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# Access Granted: A Demographic Analysis of How The Pandemic Has Disrupted the Monocentric City

Jaylin Terreau Jones
*University of Mississippi*

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By:

Jaylin Terreau Jones

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Approved By:

Advisor: Professor Sergio Garate

Reader: Professor Charles Hilterbrand

Reader: Professor Natalia Kolesnikova

Abstract

This study shows the disruption that the Covid pandemic has had on the national relationship between changes in quarterly House Price Index (HPI) values and distance from Metropolitan statistical areas (MSAs). This disruption is statistically modeled through linear regressions where quarterly changes in HPI values are set equal to distance as well as factors such as change in population, housing units, and home ownership. Special recognition is also given to the distance relationship during years affected by Covid. This disruption is then analyzed in relation to demographic factors such as age and race. The study showed that the disruption of younger cities, cities whose median age was in the bottom 25$^{th}$ percentile, was twice that of the population which could suggest that younger people relocated outside of MSAs at a greater rate than older people. The study also showed that non-minority cities, cities whose minority makeup was in the bottom 25$^{th}$ percentile, exhibited stronger monocentric characteristics prior to Covid than the entire population which could suggest that further research could be conducted on pre-existing public policies and their effect on the disruption on the distribution of home values.

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**Introduction:**

Historically, the distribution of home values has correlated to their distance from or access to factors such as job opportunities, entertainment, amenities, food, and schools resulting in many urban areas displaying characteristics of a monocentric city. The monocentric city model builds on the transportation and communication technology of employers and employees to understand and determine the subsequent bid curves (O'Sullivan, 2018).

As shown in figure 1 (Figure 14-1 Land Rent and Land Use in a Monocentric City), the residential bid curve is highest at the center of the city and gradually declines as one moves away from the city. This negative correlation reversed during the Covid-19 pandemic (Gupta et al., 2022) as over 15.9 million people moved during the pandemic, in 2019 and 2020, with 28% stating Covid-19 as their reason to move, according to the Postal Service's Change of Address Requests (Bowman, 2022). This relocation of the population has in turn severely affected the overall housing market.

On a national level, the U.S. has seen roughly a 47% increase in the National HPI provided by the US Federal Housing Finance Agency from Quarter 1 of 2019 (428.39) to Quarter 3 of 2022 (618.37). To put this into context, from Quarter 1 of 2000 (230.18) to Quarter 4 of 2018 (423.66) the US saw an increase of about 84% in the Housing Price Index which means that values have been appreciating at a much, much higher rate over the past 4 years than the previous 18.

To further clarify the seriousness, the estimated median annual earnings of full-time workers is $55,640 based on the Bureau of Labor Statistics third quarter reports for 2022. This is roughly an 18% increase from estimated median annual earnings of full-time workers of $47,060 based on the BLS first quarter reports for 2019. In comparison, the estimated median annual earnings of full-time workers were $46,462 based on the BLS fourth quarter reports of 2018. This is about a 57% increase from the BLS first quarter reports for 2000, $29,900.

The relationship between the increase in National House Price Index and median annual earnings of full-time workers from 2000 to 2018 was 84% to 57%. Meaning that the National House Price Index grew at a rate of 1.47 times that of the median annual earnings of full-time workers. In comparison, the relationship between the increase in National House Price Index and median annual earnings of full-time workers from 2019 to 2022 was 47% to 18% meaning that the National House Price Index grew at a rate of 2.61 times that of the median annual earnings of full-time workers. This leaves one to ask why the overall value of housing, HPI, is significantly outgrowing the overall ability to demand and consume housing, earnings.

The value of real estate is determined by the demand of buyers which is represented by bidding. For overall value to increase faster than overall ability to meet demand, the subsequent distribution of home values must be significantly different from the original distribution.

If one models the original distribution of home values using the monocentric city, they observe that values decrease as distance from the city center increases. To disrupt this model, one would need to increase home values away from the city center while decreasing the value close to the city center. By moving away from the city center and purchasing homes in suburban and rural areas, one is able to bid a greater surplus amount in regard to original home values while still potentially saving when compared to home values closer to the city center.

Additionally, the pandemic increased the desire to move away from the city, which caused people to be more willing to overbid on homes. This desire is supported by the 2022 report that "60% of workers with jobs that can be done from home say when the coronavirus outbreak is over, if they have the choice, they'd like to work from home all or most of the time" (Parker et al., 2022). Because of this, if one models the relationship between change in home values against distance from city centers, with special emphasis on years during the pandemic, one can quantify the effect to which the pandemic has disrupted the monocentric city model as well as attribute this disruption to demographic makeup of cities.

## Hypotheses

As mentioned earlier, the flattening of the curve is a result of a large population relocation away from the city centers and into the suburbs and surrounding rural areas. A large catalyst for these moves is the ability to work remotely. This ability to work remotely should be offered and available to all regardless of background, but this is not the expected case because of pre-existing issues in public policy that limit the ability of cities who have a greater percentage of minorities to relocate and take advantage of remote opportunities and lower home values in comparison to cities who have a greater percentage of majorities. This difference can be measured by comparing the resulting slopes of the relationship between distance from city centers and the quarterly change in home values and see that the slope of majority cities is significantly greater and more statistically significant.

