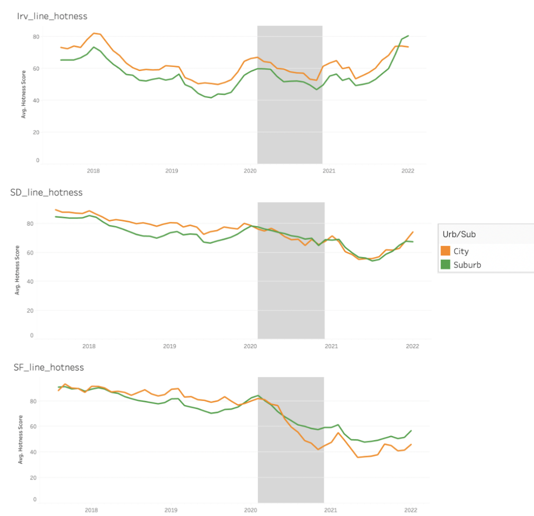

Figure 3: hotness score trends. Top: Irvine. Middle: San Diego. Bottom: San Francisco. The orange and green lines represent city and suburban, respectively. The pandemic period (February 2020 to November 2020) is highlighted in gray.

To further confirm our findings, we performed a similar analysis on hotness ranks. While hotness scores indicate how hot the real estate market of a region is, the hotness rank compares such hotness with all other regions in the US, and thus provides a good indicator for us to understand how hot a regional market is relative to other regions nationally. Because raw hotness ranks do not correspond well to human intuition, i.e. the hotter the region is, the "lower" its rank is, we did a transformation on hotness ranks to get the "hotness rank score" such that when a region has higher hotness, it will receive a higher ranking score for easier interpretation. We tested different measurements to make sure our transformed metric reflects well to the original hotness ranks. We used the following formula for our transformation:

Hotness Rank Score = {MEDIAN([Hotness Rank]) + 2*STDEV([Hotness Rank])} - [Hotness Rank]

Using this metric, we confirmed what we have stated earlier for the hotness score charts; urban and suburban areas in Irvine did not show a big difference in hotness trends, and San Diego showed such a difference, while San Francisco showed the largest visible difference. All these findings line up well with our hypothesis. We also conducted similar analysis on supply scores and demand scores and found them to be indicating similar phenomena. With these observations, our next stage was conducting statistical tests to show significance of our findings, if any.

Figure 4: hotness rank trends. Similar to figure 3, from top to bottom is: Irvine, San Diego, and San Francisco. The orange and green lines represent city and suburban, respectively, and the pandemic period is highlighted in gray.

4.3 Statistics

4.3.1 Correlation test

The hotness score is a predefined metric, calculated off of supply and demand scores for a specific zip code. We used it as an indicator to determine the concept of urban decentralization. We performed a correlation test to determine its relationship with the other important variables. A correlation test between hotness score and hotness rank, hotness score and demand score, and hotness score and supply score should show high correlations for the indicator of hotness score to be used to evaluate our hypothesis.

4.3.2 Average hotness scores

An analysis of the average hotness scores for the different location types and region densities across time was conducted to check for any shifts in buying preferences and market characteristics pre-pandemic, during the pandemic, and after the pandemic.

4.3.3 Repeated measure anova

We used repeated analysis of variance measures (anova) to check whether time, location type, and regions' densities as well as interactions between them produce any changes in the hotness score. This is useful in determining the significance of the results in (2) above. A p-value of < 0.05 would indicate that the main effect or the interaction of factors has an influence on the hotness score while a p-value of $>= 0.05$ shows the main effect or the interaction effect has no influence on the hotness score. A post hoc test was also done to analyze the difference between the different region densities across time.

4.3.4 Mean comparison test

In line with our hypothesis to determine urban decentralization as influenced by the COVID-19 pandemic, we checked how the average hotness scores changed with time using a mean comparison pairwise t-test. A p-value of < 0.05 indicates that there was a change in the average hotness score between the two times hence a shift in the demand for property during those times while a p-value of >= 0.05 means that the demand for property during the compared time period was unchanged.

5. Results

5.1 Correlation test

A correlation test between hotness score and hotness rank showed a strong negative correlation, r (3406) = -.9825, $p < .001$ while the correlation between hotness score and demand score was a strong positive one: r (3406) = .9320, $p < .001$. The correlation between hotness score and supply score was r (3406) = .7113, $p < .001$ Therefore, as hotness score increased, the demand score increased while the hotness rank decreased with the same magnitude.

