It's a Beautiful Day in the Neighborhood: A ZIP Code Level Analysis of COVID-19's Effect on the Housing Market

by

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1 Introduction

On January 20, 2020, the CDC confirmed the first case of COVID-19 in the United States. Then, in March, the World Health Organization declared COVID-19 a pandemic and President Trump declared a nationwide emergency. At the same time, state and local governments enacted stay-at-home orders to stop transmission of the virus. That spring, New York City quickly became the epicenter of the outbreak, with 203,000 confirmed cases during the first three months of the pandemic.[1] In New York, the pandemic inspired a migration, for those who could afford it, out of the city and towards less dense environments. In 2020, there were about 33,000 more move-outs registered with the postal office than average.[2]

Across the United States, the economy froze and the housing market collapsed during these first few months. But by summer, everything re-opened and the market rebounded. Inventory growth improved, but not as quickly as sales growth. This created a hyper-competitive housing market. 2020 and 2021 were already anticipated to be big home-buying years due to millennials reaching the home-buying age. Zillow found that in 2020, almost two million renters were on the tipping point—they could afford a typical starter home but not in their current location. When the pandemic hit, many of these renters no longer had to commute to work, enabling them to move further out and purchase that first home.[3]

The COVID-19 pandemic dramatically altered how Americans live and work—in the examples outlined earlier and in other ways. Therefore, the pandemic also greatly affected people's housing decisions and the value of residential real estate. There are many empirical measures of the housing market—I will focus on prices, rents, and the price-rent ratio. Buying a house is a long-term investment, while renting is short-term. Differences in the factors driving changes in prices and rents, if any, will reveal what affects long-term decision making vs short-term decision making in the housing market. The price of a home is also the discounted value of all future rents for that property. The price-rent ratio is the price divided by annualized rents.[4] So, if price goes up relative to rent, the price-rent ratio will increase. This indicates that people expect the future rents to increase. Analyzing factors that influence the price-rent ratio allow us to determine what affects expectations about the residential real estate market. These three housing outcomes enable us to identify how the pandemic affected short-term decision making (rents), long-term decision making (prices), and real estate expectations (price-rent ratio).

1. Corinne N. et al. Thompson, "COVID-19 Outbreak - New York City, February 29–June 1, 2020," November 2020, https://doi.org/10.15585/mmwr.mm6946a2.

2. Jake Offenhartz, "NYC Has Regained Three-Quarters of Residents Who Fled During COVID, Data Suggests," Gothamist, https://gothamist.com/news/nyc-has-regained-three-quarters-residents-who-fled-during-covid-data-suggests.

3. Earlene K.P. Dowell, "Remote Working, Commuting Time, Life Events All Affect Home Buyers' Decisions," Census Bureau, https://www.census.gov/library/stories/2021/10/zillow-and-census-bureau-data-show-pandemics-impact-on-housing-market.html.

4. "How to Use the Price-to-Rent Ratio," Investopedia, https://www.investopedia.com/terms/p/price-to-rent-ratio.asp.

I will contribute to the existing literature by explicitly comparing the drivers behind changes in home prices, rents, and price-rent ratios within metropolitan areas during the COVID-19 pandemic. The majority of the literature focuses on prices and rents—I believe that there are important insights to be gained from analyzing the price-rent ratio. In addition, I incorporate the public's perception of the pandemic. The existing literature uses the mechanism of time after the original COVID-19 outbreak as a way to measure the pandemic's effect on the housing market. Now, about two years after March 2020, I argue that these models do not capture the reality of the pandemic experience in the United States—multiple peaks of infections followed by times of optimism. I am interested in how the state of the pandemic, or more specifically, how the public perceived the state of the pandemic, affected housing decisions, and thus the housing market.

In this paper, I examine the effect of the pandemic on housing markets throughout the United States. More specifically, I ask: how did COVID-19, and the public's perception of COVID-19, affect home prices, rents, and price-rent ratios at the ZIP code level within major metropolitan areas? Did demand for housing in fact decline in downtown areas and rise in the suburbs, as reported in the news?

After reviewing the literature on real estate and the pandemic, I use data from Zillow.com, the Census Bureau, the New York Times, and Gallup to construct a panel data set. The panel covers 35 months—January 2019 to November 2021—and 1759 ZIP codes within 79 metropolitan areas. I then run multiple regression models, with metro area and time fixed effects, to analyze how neighborhood characteristics, local COVID-19 case rates, and national pandemic sentiment affected local housing markets.

I find that the significant factors for prices, rents, and price-rent ratios are similar overall. Local real estate markets within a metro area reacted to the pandemic differently depending on neighborhood characteristics. Density, public transportation usage, and restaurants per capita were the most significant factors across the majority of specifications.

The remainder of the paper proceeds as follows: Section 2 presents an overview of the literature, Section 3 summarizes the data, Section 4 describes the empirical methods used and details the results, and Section 5 concludes.

2 Literature Review

The existing literature focuses on the first year of the pandemic. Nanda et al. (2021) theorize that as people spend more time working and schooling from home, they will "consume" housing differently, causing the patterns of demand for housing to change. One of the major potential shifts in housing preferences is the change in choice of housing location. Economic theory tells us that the price of land per unit decreases at a declining rate as distance from the city center—typically where jobs are concentrated—increases.[5] This is because in the city center, land is in higher demand than it is in the suburbs—there are more people competing for a fixed amount of land close to job centers.[6] This relationship is represented in the bid-rent function, which relates prices and rents to the distance from city center, as shown pre- and post-pandemic in Figure 1.[7] Prices and rents are higher in the city center than they are in the suburbs.[8] So, if people begin to prefer larger houses further out from the city during the pandemic, the bid rent curve would shift, and the downward slope would become flatter. It is important to note that in reality, households consider many observable and unobservable factors when choosing where to locate. These include the built environment (i.e. structural density and green space), points of interest (i.e. education, recreation, and retail), socio-economic environment (i.e. population density, household income, and school quality), and access and accessibility (i.e. commuting time). The pandemic and resulting societal changes may have altered the importance of these various factors. The demand for green space, for instance, went up when stay-at-home orders were in place and people wanted to enjoy the outdoors without being in close proximity to those outside their household. On the other hand, the value of access to amenities, such as restaurants, most likely declined when people were concerned about contracting COVID-19.[9]

Liu and Su (2021) were able to empirically confirm some of the location preference hypotheses outlined by Nanda et al. They used ZIP code level data on inventory, home price, and asking rent to track housing demand for the 25 largest metropolitan statistical areas from January 2016 to April 2021. They estimated a regression for each of the above housing indicators at the ZIP code level, interacting the variable After (months after March 2020) with neighborhood characteristics of interest, such as density, and CaseRate (the monthly average case rate of the county that the neighborhood belongs to). They included city-time fixed effects (to absorb the differential effects of the pandemic across cities) and ZIP code fixed effects. The results of the regressions determine that neighborhoods with more telework-compatible jobs, more restaurants per capita, and higher pre-COVID-19 home values experienced a relative increase in inventory and relative decrease in housing prices. In addition, they found a shift in housing demand away from large, expensive cities. However, the magnitude of that shift is smaller than the shift towards the suburbs from central cities.[10]

5. Anupam Nanda et al., "Forced homeward: the COVID-19 implications for housing," *Town Planning Review* 92, no. 1 (January 1, 2021): 25–32, ISSN: 1478-341X, https://doi.org/10.3828/tpr.2020.79, http://www.liverpooluniversitypress.co.uk/journals/article/60454.

6. Daniel Hertz, "Why can't cheaply-built houses be an affordability solution in expensive cities?," City Observatory, https://cityobservatory.org/why-cant-cheaply-built-houses-be-an-affordability-solution-in-expensive-cities/.

7. Nanda et al., "Forced homeward."

8. Arpit Gupta et al., "Flattening the Curve: Pandemic-Induced Revaluation of Urban Real Estate," Series: Working Paper Series, no. 28675 (April 2021), https://doi.org/10.3386/w28675, https://www.nber.org/papers/w28675.

9. Nanda et al., "Forced homeward."

10. Sitian Liu and Yichen Su, "The impact of the COVID-19 pandemic on the demand for density: Evidence from the U.S. housing market," *Economics Letters* 207 (October 1, 2021): 110010, ISSN: 0165-1765, https://doi.org/10.1016/j.econlet.2021.

Yoruk (2020) also applied empirical analysis to the pandemic and U.S. housing market, but focused on the early effects of policies, and case and death rates. The paper looked at 50 major cities from February 15, 2020 to April 19, 2020. Yoruk concludes that although there is some evidence for county-level COVID-19 cases and deaths negatively impacting the number of newly listed homes, pending sales, and web traffic to for-sale homes, the effects of these indicators are relatively small. From the results of the models, the closure of non-essential business in certain states seems to be the only policy which had a significant and considerable effect on the housing market. This makes sense, as real estate agents were considered non-essential in many states.[11]

The most comprehensive study of the effects of the pandemic and characteristics of specific homes on pricing is a working paper by D'Lima et al. (2021). Using data on major metropolitan areas from January 2019 to December 2020, they found that these effects depend on both population density and size and structural density (the ratio of floor area to lot size) of properties. When looking at only the average post-shutdown pricing effects across all property types and locations, shutdown mandates and county COVID-19 case rates were not statistically significant. However, the coefficient of Re-open (the re-opening date indicator), is positive and statistically significant.