Similarly, the slope of cities who have a greater percentage of younger adults is expected to be greater than the slope of cities who have a greater percentage of older adults. The belief being that younger adults will be more likely to take advantage of remote opportunities as well as lower home values.

## Hypothesis I

*The slope derived from the relationship between the distance from city centers and the quarterly change in home values is expected to be consistent with that of the bid-rent curve in previous studies such as (Gupta et al., 2022) and show a flattening of the curve or a hollowing out of city centers and growth of suburban outer rings as described by (Ramani & Bloom, 2021).*

This should be shown by a reversal of the relationship between the distance and changes in home values. This value before Covid should be negative, and after Covid it should be positive.

**Hypothesis II**

*This disruption is expected to be seen at a greater magnitude in cities whose demographic population has a greater percentage of non-minorities.* This should be shown by the coefficient of distance being larger for non-minority cities than for minority cities.

**Hypothesis III**

*This disruption is also expected to be seen at a greater magnitude in cities whose demographic population has a greater percentage of young people.* This should be shown by the coefficient of distance being larger for young cities than for non-young cities.

$$Price\ Change_{zjq} = \alpha + \beta * Log\left(Distance_{zj}\right) + \gamma * Covid\ Year_t + \delta * Covid\ Year_t * Log\ (Distance_{zj}) + \vartheta_j + \vec{X}_{zq} + \varepsilon_{zjq}$$

**Related Literature**

This study builds on a growing body of literature that observes Covid, Working-From-Home (WFH), real estate markets, and social inequalities.

The first set of papers look at the effect that Covid had on the overall demand of housing with respect to location in a metropolitan area. (Gupta et al., 2022) view changes in the overall bid-rent curve by comparing changes in house prices versus rents in city centers and the suburbs. From this, they argue that following the pandemic, the overall bid-rent curve reversed because of urban residents leaving for suburban areas. This result is consistent with that of (Ramani & Bloom, 2021) who label the donut effect or hollowing out of city centers and growth of suburban outer rings and quantify the effect of Covid-19 on migration patterns and real estate markets in US cities. This donut effect can then be explained by (Vuuren, 2023) who observes the effect that the pandemic had on diminishing the willingness to pay for consumption amenities with respect to distance, (Gamber et al.)who examine the relationship between time/consumption at home and house prices and (Tsai et al.) who examines changes in the performance of city-center and suburban housing markets associated with tourist attractions after the lockdown in Hangzhou, China.

The second set of papers then examines one of the primary drivers and results of the pandemic, WFH, and its effects on the housing market and population relocation. (Brueckner et al.) and (Brueckner and Sayantani) examine the impacts of WFH in the housing market from both intercity and intracity perspectives. Their results show that WFH tends to flatten intracity house-price gradients, weakening the price premium associated with good job access and that the population relocation of non-remote workers is in the opposite direction to that of remote workers. Lastly, (Davis et al.) examine the impact of widespread adoption of WFH technology using an equilibrium model where people choose where to live, how to allocate their time between working at home and at the office, and how much space to use in production.

The final two papers expand on the previous body of literature by exploring whether spatial urban housing submarket boundaries shift over time and assess the role of several drivers of such change (Costello et al.) and examining the impact that Covid-19 had on a socio-economic level because of pre-existing inequalities and policy challenges (Blundell et al.).

**Methodology**

This study complements the previous results of a flattening curve and hollowing out of city centers while explaining these results through demographic factors to measure the impact that Covid-19 had because of pre-existing inequalities.

First, ArcGIS mapping data was used to pair MSA’s with the closest 3-Digit zip code with the belief that these will be the areas that most closely exhibit the characteristics of a monocentric city. The standard principle of the monocentric city is that as one moves away from the center, land value and subsequently home value decreases. By pairing each MSA with a 3-Digit zip code, an entire data set of monocentric cities has been created.

This was then supplemented with the monthly change in HPI value from years 2000 through 2022 to create a common base to observe the overall effect of Covid. By pairing the overall changes rather than the actual values, the possibility of areas with higher values greatly shifting the results was eliminated.

Pairing the overall monthly changes also allowed for the change in the rate of change, or slope, that describes the relationship between change in home values and distance to be measured. Distance, for the purposes of this study, is the distance that the center of the 3-digit zip code is from the center of its respective MSA.

Finally, the study created a base model using R which measures the slope as well as the change in slope during the pandemic of our dataset. From this base model, one is also able to compare change with respect to demographic makeup by creating subsets that only include data from cities in the top 75th or bottom 25th percentile for the variable being compared.

## Data

In this analysis a linear regression model was estimated by using changes in the quarterly HPI value at the 3-Digit Zip Code level across the United States. By observing the change in the index value, one can easily compare values before and after Covid, and by observing this change at the 3-Digit level one can have a large population that consists of many different distances and demographics while still being statistically relevant.

$$Price\ Change_{zjq} = \alpha + \beta * Log\left(Distance_{zj}\right) + \gamma * Covid\ Year_t + \delta * Covid\ Year_t * Log\ (Distance_{zj}) + \vartheta_j + \vec{X}_{zq} + \varepsilon_{zjq}$$

The empirical approach is to first explain the change in quarterly HPI value ($Price\ Change_{zjq}$) using the coefficients of log of distance( $\beta * \ Log\ (Distance_{zj})$), log of distance during a Covid year ($\delta * Covid\ Year_t * Log\ (Distance_{zj})$), a Covid year factor ($\gamma * Covid\ Year_t$), population change , housing units change, and home ownership change ($\vartheta_j + \vec{X}_{zq} + \varepsilon_{zjq}$).