5.2 Average hotness scores

When compared across time, the urban areas had an average hotness score of 76.13 pre-pandemic, 68.23 during the pandemic and 59.43 after the pandemic. Suburbs, on the other hand, had an average hotness of 72.89 pre-pandemic, 70.69 during the pandemic and 58.61 after the pandemic. While both location types experienced a decline in hotness after the pandemic as compared to before the pandemic, the decrease is higher in the urban areas. Calculations of the average hotness scores based on region densities across time showed that before the pandemic, high density region had an average hotness score of 76.52, medium density had 75.27 and low density region had 51.87. During the pandemic, the average hotness score of high density regions was 68.82, 75.88 for medium density and 58.79 for low density. After the pandemic, the medium density region had the highest average hotness score of 63.78, followed by low density region at 59.46 and the high density region had 54.75. Our data also shows that the urban areas and suburbs of low density region (Irvine) had an increase in hotness after the pandemic, while San Francisco and San Diego's urban and suburbs had significant decreases in their hotness post-pandemic. Medium density suburbs showed an increase in hotness from pre-pandemic to pandemic times though the hotness decreased afterwards.

5.3 Repeated measure anova

While there was a significant main effect of Region density (F (2,2) =17.81, $p < .001$) and time (F (2,4) = 319.8, $p < .001$), that was not the case with location type (F (1,2) = 0.194, $p = .661$). The interactions between time and region density (F (4,4) = 60.01, $p < .001$), time and location type (F (2,4) = 11.84, $p < .001$), and time and region density and location type were significant (F (4,4) = 3.294, $p = .01$) while that between region density and location type (F (2,4) = .383, $p = .682$) was not. A post hoc test shows that for each region density, there is a difference in hotness before and after the pandemic. Both the high and medium density regions had a decrease in hotness while the low density region experienced an increase in hotness as shown in figure 5.

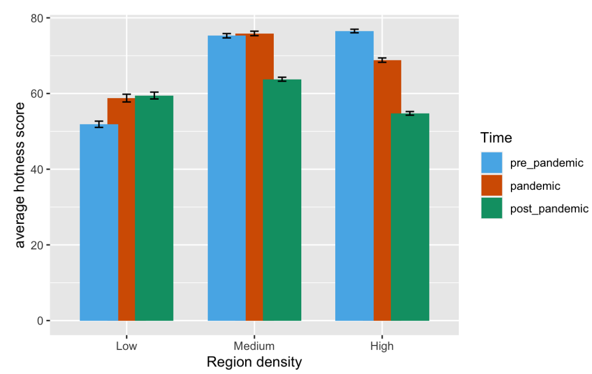

Figure 5: Average hotness scores across time and region densities.

5.4 Mean comparison test

A pairwise test comparing hotness scores across time produced a p-value of .088 for pre-pandemic and pandemic, < .001 for pre-pandemic and post-pandemic and < .001 for pandemic and post-pandemic. This means that there is no significant difference in the mean hotness scores between pre-pandemic and pandemic times but a significant difference between pre-pandemic and post-pandemic as well as between pandemic and post-pandemic times was present.

6. Discussion

The COVID-19 pandemic has affected the real estate market in the US shifting people's home buying preferences. Increased demand in an area made it hotter hence increasing its hotness score and the side effect of enhanced hotness rank. Our analysis considered the change in hotness scores of the different locations and region densities across time to evaluate this phenomenon.

Even though urban areas had higher hotness scores than suburbs before and after the pandemic, its hotness reduced more dramatically following the pandemic. High and medium density regions also had drops in their hotness after the pandemic while the low density region of Irvine posted an increase with its market now being hotter than it was before the pandemic. This is in line with D'Lima et al.'s explanation that people were stuck in their houses due to stay-at-home orders and they wanted bigger home spaces. Therefore, they were attracted to properties with such attributes, which are more likely to be found away from high density regions.

Looking at urban areas before the pandemic, the high density city (San Francisco) had the highest average hotness score, followed by medium density city (San Diego) then low density city (Irvine). Contrastingly, for suburbs, the medium density city had a slightly higher average hotness score than the high density city while the low density city had the least. The transition into the pandemic saw high density's urban area and suburb, and medium density's urban area undergo a considerable decrease in their hotness scores, while the hotness of the low-density urban area and suburbs, and medium density suburbs increased. This can be attributed to how COVID-19 spread faster in highly populated areas where implementation of social distancing was difficult therefore encouraging people to move away from those areas. We also agree with Liu et al. that the move away from high density regions and medium density cities was also influenced by the reduced need for people to go to their workplaces or use social amenities which were closed down due to the lockdown measures. During this time, low density regions had the smallest supply scores meaning less days spent on the market while high density cities spent a lot of time in the market which is consistent with Liu et al. observation of higher home inventory growth in the urban areas.