The paper also analyzes whether pricing differentials around shutdown orders differ by demography. As with the findings of Liu and Su, population density was significant—shutdowns caused price decreases in densely population locations, but price increases in locations with low population density. Finally, D'Lima et al. determined that structural density is significant when interacting with shutdown and population density. Properties with the highest levels of structural density experienced a negative price shock from shutdown orders. On the other hand, in the triple-interaction framework, the marginal price of additional structural density (i.e. an additional room) increased in high population density locations after the shutdowns, potentially offsetting the negative pricing effects of being downtown. Ultimately, D'Lima et al. conclude that "the events following the introduction of shutdowns collectively led to a change in preferences and behaviors that has affected not only the value of living near the workplace but also the price households are willing to pay for more bedrooms or space in various locations."[12]

In a NBER working paper, Gupta et al. (2021) analyze another housing market indicator—the price-to-rent ratio. The price-rent ratio for a geographical area is that area's average home value divided by the annualized average rent. Gupta et al. focus on the difference in housing trends between urban and suburban

110010, https://www.sciencedirect.com/science/article/pii/S0165176521002871.

11. Baris Yoruk, "Early Effects of the COVID-19 Pandemic on Housing Market in the United States," (Rochester, NY), no. 3607265 (May 21, 2020), https://doi.org/10.2139/ssrn.3607265, https://papers.ssrn.com/abstract=3607265.

12. Walter D'Lima, Luis A. Lopez, and Archana Pradhan, "COVID-19 and Housing Market Effects: Evidence from U.S. Shutdown Orders," (Rochester, NY), no. 3647252 (September 23, 2020), https://papers.ssrn.com/abstract=3647252.

ZIP codes for the 30 largest metro areas in the United States. They found that the urban price-rent ratio increased relative to the suburban price-rent ratio. This indicates that during the pandemic, urban ZIP codes experienced greater declines in rents relative to prices, while suburban ZIP codes experienced greater increases in rents relative to prices. This suggests that there is higher expected rent growth in the urban center than in the suburbs for the next few years (as we recover from the pandemic).[13]

This paper contributes to the already-existing literature in multiple ways. First, the majority of the literature analyzes 2020 and early 2021. This was before the COVID-19 vaccine was available to the majority of the United States population. Do the results of the literature hold true when including data for the rest of 2021? In addition, I build off the literature by comparing the drivers behind changes in home prices, rents, and price-rent ratios. Lastly, I incorporate the public's perception of the pandemic.

3 Data

I construct a panel data set spanning 35 months—January 2019 through November 2021— and 1759 ZIP codes. This represents 732 cities, 209 counties, and 79 metropolitan areas. Although the average ZIP code population in the data set is 40,865 people, which is larger than what most people would consider a neighborhood, I will use ZIP code and neighborhood interchangeably from now on. I select January 2019 as the first month in order to have a sufficient set of pre-pandemic observations. The data set ends in November 2021 because at the time of data collection, it was the last month I could obtain complete survey data for.

3.1 Prices, Rents, and Price-Rent Ratios

I obtain information on home prices and rents, at a monthly frequency, at the ZIP code level from Zillow.[14] I use Zillow's Home Value Index (ZHVI) as the price index for my analysis. The ZHVI measures changes in the typical home value of a given neighborhood over time. The ZHVI is seasonally-adjusted and smoothed. Its monthly changes are calculated using a weighted mean of the appreciation of individual homes (including those off-market) in the neighborhood. The ZHVI is interpreted as the dollar value of a typical home.[15]

I also use Zillow's Observed Rent Index (ZORI). The ZORI represents the typical observed monthly market rate rent for a given neighborhood. It is a smoothed and repeat-rent index, calculated using a weighted average to reflect the entire rental market, not just homes currently listed.[16]

13. Gupta et al., "Flattening the Curve."
14. Zillow data can be accessed at https://www.zillow.com/research/data.
15. The ZHVI represents the value of homes in the 35th to 65th percentile range.
16. The ZORI represents the rent of homes in the 40th to 60th percentile range.

The price-to-rent ratio is the ratio of home prices to annualized rent. I calculate the ratio for each ZIP code at a monthly frequency by dividing the ZHVI by twelve times the ZORI.[17]

3.2 Local Characteristics

I obtain ZIP code level local characteristics, including population density, public transportation usage, racial composition, and median household income (in 2019 dollars), from the 2015-2019 American Community Survey estimates via Social Explorer.[18]

3.3 Restaurants

For each ZIP code, I obtain the number of restaurants and drinking places from the 2019 County Business Patterns data set. [19] I then calculate the number of restaurants and drinking places per capita per ZIP code using population counts from the 2015-2019 ACS.[20]

3.4 Distance to Downtown

For each ZIP code, and corresponding ZCTA, I obtain values of longitude and latitude from the 2021 ZCTA Gazetteer.[21] Following Gupta et al. 2021, I define the center of the metro area as city hall.[22] Using city hall coordinates obtained from Google Maps, I calculate the Euclidian distance (in degrees) to city center for each ZIP code.

3.5 County-Level Case Rate of COVID-19

I download the COVID-19 county-level case rates from the New York Times.[23] For each month, beginning March 2020, I identify the average monthly case rate as the seven-day trailing average of new cases reported per 100,000 people from the last day of that month.

17. "How to Use the Price-to-Rent Ratio."
18. American Community Survey tables can be accessed at https://www.socialexplorer.com/explore-tables.
19. Defined as NAICS codes 7224//, 72241/, 722410, 7225//, 72251/, 722511, 722513, and 722514.
20. The 2019 CBP data and NAICS code descriptions can be accessed at https://www.census.gov/data/datasets/2019/econ/cbp/2019-cbp.html.
21. The 2021 ZCTA Gazetteer file can be accessed at https://www.census.gov/geographies/reference-files/time-series/geo/gazetteer-files.html.
22. Except the New York City metro area, for which city center is defined as Grand Central.
23. The New York Times COVID-19 data can be accessed at https://github.com/nytimes/covid-19-data. Note that all five boroughs of New York City are grouped together into a single area.

3.6 National Surveys

To measure the public's perception of the COVID-19 pandemic, I use national polling from Gallup.[24] I calculate monthly averages for the results of the following poll questions:

- How worried are you that you will get the coronavirus?

- How long do you think the level of disruption occurring to travel, school, work and public events in the U.S. will continue before it starts to improve?

- What's your impression of the coronavirus situation in the U.S. today? Is it getting a lot worse, getting a little worse, staying about the same, getting a little better or getting a lot better?

3.7 Data Description

In Table 1, I report the summary statistics for each variable. Note that before March 2020, county average case rate is 0. The share of the United States population who believes the pandemic will end in a few months or less was first measured in March 2020—before then, it is 0. The polling for the share worried about getting COVID-19 and the difference between the share who believes the pandemic is improving and the share who believes it is worsening began in April 2020.

The price index ranges from $40,611 in Dayton, Ohio (March 2019) to $4,623,761 in Pacific Palisades, California (September 2021). The mean is $491,484. The rent index ranges from $621/month in Albuquerque, New Mexico (January 2019) to $6,689/month in the Tribeca neighborhood of Manhattan (November 2021). The mean is $1,792/month. Finally, the lowest price-rent ratio in the sample is 3.9 in the Englewood neighborhood of Chicago (January 2019), while the highest is 94 in Newport Beach, California (October 2019). The mean is 21.

Figure 2 shows the average monthly COVID-19 new case rate for the sample from March 2020 to November 2021. Cases peaked in April 2020, July 2020, December 2020, and August 2021. Then, Figure 3 shows the three nationwide survey variables from April 2020 to November 2021. The vertical lines indicate key moments in the pandemic—the first vaccine was approved by the FDA in December 2020, the vaccine was available to all Americans over the age of 16 in April 2021, and the Delta variant wave peaked in August 2021. December 2020 to June 2021 was a time of optimism, with more people reporting a positive outlook on the pandemic, less reporting concern, and more expecting the pandemic to end shortly. This makes sense, as people knew there was a vaccine, and then were able to actually receive it. Then in June, these survey

24. The Gallup survey data can be accessed at https://news.gallup.com/poll/308222/coronavirus-pandemic.aspx.

trends reversed, as the Delta variant took over and cases began to increase again in the United States. After August, optimism returned, until October and November and the rise of the Omicron variant.