Because of the large data set, log of distance was used to improve the fit of the model. Log of distance during a covid year represents the relationship between distance and the dependent variable specifically during years affected by Covid. The Covid factor represents the years affected by Covid. Changes in population, housing units, and home ownerships are the changes from 2000 to 2010 and from 2010 to 2020.

The second step of the empirical approach measures these characteristics with respect to demographic makeup. After confirming that there is a significant disruption in the monocentric city model, it must be determined if or not a particular group is the cause of the disruption by creating additional models that only includes cities above the 75th percentile or below the 25th percentile in terms of population size, minority percentage, and median age. By doing so, one can determine whether there is any relation between the disruption and the demographic makeup of a city. If there is, it would show that certain demographics had more or better access to remote jobs and/or better opportunities to move away from city centers.

The data includes the quarterly HPI values at the 3-digit provided by the FHFA[1], distance values from CBSA's provided by ArcGIS, and demographic values at the 5-digit zip code level provided by the US census bureau and S&P Capital IQ for years 2000, 2010, and 2020. After consolidating the demographic data down to the 3-digit zip code level, the HPI values were merged with the corresponding demographic data change. HPI values for the years 2000 to 2010 were matched with the change in the value from 2000 to 2010, and HPI values for years 2011 to 2022 were matched with the change in the value from 2010 to 2020. Lastly, these values were

[1] Accessed in March 2023

then merged with distance data from ArcGIS where I mapped the distance of US 3-Digit Zip Codes from the nearest CBSA in kilometers. After data cleaning (removing outliers as well as inaccurate and/or missing information), the data includes 81,800 observations with 55 total columns. Tables 1 through 2 describe the data using summary statistics.

Table 1 provides a description of values best described using only 1 significant digit such as ID variables and whole numbers. ZIP3 values range from 010 all the way to 999. Year ranges from 2000 to 2022, and Quarter ranges from 1 to 4. The population values range from as low as 20,749 to 2,531,191 with the average population being 343,528. The median population age ranges from 27 to 56 with a mean of 41. Covid year ranges from 0 to 1 with 0 representing a year unaffected by Covid and 1 representing a year affected by Covid.

Table 2 provides a complete description of the percentages and changes used during the analysis. The percentages represent the demographic makeup of cities both current and previous while changes measure the change on a quarterly basis. City growth ranges from 0 to 1 with 0 representing a city that did not grow and 1 representing a city that did grow following the pandemic. Distance_km represents the distance in kilometers the center of a 3-digit zip code was away from the center of a CBSA, and this value ranges from .14 kilometers to 221 kilometers with an average distance of 41 kilometers.

The approach is to estimate a linear regression with the dependent variable for the regression being the quarterly change in HPI values at the 3-digit zip code level. The independent variables are the log of distance (in kilometers), Covid year (0 or 1), log of distance (in kilometers) with respect to Covid year, population change, housing units change, and home ownership change. Additionally, to ensure that outliers do not overly affect the outcome only values where price change was greater than -50% were used.

The relationship between price change and distance is the primary concern of this analysis and represents the overall relationship across the entire data set, but to accurately measure the effect that Covid has had on this a Covid year variable as well as a separate distance variable with respect to Covid was included. The Covid year variable simply tells whether the value occurred during a year affected by Covid and for the purpose of this analysis this is represented by years 2020 and above. When the year is 2020 or above the Covid year variable is 1, and when the year is 2019 or below the Covid year variable is 0. By doing this the study will be able to test if Covid has significantly affected changes in home value. Additionally, a distance measure with respect to Covid was included to see how much of a change occurred.

The distance variable with respect to Covid is essentially a separate test that measures the relationship between distance and home value during the years 2020 and above. Comparing the difference between this variable and the base variable identifies the disruption that Covid has had on the relationship between distance and home value. Then taking this number and comparing it to the changes in demographic makeup shows if there is any correlation between the disruption and changes in certain groups.

Population change, housing units change, and home ownership change were added to the linear model to normalize the results and ensure that change in home value was not solely attributed to distance (Costello et al.). Population change in a city can signify an increase or decrease in overall demand and desirability as well as an increase or decrease in the available workforce. Following the pandemic, many workers began working remotely and therefore moved out of major cities. By including population change in the regression one can ensure that the resulting value for distance is a clear and independent representation. Changes in housing units and changes in home ownership were used in the model to control for the changes in available supply. Housing units represent the total number of homes in the area, so the change represents either an increase or decrease in total supply. Home ownership represents the percentage of homes owned, and the change can be a result of an increase or decrease in either homes owned or homes available. Both have significant impacts on overall value and therefore must be accounted for because they are representative of the available supply of homes (O'Sullivan).