On the other hand, in the post-pandemic phase, the demand in low density urban areas overtook that of high density areas and the same pattern was observed in the suburbs. Overall, medium density urban and suburban areas had higher demand and hence were the hottest market in the months following the pandemic. Low density urban and suburbs had higher hotness post-pandemic as compared to pre-pandemic time while for the high density region, its suburbs had a higher hotness score than the urban post-pandemic.

While these changes are observed and seemed to be plain in some charts, not all of them were confirmed by our statistical tests. After running the mean comparison t-test, we confirmed that there was no significant difference in hotness scores between pre-pandemic and the pandemic period. On the other hand, the hotness scores of pre-pandemic and post-pandemic did show a significant difference; the same thing holds true for the pair of pandemic and post-pandemic. Therefore, the real estate market underwent changes during the times when there was a difference in demand. Moreover, we noticed (i) high density urban areas were drastically cooling down, (ii) their suburbs were more or less cooling down, and (iii) the low density region became hotter post-pandemic. These observations indicate the pandemic time was the point at which buyers started to (1) shift their interests from high density urban areas to suburbs and (2) show new interest in low density urban and suburbs.

In line with our hypothesis, region density significantly influenced its market hotness, e.g. San Francisco markets behave very differently from the Irvine markets, while the area being urban or a suburb does not. Similarly, the interaction between location type and region density was not important in evaluating the hotness. This is a discrepancy from one of the aforementioned prior work which stated that the location type, i.e., whether it's a suburb or an urban area, is a major factor in determining the hotness of an area. For our case, this could be attributed to the choice of the cities and zip codes used in the analysis. For example in San Francisco, there is a very thin line between its urban and suburban regions. And such classification of urban and suburban areas may have influenced the result we saw.

The interaction of time and region density shows that for each region, there was a difference in their hotness between the pre- and post-pandemic phases. Also, the areas had different hotness scores after the pandemic, despite medium and high density areas having similar hotness before the pandemic. This interaction and the main effect of time, location type, and both location type and region density, supports our hypothesis that there was an effect of the COVID-19 pandemic on the real estate market. It is true that it reshaped the demand for homes for sale thus investment decisions in the different region densities and location types experienced a shift.

Even though we classified the time after November 2020 as post-pandemic, the end of the COVID-19 pandemic is yet to be confirmed by the World Health Organization as of 1st May 2022. However, from our analysis, the timeframe categorized as post-pandemic showed market characteristics that are different from the rest. This is partially due to the efforts made by the government to stimulate the economy by offering lower mortgage rates and stimulus funding which motivated buyers to continue buying property. The availability of vaccines also allowed the world to go back to normal hence people have started returning to their workplaces.

7. Conclusion

In this paper, we examined how the COVID-19 pandemic has affected the real estate housing market by inspecting a set of predefined indicators including the hotness score and the hotness rank. We found in our preliminary analysis that region density may be an important factor that dictates how differently urban and suburban areas of a city behave during the three phases that we are interested in: pre-pandemic, pandemic, and post-pandemic. These early findings corresponded well with our hypothesis. We then moved on to test the statistical significance using a series of correlation tests, repeated measures ANOVA, and mean comparison tests. We concluded that some of our early observations are statistically significant, while some are not. We also provide our observations and summaries of the real estate housing market on a high level. Summing up, our work establishes a foundation that encompasses much flexibility and upon which future works may be built upon.

8. Future Work

Even though our statistical analysis shows the presence of urban decentralization following the pandemic, this study could have benefitted more if the information was included on whether the property was taken off the market because it was sold or because the seller decided otherwise. That would have been useful in determining whether the property should be part of the analysis as the property didn't change ownership, or not. Additional information on how the investment was financed, e.g. cash or mortgage, is also useful to address the extent of the influence of the confound of government stimulus programs.

Thirdly, the number of zip codes we collected is relatively small, which could be a limiting factor of our analysis, for insufficient data is more likely to suffer from bias. Gathering more zip codes for each region and conducting the analysis on a larger scale would be a reasonable way of improving robustness. Another future step would be to generalize the procedure to a broader region. For example, comparing the market hotness between the West and East coasts and drawing insights from it. Contrastingly, we may also generalize our analytic procedure to richer datasets to compare other sectors of the real estate market. For instance, utilizing rental data to investigate the rental market and the commercial real estate market. An extension of this study is to investigate whether the effects observed post-pandemic are permanent or temporary.

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Teammates Contributions

Patrycja Przewoznik: data collection, data cleansing, data preprocessing, presentation slides write up, paper write up

Rehan Edin (rae2150): pre-analysis, data visualization in R, Statistical analysis in R, post analysis, paper write up

Evan Ting I Lu (tl3098): data collection and processing (for population density) pre-analysis and data visualization, paper write up