4 Empirical Analysis and Results

4.1 COVID-19 and U.S. Housing Market Trends

The mean price index and mean rent index of the 1759 ZIP codes included in the sample saw very modest growth from January 2019 to the beginning of the pandemic, in March 2020 (as shown in Figures 4 and 5). The price index experienced a slight dip from April 2020 to June 2020, most likely due to the economic fallout from the pandemic and associated shutdowns. Given the dramatic rise in unemployment in April and May, it may seem surprising that home prices barely fell. But given that home values are anchored in a long horizon of future values, and that people thought the pandemic would be over quickly—almost 75% of the population expected the pandemic would end in a few months or less in April 2020—it makes sense that prices remained relatively stable during this early pandemic economic shock. In addition, the Federal Reserve lowered interest rates, which subsequently lowered mortgage rates and made home-buying relatively more affordable. Rents did not fall during that time period but grew at a slower rate than they had pre-pandemic. This stability is surprising, but perhaps can be explained by macroeconomic government interventions—stimulus checks, expanded unemployment insurance, and the eviction moratorium. Beginning in July 2020, the mean price index began to grow at a much faster rate than it had previously. This trend continued until August 2021, when the slope seems to decrease slightly. The mean rent index saw similar growth over that time period, without a mild slowdown in August 2021.

From Figure 6, it is clear that the price-rent ratio, on the other hand, has been much more variable. In 2019, it declined and then rebounded to its original level as the pandemic hit in March 2020. After flattening out, the price-rent ratio increased sharply in June 2020 before remaining stagnant once again for the first few months of 2021. This means that between June 2020 and January 2021, home prices in the sample grew faster than rents. People expected rents to increase in the future. Between April 2021 and August 2021 the price-rent ratio grew. It slightly declined in the fall of 2021, indicating faster rent growth than price growth, or the flattening of future rent expectations.

4.2 Neighborhood-Level Analysis

To identify how local housing characteristics affected the pandemic housing market, I examine Figures 7 - 24. Figures 7, 8, and 9 show the change in prices, rents, and price-rent ratios over time for each quartile of population density. The densest ZIP codes (i.e. ZIP codes in the fourth quartile of population density) had the highest mean price index, rent index, and price-rent ratio. There are strong differences in the trend for the rent index over time between each group. The top quartile of ZIP codes by density experienced a decline in rents between March 2020 and December 2020, while the rents of the remaining 75% of ZIP codes increased during that time period. The first quartile group of population density began as the lowest rent index, but then surpassed the third quartile in early 2021. This suggests that the pandemic disproportionately affected the housing market of different neighborhoods depending on density—the densest neighborhoods, for example, had rents decrease at the beginning of the pandemic up until the approval of the vaccine. This makes sense, as denser neighborhoods were hit much harder by COVID-19, and hence became less desirable places to live.

The graphs for housing outcomes over time by public transportation usage (Figures 10-12) and by number of restaurants per capita (Figures 19-21) draw similar conclusions. The prices, rents, and price-rent ratios are highest for the neighborhoods with the greatest access to public transportation and restaurants. The differences between groups are highest for the price index and price-rent ratio—rents for the lowest three quartiles of both characteristics essentially converge in 2021. This suggests that people pay a premium to live in neighborhoods with amenities like public transportation and restaurants. The high price-rent ratio indicates that they expect rents in such neighborhoods to increase in the future (after they declined during the pandemic). Between March 2020 and December 2020, the mean rent index for the fourth quartile of public transportation and restaurants declined dramatically. During that time period, prices and price-rent ratios increased for all quartiles of public transportation usage and restaurants per capita.

Figures 23, 24, and 25 chart the mean price index, mean rent index, and mean price-rent ratio for by distance to city hall, or downtown, over time. The neighborhoods furthest from downtown have the highest baseline prices, rents, and price-rent ratios on average. While this may seem to contradict the bid-rent curve, the theory applies only to the value of land per unit. I am analyzing the prices of a package of land and housing. The prices and quantities of both can vary. For instance, for a specific metro area, there may be larger properties, which have more land, further from the center, while the center may have smaller apartments. So, even though the price of land per unit is higher in the city center, the total land and house ”package” can be higher in the suburbs. The top quartile for distance from downtown also saw the greatest price and price-rent ratio appreciation from mid-2020 to November 2021. In 2019, the second quartile had a higher mean price index than the third quartile by a thin margin—this changed at the end of 2020. This suggests that people moved outwards from city center during the pandemic. Each quartile of distance to downtown experienced similar trends over time for the rent index.

Figures 13 through 18 show the effects of the demographic controls—share of whites and median household income—on housing outcomes over time. Both characteristics have differences in baseline housing outcomes between percentile groups. The trends for price index and rent index by share of whites diverge in mid-2020. The trends for price-rent ratio by share of whites and all three housing outcomes by median household income are similar across groups.

We can conclude that the price index, rent index, and price-rent ratio vary based on observable neighborhood characteristics (i.e. low density vs high density). These neighborhood characteristics affect both the baseline housing market outcomes as well as the housing market trends over the course of the pandemic. Additionally, for neighborhoods with similar characteristics, the pandemic affected the three housing market outcomes differently. In order to account for all of these factors simultaneously, I will regress each housing market outcome on neighborhood characteristics, county-level COVID-19 case rates, measures of pandemic sentiment, and the interactions of characteristics and pandemic sentiment.

4.3 Method

To determine how local characteristics and the pandemic affected the housing market across neighborhoods (ZIP codes) within metro areas, I modify the model proposed by Liu and Su (2021). The most significant change is replacing months after March 2020 with the survey variables. I run multiple regression models of the following form:

$$log(Housing_{ncmt}) = \beta_1 x_{ncm} + \beta_2 Cases_{cmt} + \beta_3 Survey_t + \beta_4 Pandemic_t$$

$$+\beta_5 Survey_t * x_{ncm} + \beta_6 Survey_t * Cases_{cmt} + \delta_m + \pi_t + \varepsilon_{ncmt}$$

where $Housing_{ncmt}$ is a housing market outcome (price index, rent index, or price-rent ratio) in neighborhood n within county c in metro area m at time t.[25] x_{ncm} denotes neighborhood characteristics. $Cases_{cmt}$ is the average new case rate of COVID for county c at time t. $Survey_t$ is a national survey variable (pandemic concern, pandemic expected duration, and pandemic outlook) at time t. $Pandemic_t$ is an indicator for the pandemic and availability of survey data—it takes a value of 0 for the months pre-pandemic and 1 for the months post-pandemic.[26] δ_m denotes metropolitan area fixed effects to account for unobserved characteristics of metropolitan area housing markets. I choose metro area (rather than ZIP code, city, or county), because

25. The units of time are month-year. t ranges from January 2019 to November 2021.

26. When the survey variable is expected duration of pandemic, Pandemic = 1 March 2020 and on. When the survey variable is level of worry or outlook, Pandemic = 1 April 2020 and on.

assuming someone remains at the same job, they can move within the metro area but will not leave it. This allows us to identify differences between neighborhoods within metro areas. π_m denotes time fixed effects, to absorb common shocks at time t impacting all housing markets in the United States.

4.4 Results

4.4.1 Effects of Neighborhood Characteristics

I begin with the baseline model—estimating the effects of the ZIP code level characteristics and county level monthly case rate on housing outcomes. Table 2 presents the results. Each column reports the regression results for a different housing market outcome variable.

Holding all else constant, population density has a positive effect on the price. Distance to downtown has a negative effect. This suggests people are willing to pay a premium to live in denser neighborhoods and closer to downtown, confirming the predictions of the bid-rent function—all else equal, prices decrease as distance from the center increases. This seems to contradict the findings from Section 4.2, where average price was higher for neighborhoods furthest from downtown. The difference is that in the regression I am controlling for other factors that influence price. So, holding all else constant, distance from downtown does have a negative effect. Restaurants per capita has a positive effect, indicating people are willing to pay for access to amenities and things to do. Public transportation usage also has a positive effect on the price index. The neighborhood demographic controls (share of whites and median household income) are significant. In this specification, average case rate does not have a significant effect on price.

The results using the rent index, as shown in column 2, are similar to those using the price index. The coefficients on population density, public transportation usage, share of whites, median household income, and restaurants per capita are positive. However, distance to downtown is not significant. Holding all else constant, the county's average case rate had a positive effect on rent indices for neighborhoods within that county.

Column 3 shows the regression results for the price-rent ratio. Public transportation usage, share of whites, and median household income have a positive effect. So, within a metro area, neighborhoods that have better access to public transportation are more expensive to purchase a home, compared to renting. In addition, the positive coefficient indicates that neighborhoods with more public transportation are expected to see a greater increase in rents in the future. Distance to downtown has a negative coefficient. This suggests neighborhoods further from city center have low expectations for future rent growth. Finally, average case rate has a negative coefficient. When a county's average case rate was high, rents rose relative to prices in the neighborhoods within that county. In such neighborhoods, rents were expected to decline in the future.

4.4.2 Effects of Public Perception of the Pandemic

Next, I add the Gallup survey data to my regression. Since a 0 for the measures of pandemic concern, expected duration, and outlook represent different things pre- and post-pandemic. Pre-pandemic, a 0 for a survey variable means the polling had not yet begun and represents missing data. Whereas post-pandemic, a 0 means no one is concerned about COVID, no one expects the pandemic to end shortly, or overall people perceived that the pandemic was neither improving nor declining. I add a pandemic indicator to account for this difference in meaning. The indicator causes the pre-COVID-19 survey variable zeroes to have a different effect on the dependent variable than the COVID-19 era zeroes. The indicator takes a value of 0 before the associated survey variable began, and a value of 1 afterwards.