**Results**

The results for the regression analysis are broken into 5 sections. The Base Model section reports the results for the base model which gives an overview of the regression. The State vs City Model section reports the results for the base model adjusted to report results with both state and city fixed effects allowing us to compare results at the state and city level. The Minority vs Non-Minority Model section reports the results for the base model adjusted to report results with respect to racial makeup at the city level allowing us to compare results of minority cities to the results of non-minority cities. The Young vs Non-Young Model section reports the results for the base model adjusted to report results with respect to age makeup at the city level allowing us to compare results of young cities to the results of non-young cities. Lastly, the Model 4 section reports the results of the base model when demographic variables are included as dummy variables rather than as separate models.

**Base Model**

Table 3, Base Model Results, reports the results of my base model. The table reports the coefficients and significance of the 6 independent variables with regard to change in the HPI value. Overall, the results are consistent with prior research and the hypothesis.

The significance of distance went from being <0.05 over the entirety of the data set to <0.01 within the Covid year subset while the coefficient multiplied by 5. The increase in significance means that during the years affected by Covid 2020 to 2022, distance played a more significant role in change in home value compared to the years 2000 to 2022. Additionally, the increased coefficient tells us that during the years affected by Covid, a change in distance was 5 times more effective than it was over the entire data set. The coefficient is also positive which tells us that over the entire data set there is both a significant and positive correlation between distance and change in HPI value. This result directly contradicts the fundamentals of the monocentric city model which states that there should be a negative correlation between the two. This positive correlation, however, is the result of Covid and is consistent with expectations.

In years affected by Covid there were drastic price changes across the nation, and the locations most affected by these price changes were the cities on the outskirts because the supply was higher, and the previous demand was lower when compared to areas closer to the city. The drastic and quick uptrend in demand caused volatile price changes away from CBSA's.

In short, areas further away from city centers had more room to grow in terms of satisfying demand and increasing home value. So much so that the overall relationship between the two now shows a positive correlation. This conclusion is also supported by the coefficient of Covid year variable which shows that simply being in a year affected by Covid (represented by a value of 1) causes the quarterly HPI value to increase by 2.1% as well as figures 2 and 3 which show the relationship between price change and distance over time for years before and after Covid.

**State vs City Model**

Table 4, Model 1 Results, shows the results of the analysis when controlling at the state and city level. The goal of this analysis was to determine whether variables behaved differently as a result of the pandemic when comparing at the state level and at the city level. When comparing the results at the state level and the city level, many results are consistent in magnitude and in significance apart from home ownership change. When observing the results at the city level, home ownership has a significance of $p<.05$ while at the state level there is little to no significance. It is also observed that at the state level population change has a significance of

$p<.01$ while at the city level the population change only has a significance of $p<.05$. Meaning that the effect that population change has on home value change is more significant at the state level than at the city level.

**Minority vs Non-Minority Model**

Table 5, Model 2 Results, shows the results of the analysis when controlling demographic makeup with respect to race. For this analysis minority is used to represent areas who had a minority population in the upper 75th percentile, and non-minority is used to represent areas who had a minority population in the lower 25th percentile. The goal of this analysis was to determine if minority and non-minority cities behaved differently as a result of the pandemic. For example, if it was observed that one type of the cities was disrupted at a greater rate than the other, one could conclude that those types of cities had better accessibility to remote jobs and therefore were able to move away more freely from cities. On the other hand, it could be concluded that the opposite is true for the other types of cities. From the results, one can see that while many variables remained consistent, the overall relationship between distance and change in HPI value greatly differed between the two types of cities.

For areas within the upper 75th percentile for minority makeup, distance had no statistical significance when determining the change in quarterly HPI value from 2000 to 2022 while for areas within the bottom 25th percentile for minority makeup, distance had a significance level of $p<0.05$. When compared to the base model, it is also observed that the distance coefficient for non-minority cities, -.0003, is 150% lesser than that of the distance coefficient for the entire population, .0002, while having equal significance. This means that even following the pandemic, non-minority areas have continued to exhibit the fundamental characteristics of the monocentric city model which either means that they were less affected by Covid or that they simply exhibited stronger characteristics before Covid.

When observing the distance coefficient during covid, non-minority cities and the entire observation had the same coefficient of .001, but for the entire observation the effect was greatly more significant, $p<0.001$ compared to that of $p<.01$. From this one can conclude that non-minority areas exhibited stronger characteristics of monocentric behavior before Covid than the population.

**Young vs Non-Young Model**

Table 6, Model 3 Results, shows the results of the analysis when controlling demographic makeup with respect to median age. For this analysis young is used to represent areas who had a median age in the lower 25th percentile, and non-young is used to represent areas who had a median age in the upper 75th percentile. The goal of this analysis was to determine if young and non-young cities behaved differently because of the pandemic with the thought being that cities with lower median ages would see greater amounts of people leaving the city because younger individuals would be more drawn to remote and flexible job opportunities since they generally have less commitments to a city or area.

From the results of the analysis, one can see that the overall significance and magnitude of the variables varied greatly between the two types of cities.

For areas within the upper 75th percentile for median age, distance had no statistical significance when determining the change in quarterly HPI value from 2000 to 2022 while for areas within the bottom 25th percentile for median age, distance had a significance level of $p<0.01$.

When compared to the base model, one can also observe that the distance coefficient for young cities, .0004, is twice that of the distance coefficient for the entire population, .0002, while having greater significance, $p<0.01$ compared to $p<0.05$.

Additionally, when observing the results of the young city model, the distance coefficient during Covid is not statistically significant meaning that even before the pandemic, younger cities were already displaying characteristics in opposition to the monocentric city. The non-young city model however shows that distance, while not statistically significant over the entire observation period, was statistically significant during the years affected by Covid at the same rate at which the population was affected.

**Model 4**

Table 7, Model 4, shows the results of the analysis when racial makeup and median age are included as dummy variables. For this analysis minority is used to represent areas who had a minority population in the upper 75th percentile, non-minority is used to represent areas who had a minority population in the lower 25th percentile, young is used to represent areas who had a median age in the lower 25th percentile, and non-young is used to represent areas who had a median age in the upper 75th percentile. The goal of this analysis was to determine if the previous results would differ if all models were combined into a single regression.

From the results of the analysis, one can see that the overall significance and magnitude of the variables varied from the results of the previous models.

For Model 4, distance and high minority makeup were not statistically significant while distance during a Covid year, low minority makeup, high median age and low median age were statistically significant.

From these results one can see that by attributing the change in HPI to additional dummy variables distance became less significant suggesting that a more complex model could portray a clearer representation of the overall disruption.

**Conclusion**

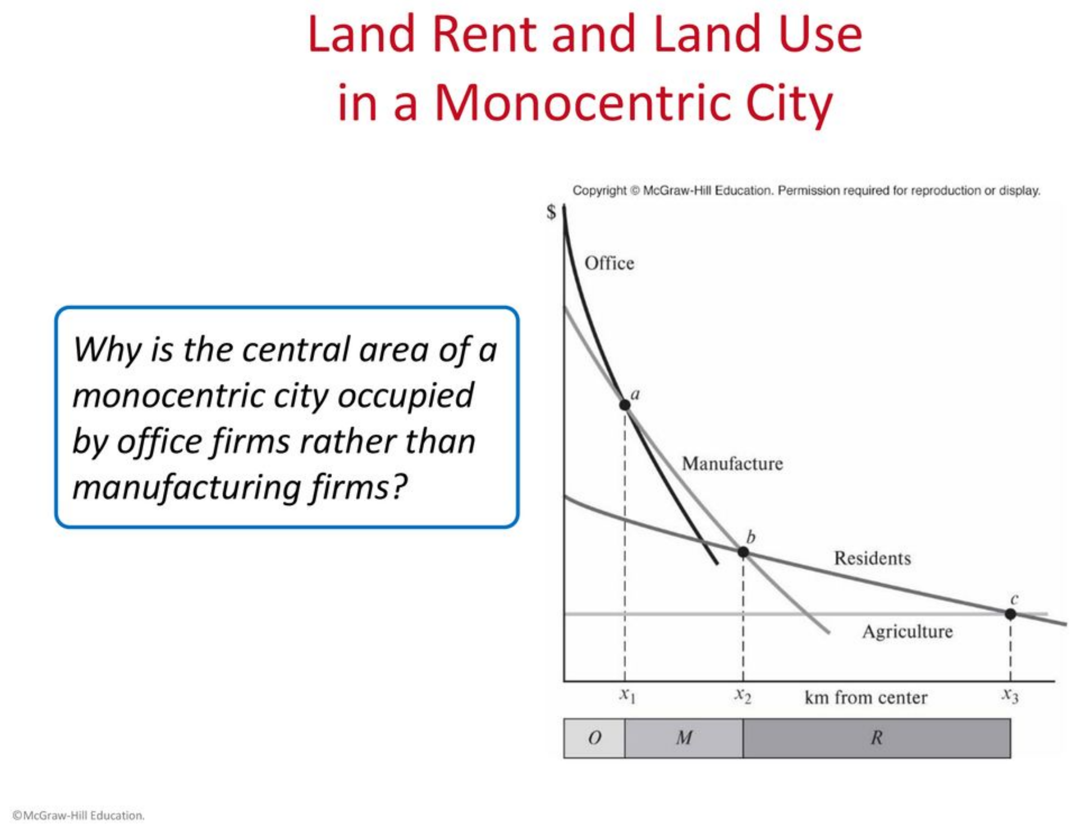
The results of the study were consistent with the initial findings and support the flattening of the curve and hollowing out effect that Covid has had on the overall residential real estate market. This can be seen by the positive relationship found between the log of distance and price change over the course of the study as well as the relationship between the log of distance and price change with respect to covid.

The results of the minority versus non-minority model did not produce significant results to support or contradict the initial hypothesis as log of distance was not a significant variable for minority cities. The results, however, did suggest that over the entirety of the study, non-minority cities continued to exhibit characteristics of a monocentric city while being affected at the same level as the population during covid. This result could suggest that non-minority cities exhibited stronger monocentric characteristics to start with in comparison to the entire population which may have resulted from pre-existing issues in public policy.

The results of the young versus non-young model could support the hypothesis that younger adults were able to take advantage of remote opportunities and lower home values as the log of distance for the young cities model was twice that of the base model.