In Table 3, I add the share of the U.S. population who are worried about getting COVID to the baseline model. Concern for the pandemic has a positive effect on both the price index and rent index. This suggests that prices and rents increased during months when people became more worried about contracting the virus. However, the coefficient on concern for the regression on the price-rent ratio is insignificant. The coefficients on the pandemic indicator in the price index and rent index regressions are significant and negative. The coefficient on the indicator in the price-rent ratio regression is significant and positive. Controlling for case rates and COVID-19 worry, the price index decreased by 17.3% post pandemic, compared to pre-pandemic. The rent index decreased by 23.3% and the price-rent ratio increased by 5.95%. So, the change in the price-rent ratio was caused by a greater relative decline in rents than the decline in prices.

In Table 4, I add the share of the U.S. population who believes the pandemic will end in a few months or less to the baseline model. This variable had a negative effect on prices and rents and no significant effect on the price-rent ratio. The pandemic indicator has positive coefficient for all three housing outcomes. Controlling for case rates and pandemic duration expectations, prices, rents, and the price-rent ratio increased post-pandemic.

Finally, in Table 5, I analyze the effect of the public's overall COVID outlook on the housing market. I add the difference between the share of the U.S. population who believes the pandemic is improving and the share who believes the pandemic is worsening to the baseline model. The coefficient for outlook is negative and significant for the price index and rent index. This aligns with the results of Table 4, where times of optimism saw a decrease in prices and rents, and no significant change in the price-rent ratio, all else held constant. In these regressions, the pandemic indicator has a positive effect on all three housing outcomes.

4.4.3 Interaction of Neighborhood Characteristics and Pandemic Concern

I then interact the national survey variables with neighborhood characteristics in order to determine how the effect of pandemic sentiment varied by neighborhoods within a metro area. Table 6 reports the effects across neighborhoods by pandemic concern. For the regression on price index, shown in Column 1, the coefficients of Worried x Population density, Worried x Public transportation usage, Worried x Household income, and Worried x Restaurants per capita are negative and statistically significant. This suggests that when people were more concerned about contracting COVID-19, they preferred to live in a neighborhood with lower density, less public transportation, and less restaurants per capita. This makes sense—the value of being able to commute to work via public transportation or go out to eat declines dramatically when one is avoiding being indoors with strangers due to fear of COVID-19 (or, as in spring 2020, when offices and restaurants were closed due to local shutdown orders). When concerned about getting COVID-19, people's preferences shifted towards areas with less density and amenities within their metropolitan area. These results also identify that higher income neighborhoods saw greater declines in home values during times of higher COVID-19 worry.

Column 2 reports the results of the regression on rent index. As with the results for the prices, Worried x Population density, Worried x Public transportation usage, Worried x Household income, and Worried x Restaurants per capita have a negative effect on rents. In addition, the coefficient on Worried x Average case rate is negative and significant. In counties where case rates were high, pandemic concern had a greater negative effect on rents. This is because even though nationally a high proportion of people may be worried, only those in places that are currently experiencing a spike in cases are going to change their short-term housing decisions.

None of the interaction terms for price-rent ratio, reported in Column 3, are significant. This suggests that these factors, while significant for the price index and rent index, did not cause prices to decrease disproportionately compared to rents. In times of greater worry, for example, higher density neighborhoods saw proportional decreases to both prices and rents.

4.4.4 Interaction of Neighborhood Characteristics and Pandemic Duration Expectations

Table 7 reports the regression results for the baseline model with the addition of the interactions of the percent of the U.S. population who believe the pandemic will end in a few months or less and neighborhood characteristics. As shown in Column 1, Few months or less x Population density, Few months or less x Public transportation usage, Few months or less x Household income, and Few months or less x Restaurants per capita each have a negative effect on the price index. This is the same result as Column 1 of Table

6. This is surprising, as I expected amount of COVID-19 concern (pessimism) to have the opposite effect on prices to that of the amount of the population who expects the pandemic to end soon (optimism). One explanation for this is that in the first few months of the pandemic, COVID-19 concern and expectation that the pandemic will end soon followed a similar trend, as shown in Figure 2. Initially, people were very fearful of getting the coronavirus, but expected it to be over after a short period of lockdowns and social isolation—even the president of the United States assured the public we'd be able to go to church for Easter 2020. So, both variables were at high levels. Then, for the rest of 2020, people became slightly less concerned but also realized that the pandemic would go on for much longer than originally expected, so both variables decreased.

Also of interest is that the coefficient for Few months or less x Average case rate is positive and significant. This suggests that when people expected the pandemic to be over soon, the value of real estate in areas greater affected by COVID-19 went up, compared to areas with lower case rates. People planned to return to those areas in the near term. People planned and hoped to return or move to those areas in the near term. On the other hand, in an area with low case rates, when the pandemic ends wasn't as big a consideration because it hadn't affected behavior as much.

As reported in Column 2, the significant interaction terms in Column 1 have the same effects on rents. Then, looking at Column 3, the coefficient on Few months or less x Population density is negative and significant. Although neighborhoods of greater population density experienced falls in both prices and rents during times of optimism (duration expectations wise), the price-rent ratio decreased, and so the effect on prices was greater (i.e. prices fell more than rents). The interaction of duration and average case rate has a positive effect on the price-rent ratio. This suggests that when the public expected the pandemic to end in the near term, prices increased more than rents in high case rate areas, as they expected rents in those areas to increase in the future (when things returned to normal).

4.4.5 Interaction of Neighborhood Characteristics and Pandemic Outlook

In Table 8, I add the interactions of pandemic outlook and neighborhood characteristics. Column 1 reports the results for the regression on price index. Outlook x Population density, Outlook x Public transportation usage, Outlook x Household income, and Outlook x Restaurants per capita have negative and significant coefficients. So, within a metropolitan area, home prices declined in denser and wealthier neighborhoods with more public transportation and restaurants during times of higher pandemic outlook. As discussed in Section 4.4.4, these results are surprising.

With the exception of Outlook x Population density (which is insignificant), Column 2 reports similar results.

In Column 3, only Outlook x Population Density and Outlook x Restaurants per capita were significant. They both had a negative effect on the price-rent ratio. During these times of positive outlook, prices fell more than rents in dense neighborhoods and neighborhoods with a high number of restaurants per capita, compared to other neighborhoods in that metropolitan area.

5 Discussion and Conclusion

In this thesis, I document the effects of neighborhood characteristics and the COVID-19 pandemic—via case rates and public polling—on the housing market of 79 metropolitan areas in the United States. Using panel data and linear regression with fixed effects, I find evidence that within a metro area, higher density neighborhoods that are closer to downtown, and have more public transportation and restaurants per capita, have higher prices and rents. During the pandemic, such neighborhoods experienced price and rent declines relative to other neighborhoods in the metro area. The interactions of each survey variable and neighborhood characteristics told a story more similar than I predicted. Case rate and pandemic sentiment did have a significant effect on the housing outcomes. Overall, the variables included in my regressions better explained differences in prices and rents than differences in price-rent ratios.

I began by reviewing the existing literature, which focused on the first year of the pandemic. I built off these contributions by extending the analysis through the majority of 2021 and incorporating polling data to measure public perception of COVID-19. I then constructed my data set and analyzed trends both across the sample and between groups. Finally, I explained my method and reported the results. In the future, it would be interesting to run similar regressions on other housing market outcomes, such as inventory and average time on the market. I am also interested in researching more about what drives the price-rent ratio in particular, as most of my results were more significant for prices and rents.

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Figure 1: Bid-Rent Curve (from Nanda et al. (2021))

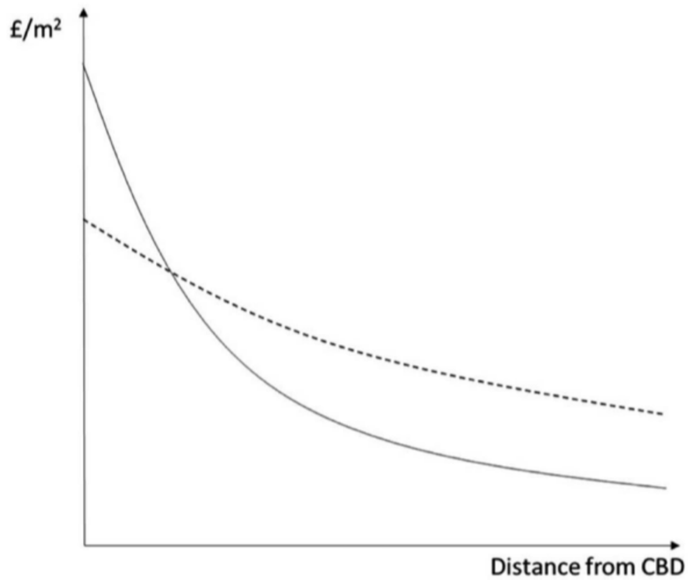


Figure 1 Bid rent curves before (solid line) and after (broken line) COVID-19
Source: Adapted from Brueckner (2011, 47)