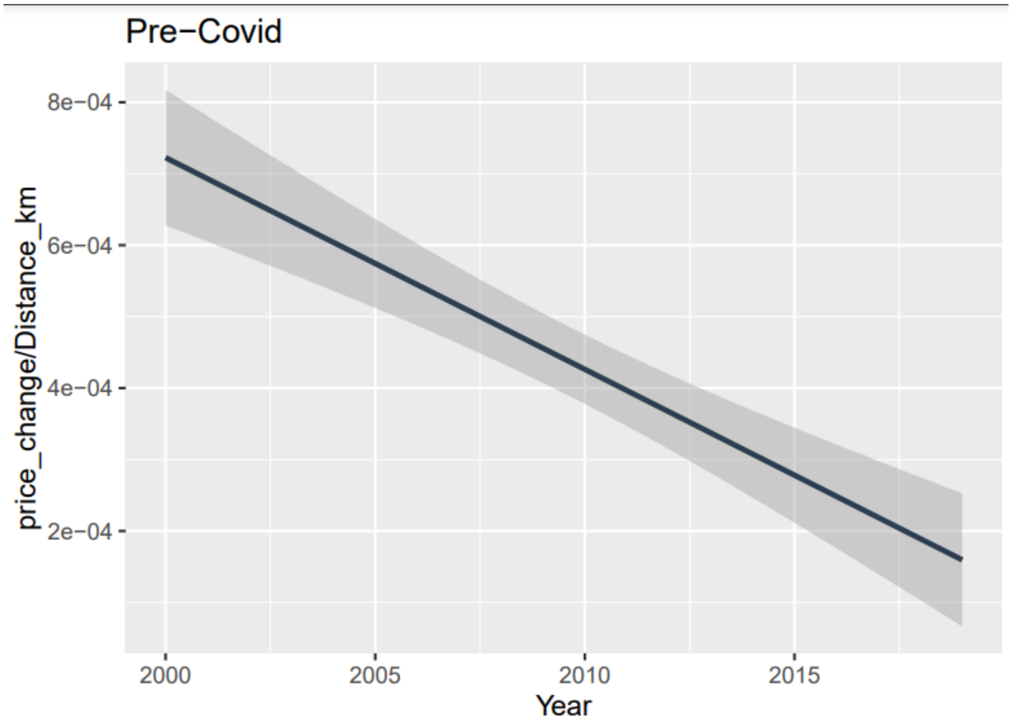
In conclusion, the study offered some input into how the disruption of the monocentric city model could be attributed to key demographic variables such as age. The study also suggests that non-minority cities could have stronger monocentric characteristics than the total population leaving room for further research into how pre-existing public policy issues played a role in the disruption of the residential real estate market.

Figure 1: Land Rent and Land Use in a Monocentric City



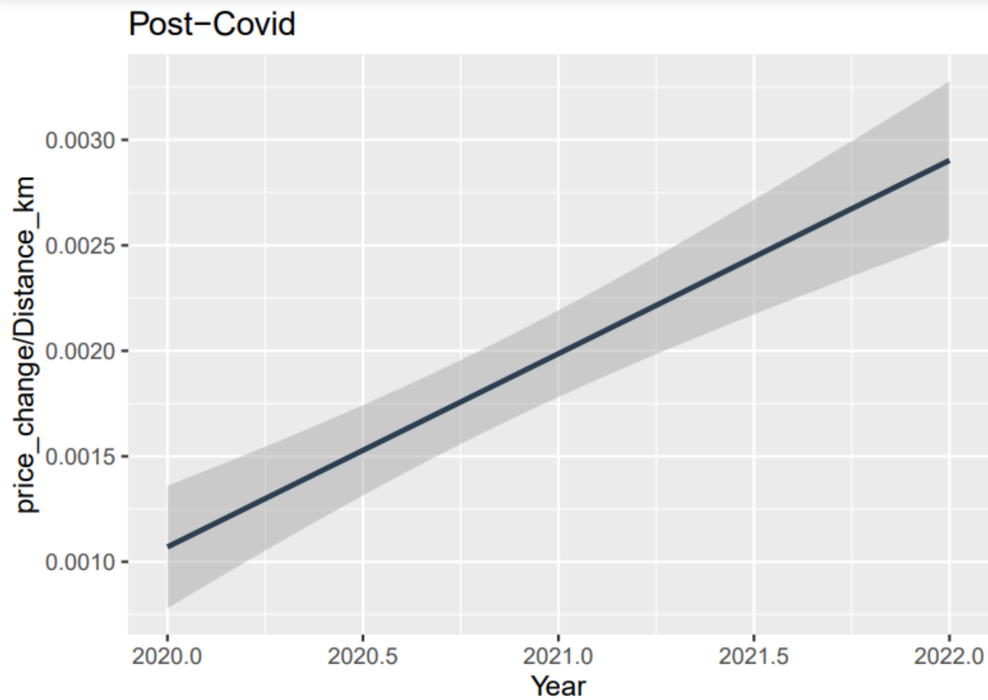

This figure shows the consumption of land with respect to the bidding from Office, Manufacture, Residents, and Agriculture.

Figure 2: Pre-Covid Graph of Price Change/Distance in Km vs Year




This figure shows the relationship between price change and distance in kilometers between the years 2000 and 2019.

Figure 3: Post-Covid Graph of Price Change/Distance in Km vs Year




This figure shows the relationship between price change and distance in kilometers between the years 2020 and 2022.

Table 1: Description of Variables

| Variable | Description |
| --- | --- |
| Distance_km | The distance a 3-digit zip code is from a MSA |
| covidyear | 1 if the year is between 2020 and 2023 and 0 otherwise |
| minority | 1 if the percentage of minority makeup is in the upper 75th percentile and 0 otherwise |
| non_minority | 1 if the percentage of minority makeup is in the lower 25th percentile and 0 otherwise |
| young | 1 if the median age is in the lower 25th percentile and 0 otherwise |
| non_young | 1 if the percentage of median age is in the upper 75th percentile and 0 otherwise |
| population_change | The percentage change in population |
| housing_units_change | The percentage change in housing units |
| home_ownership_change | The percentage change in home ownership |

Table 2: Summary Statistics

| Statistic | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|
| ZIP3 | 538 | 254 | 10 | 999 |
| Year | 2,011 | 6 | 2,000 | 2,022 |
| Quarter | 2 | 1 | 1 | 4 |
| population | 343,528 | 305,959 | 20,749 | 2,531,191 |
| density | 546 | 1,810 | 1 | 61,822 |
| age_median | 41 | 4 | 27 | 56 |
| male | 80,505 | 127,362 | 48 | 1,116,357 |
| female | 82,726 | 131,782 | 52 | 1,158,541 |
| housing_units | 139,245 | 116,616 | 8,324 | 876,047 |
| population_pre | 317,269 | 268,962 | 17,143 | 2,274,898 |
| density_pre | 739 | 2,190 | 3 | 61,822 |
| age_median_pre | 39 | 4 | 27 | 53 |
| female_pre | 161,003 | 137,086 | 8,170 | 1,158,541 |
| male_pre | 156,266 | 131,990 | 8,674 | 1,116,357 |
| housing_units_pre | 136,430 | 109,631 | 8,160 | 846,498 |
| price_change | 0.0101 | 0.0199 | -0.1666 | 0.1371 |
| home_ownershi | 66.8567 | 10.9709 | 16.3291 | 88.0765 |
| race_whit | 82.3046 | 14.6756 | 16.8972 | 98.3633 |
| race_black | 8.6483 | 12.4970 | 0.0588 | 67.4333 |
| race_asian | 1.5998 | 3.3434 | 0.0077 | 52.2684 |
| race_native | 1.5616 | 4.8182 | 0.0000 | 75.3862 |
| race_pacific | 0.1159 | 0.7224 | 0.0000 | 14.5366 |
| race_other | 2.7884 | 3.6364 | 0.0483 | 28.9619 |
| race_multiple | 2.9805 | 2.2903 | 0.3818 | 28.9252 |
| hispanic | 9.6754 | 13.4603 | 0.1500 | 90.0060 |
| race_white_pre | 83.5334 | 14.4595 | 16.8972 | 99.0357 |
| race_black_pre | 8.5080 | 12.3985 | 0.0324 | 65.0907 |
| race_native_pre | 1.5787 | 4.7645 | 0.0645 | 75.3862 |
| race_asian_pre | 1.3027 | 3.1249 | 0.0441 | 52.2684 |
| race_pacific_pre | 0.1007 | 0.6854 | 0.0000 | 12.8587 |
| race_other_pre | 3.0852 | 4.4327 | 0.0349 | 28.5666 |
| race_multiple_pre | 1.8912 | 1.7302 | 0.3165 | 28.9252 |
| hispanic_pre | 8.0917 | 12.7878 | 0.3444 | 88.2767 |
| home_ownership_pre | 61.3289 | 7.6696 | 12.1771 | 78.1814 |
| population_change | 1.0572 | 0.0977 | 0.7134 | 1.7819 |
| age_median_change | 1.0650 | 0.0426 | 0.8061 | 1.2412 |
| density_change | 0.9675 | 1.6929 | 0.0271 | 52.5742 |
| male_change | 0.5370 | 0.5417 | 0.0020 | 1.7605 |
| female_change | 0.5321 | 0.5379 | 0.0020 | 1.8029 |
| home_ownership_change | 1.0959 | 0.1731 | 0.6045 | 2.6200 |
| housing_units_change | 1.0056 | 0.1561 | 0.4992 | 1.7795 |
| race_white_change | 0.9847 | 0.0372 | 0.7322 | 1.1646 |
| race_black_change | 1.1978 | 0.6826 | 0.0470 | 14.4865 |
| race_asian_change | 1.3528 | 0.4588 | 0.1358 | 6.4311 |
| race_native_change | 0.9883 | 0.3778 | 0.0000 | 4.6366 |
| race_pacific_change | 1.5870 | 3.0674 | 0.0000 | 58.7791 |
| race_other_change | 1.2878 | 1.0484 | 0.0908 | 30.1179 |
| race_multiple_change | 1.6534 | 0.5931 | 0.3334 | 7.9552 |
| hispanic_change | 1.4237 | 0.3983 | 0.2508 | 4.4606 |
| citygrowth | 0.7054 | 0.4559 | 0 | 1 |
| Distance_km | 41.1074 | 27.3261 | 0.1401 | 221.2220 |
| non_minority | 0.2498 | 0.4329 | 0 | 1 |
| minority | 0.2500 | 0.4330 | 0 | 1 |
| non_young | 0.2501 | 0.4331 | 0 | 1 |
| young | 0.2498 | 0.4329 | 0 | 1 |
| covidyear | 0 | 0 | 0 | 1 |