Table 1: Summary Statistics

	Mean	Median	SD	Min	Max
Housing outcomes					
Price index	491,484	367,904	392,951	40,611	4,623,761
Rent (per month) index	1,791.7	1,655	612.1	621	6,689
Price-rent ratio	21.0	18.9	9.58	3.90	94.0
ZIP code characteristics					
Population density (per sq mi)	7,697.1	3,895.8	14,116.3	58.5	149,289.8
Public transportation usage (%)	8.32	2.57	14.0	0	78.3
Share of whites (%)	65.3	70.5	19.8	1.57	96.1
Median household income	79,206	75,525	30,290	20,326	224,063
Restaurants per capita	0.0079	0.0058	0.0092	0	0.15
Distance to downtown	0.65	0.51	0.51	0	2.51
County characteristics					
Average case rate (per 100k population)	12.7	4.66	19.1	0	184.5
National survey					
Share worried about getting COVID-19 (%)	24.9	29	23.5	0	59
Share who believe pandemic will end in a few months or less (%)	17.5	13	20.9	0	85.3
Share who believe pandemic is improving - worsening (%)	0.68	0	33.7	-62	86

Figure 2: COVID-19 Case Rate Over Time

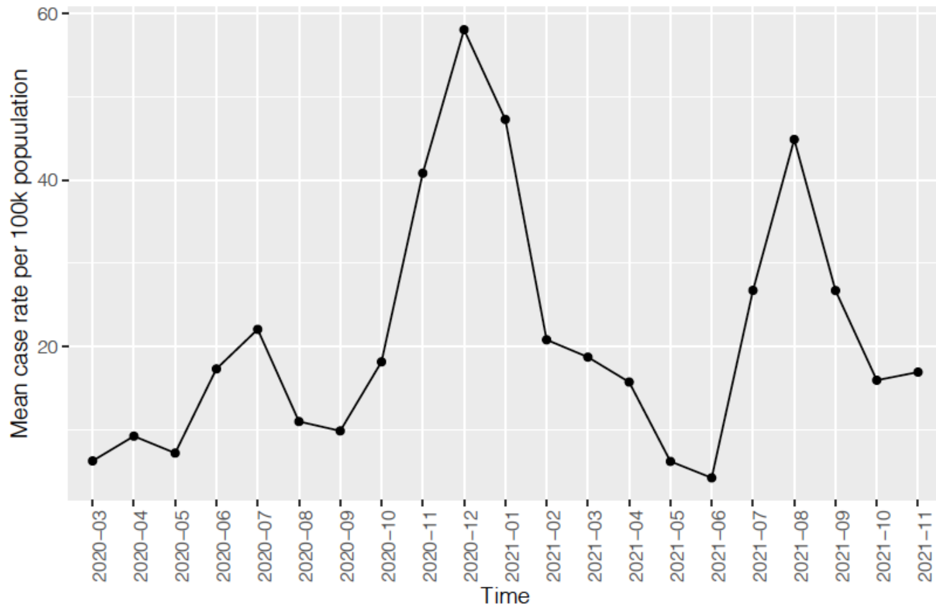
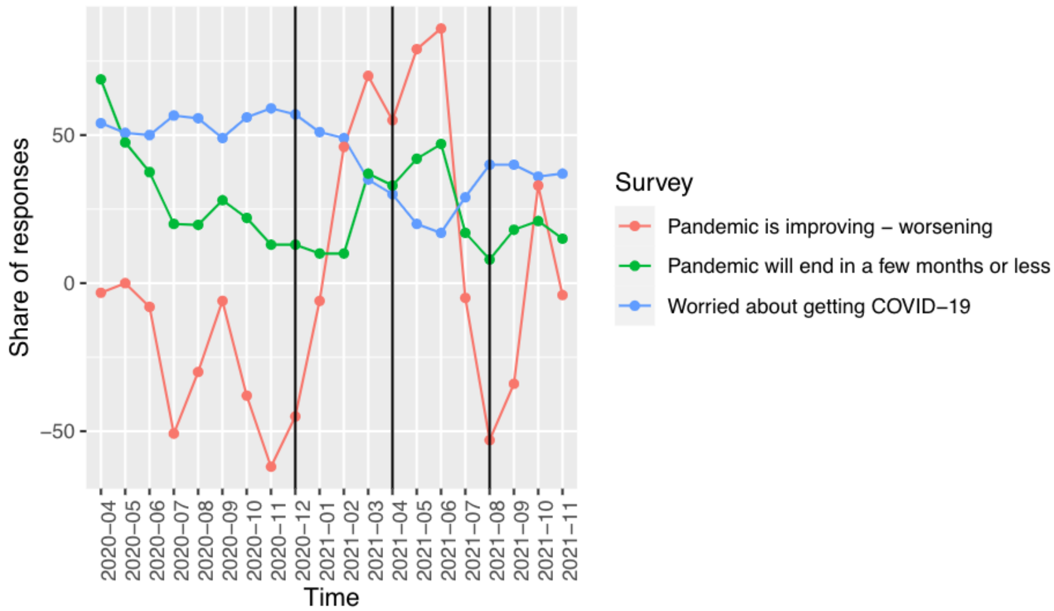
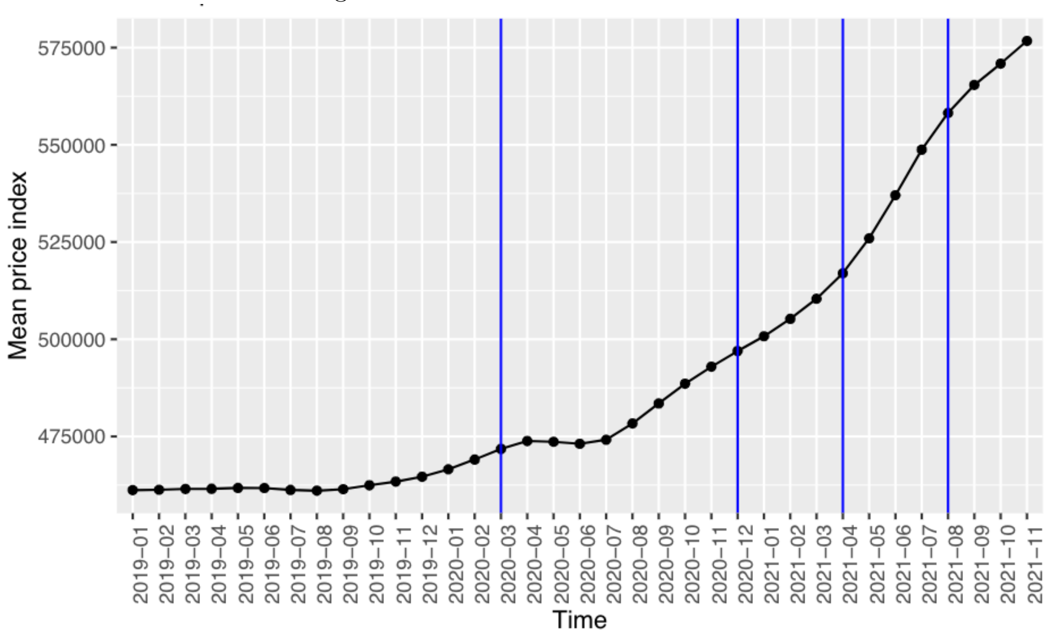


Figure 3: COVID-19 Sentiment Over Time



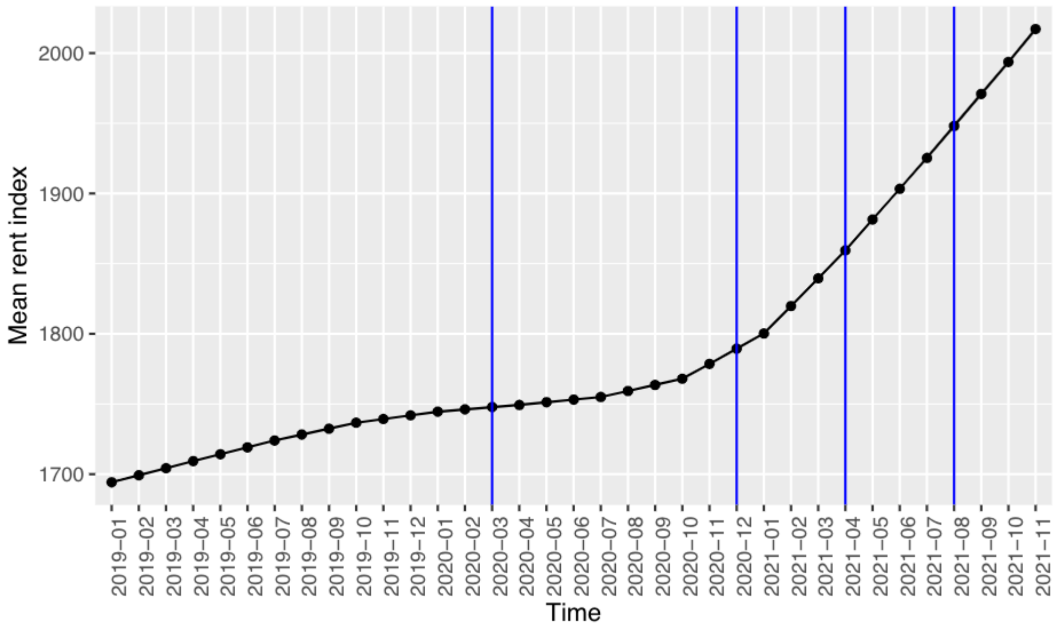
The vertical lines indicate when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 4: Mean Price Index Over Time



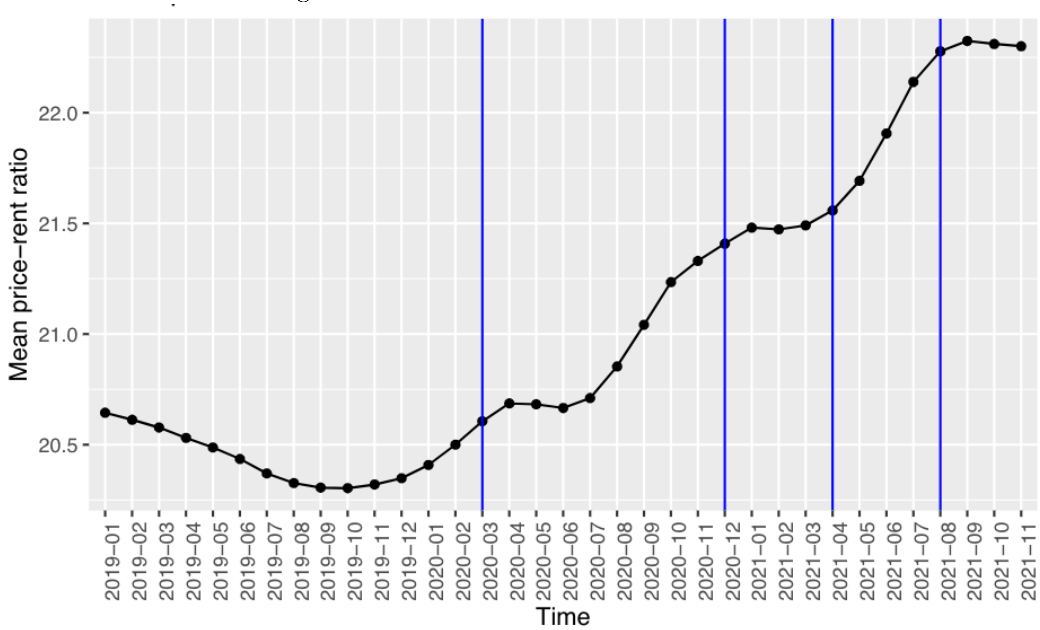
The vertical lines indicate when pandemic disruption began in the United States, when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 5: Mean Rent Index Over Time



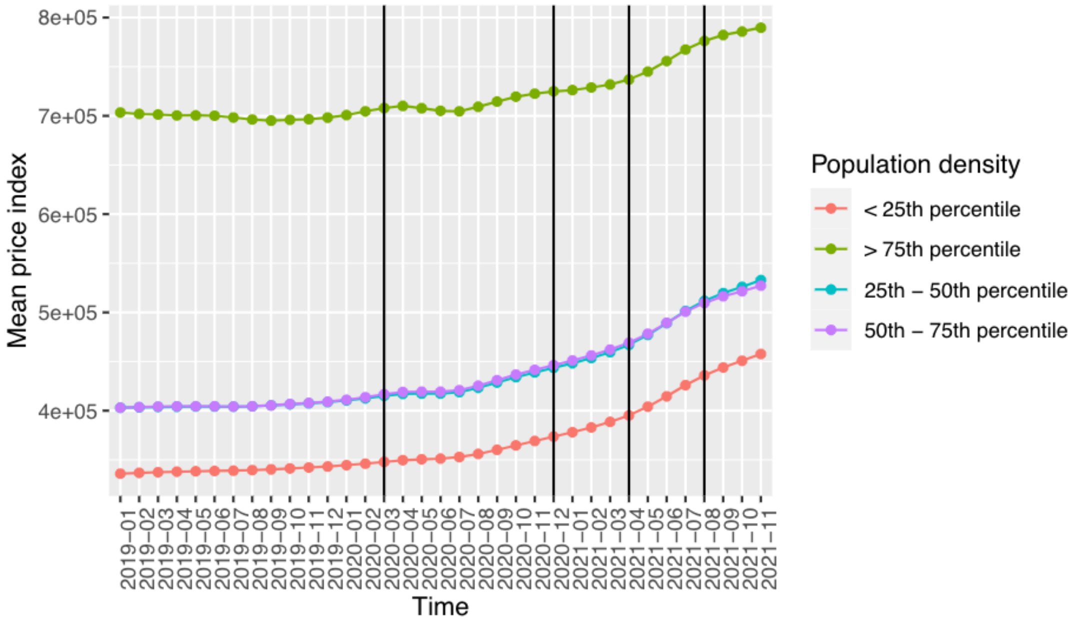
The vertical lines indicate when pandemic disruption began in the United States, when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 6: Mean Price-Rent Ratio Over Time



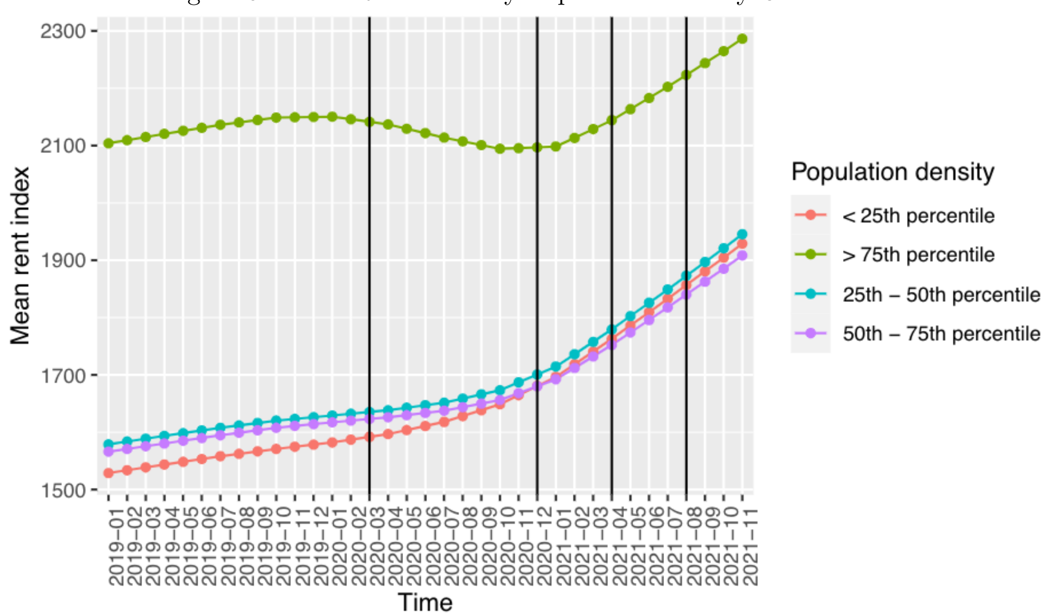
The vertical lines indicate when pandemic disruption began in the United States, when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 7: Mean Price Index by Population Density Over Time



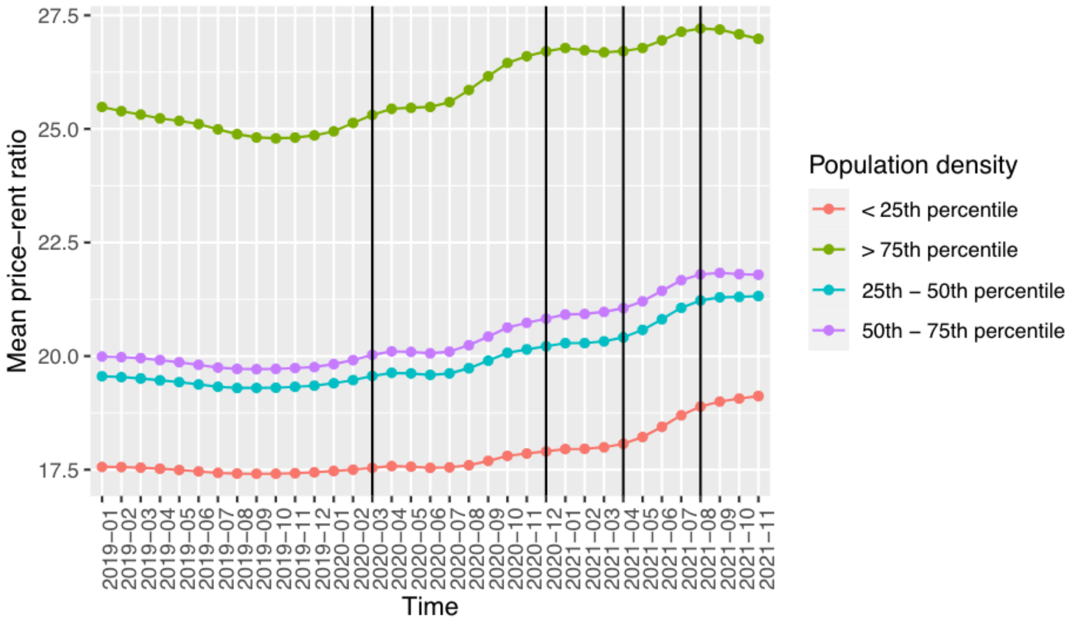
The vertical lines indicate when pandemic disruption began in the United States, when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 8: Mean Rent Index by Population Density Over Time