Note: 81,880 observations

Table 3: Base Model Results

| | Dependent variable: |
| --- | --- |
| | Price Change |
| log(Distance_km) | 0.0002** |
| | (0.0001) |
| log(Distance_km):covidyear | 0.001*** |
| | (0.0002) |
| covidyear | 0.021*** |
| | (0.001) |
| population_change | 0.014*** |
| | (0.001) |
| housing_units_change | -0.003*** |
| | (0.001) |
| home_ownership_change | 0.0001 |
| | (0.001) |
| Constant | -0.006*** |
| | (0.001) |
| Observations | |
| R2 | 0.148 |
| Adjusted R2 | 0.148 |
| Residual Std. Error | 0.018 (df = 81873) |
| F Statistic | 2,373.368*** (df = 6; 81873) |
| Note: | *p<0.1; **p<0.05; ***p<0.01 |

Table 4: Model 1 Results

| | Dependent variable: | |
| --- | --- | --- |
| | Price Change | |
| | State FE | City FE |
| | (1) | (2) |
| log(Distance_km) | -0.0001 | -0.001 |
| | (0.0001) | (0.002) |
| log(Distance_km):covidyear | 0.001*** | 0.001*** |
| | (0.0002) | (0.0002) |
| covidyear | 0.021*** | 0.021*** |
| | (0.001) | (0.001) |
| population_change | 0.004*** | -0.005** |
| | (0.001) | (0.002) |
| housing_units_change | -0.001 | 0.001 |
| | (0.001) | (0.001) |
| home_ownership_change | -0.001 | -0.002** |
| | (0.001) | (0.001) |
| Constant | 0.006*** | 0.020*** |
| | (0.002) | (0.008) |
| City or State F.E. | Yes | Yes |
| Observations | | |
| Adjusted R2 | 0.155 | 0.150 |
| Note: | *p<0.1; **p<0.05; ***p<0.01 | |

Table 5: Model 2 Results

| | Dependent variable: Price Change | |
|---|---|---|
| | Minority Cities | Nonminority Cities |
| | (1) | (2) |
| log(Distance_km) | -0.00005 | -0.0003** |
| | (0.0002) | (0.0001) |
| log(Distance_km):covidyear | 0.001* | 0.001* |
| | (0.0005) | (0.0005) |
| covidyear | 0.021*** | 0.020*** |
| | (0.002) | (0.002) |
| population_change | 0.017*** | 0.015*** |
| | (0.003) | (0.003) |
| housing_units_change | -0.004 | 0.004 |
| | (0.002) | (0.002) |
| home_ownership_change | -0.001 | 0.00005 |
| | (0.002) | (0.002) |
| log(Distance_km):covidyear | 0.001* | 0.001* |
| | (0.0005) | (0.0005) |
| Constant | -0.006** | -0.011*** |
| | (0.002) | (0.003) |
| Observations | 20,467 | 20,454 |
| Adjusted R2 | 0.133 | 0.158 |

Note: *p<0.1; **p<0.05; ***p<0.01

Tabel 6: Model 3 Results

| | Dependent variable: | |
|---|---|---|
| | Price Change | |
| | Young Cities | Nonyoung Cities |
| | (1) | (2) |
| log(Distance_km) | 0.0004*** | 0.00002 |
| | (0.0001) | (0.0002) |
| log(Distance_km):covidyear | 0.0005 | 0.001** |
| | (0.0005) | (0.0005) |
| covidyear | 0.022*** | 0.022*** |
| | (0.002) | (0.002) |
| population_change | 0.017*** | 0.021*** |
| | (0.003) | (0.002) |
| housing_units_change | -0.011*** | -0.002 |
| | (0.002) | (0.002) |
| home_ownership_change | -0.0004 | 0.0001 |
| | (0.001) | (0.001) |
| Constant | 0.0003 | -0.012*** |
| | (0.002) | (0.002) |
| Observations | 20,452 | 20,477 |
| Adjusted R2 | 0.122 | 0.169 |
| Note: | *p<0.1; **p<0.05; ***p<0.01 | |

Table 7: Model 4 Results

| | Dependent variable: |
|---|---|
| | Price Change |
| log(Distance_km) | 0.0001 |
| | (0.0001) |
| log(Distance_km):covidyear | 0.001*** |
| | (0.0002) |
| covidyear | 0.021*** |
| | (0.001) |
| minority | -0.0003 |
| | (0.0002) |
| non_minority | -0.001*** |
| | (0.0002) |
| young | 0.001*** |
| | (0.0002) |
| non_young | 0.001*** |
| | (0.0002) |
| population_change | 0.013*** |
| | (0.001) |
| housing_units_change | -0.002* |
| | (0.001) |
| home_ownership_change | -0.0002 |
| | (0.001) |
| Constant | -0.005*** |
| | (0.001) |
| Observations | |
| R2 | 0.149 |
| Adjusted R2 | 0.149 |
| Residual Std. Error | 0.018 (df = 81869) |
| F Statistic | 1,430.634*** (df = 10; 81869) |
| Note: | *p<0.1; **p<0.05; ***p<0.01 |

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