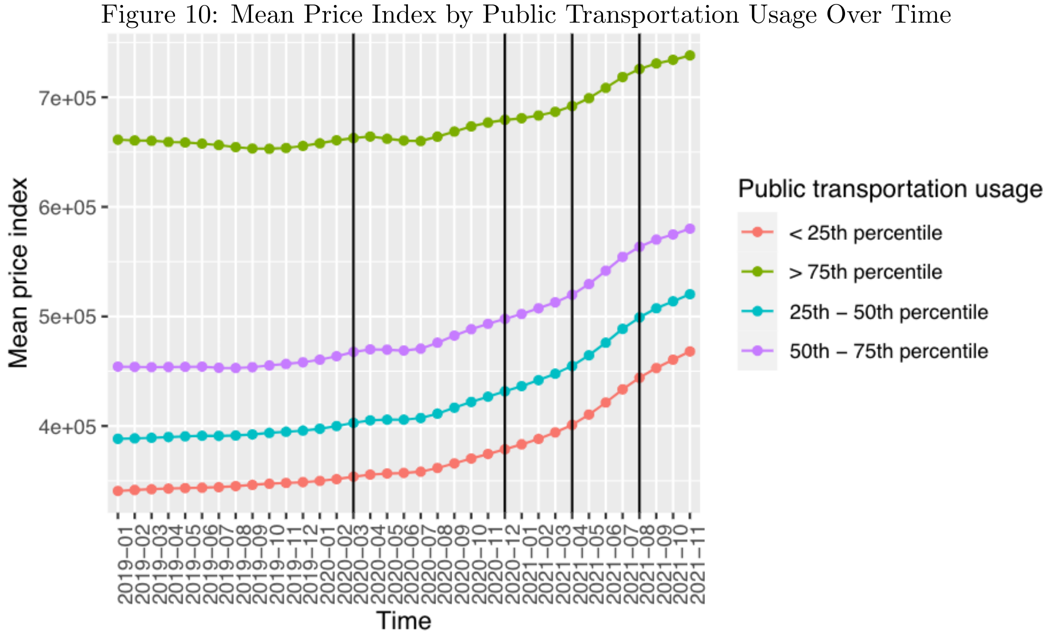
The vertical lines indicate when pandemic disruption began in the United States, when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 9: Mean Price-Rent Ratio by Population Density Over Time



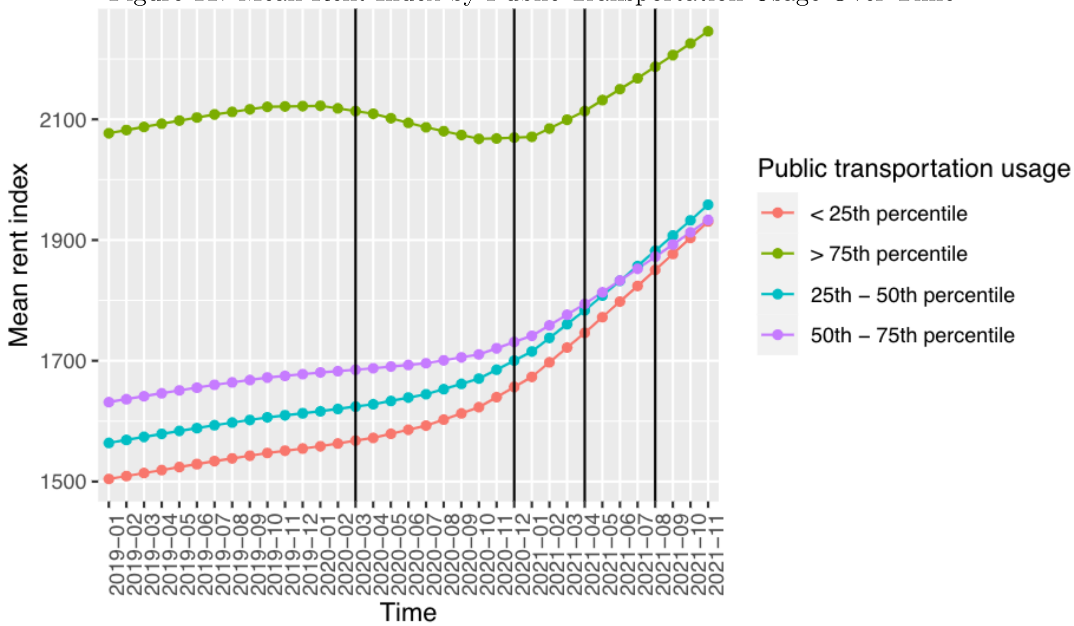
The vertical lines indicate when pandemic disruption began in the United States, when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 10: Mean Price Index by Public Transportation Usage Over Time



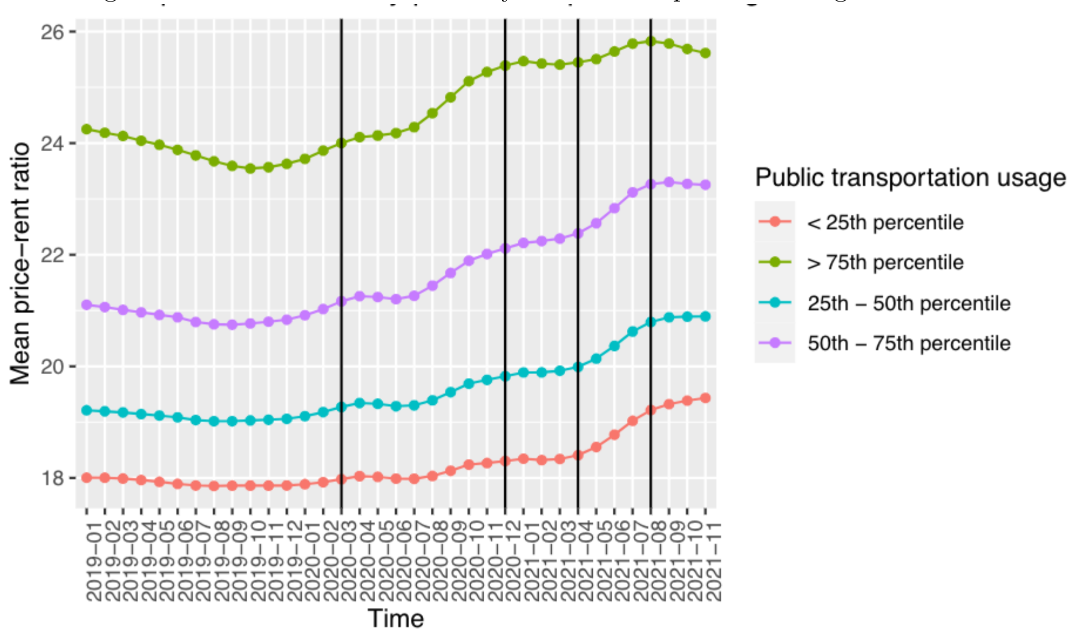
The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 11: Mean Rent Index by Public Transportation Usage Over Time



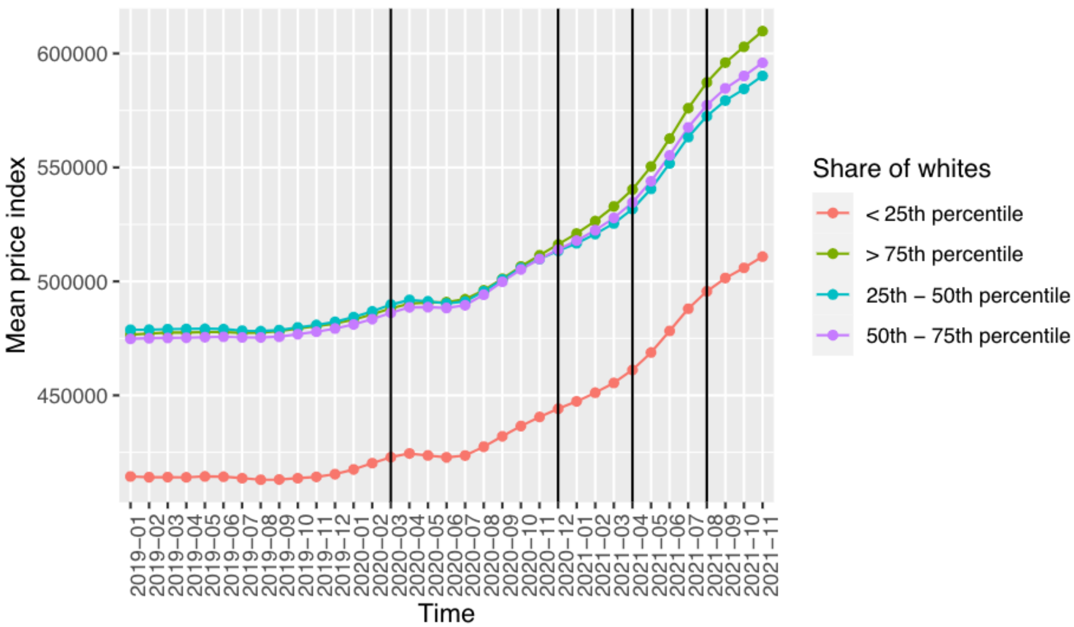
The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID–19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 12: Mean Price-Rent Ratio by Public Transportation Usage Over Time



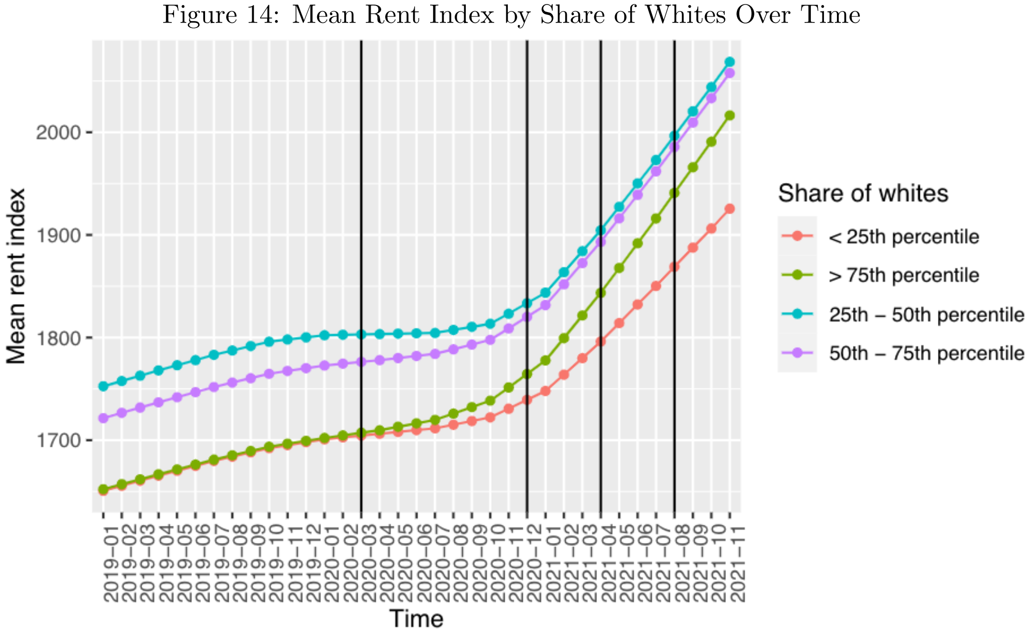
The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID–19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 13: Mean Price Index by Share of Whites Over Time



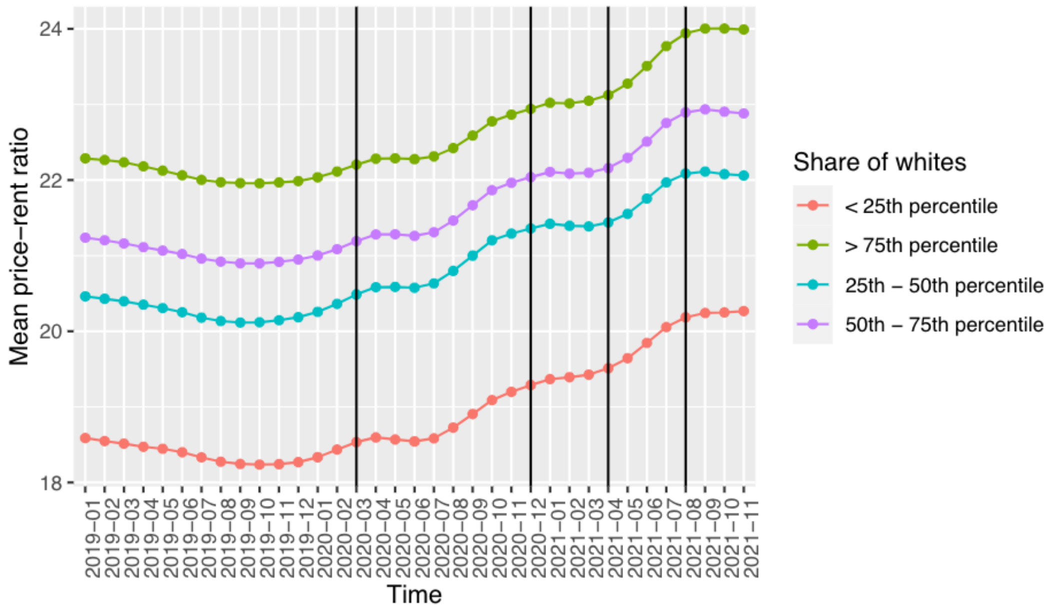
The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 14: Mean Rent Index by Share of Whites Over Time



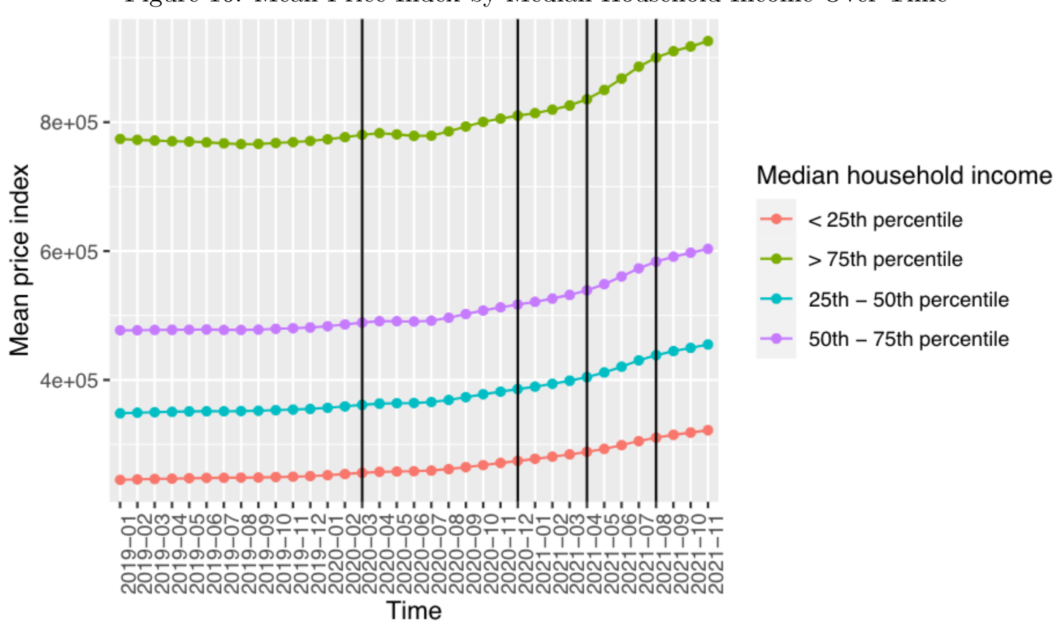
The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 15: Mean Price-Rent Ratio by Share of Whites Over Time



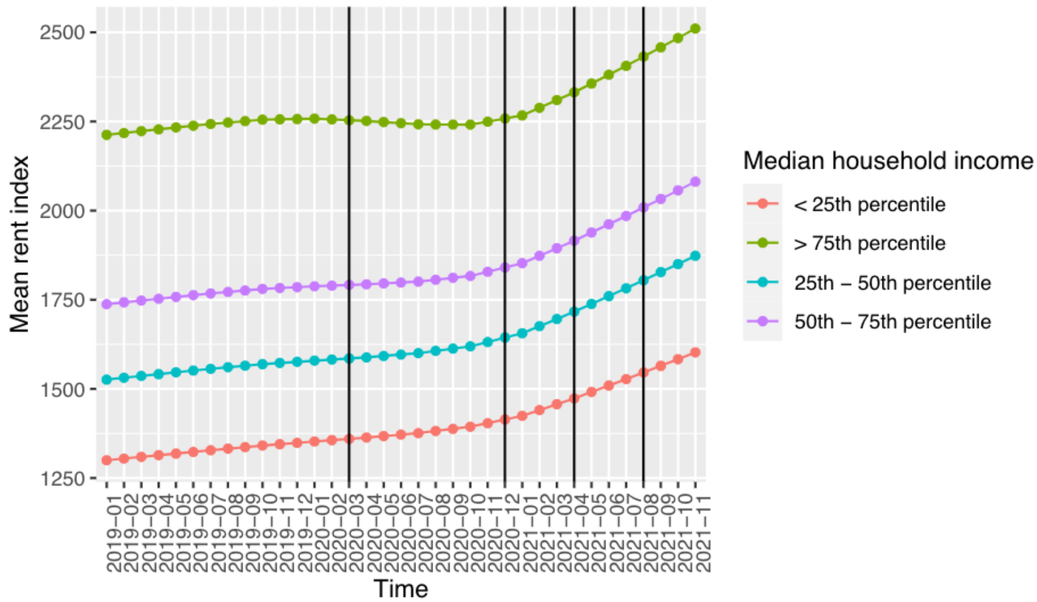
The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 16: Mean Price Index by Median Household Income Over Time



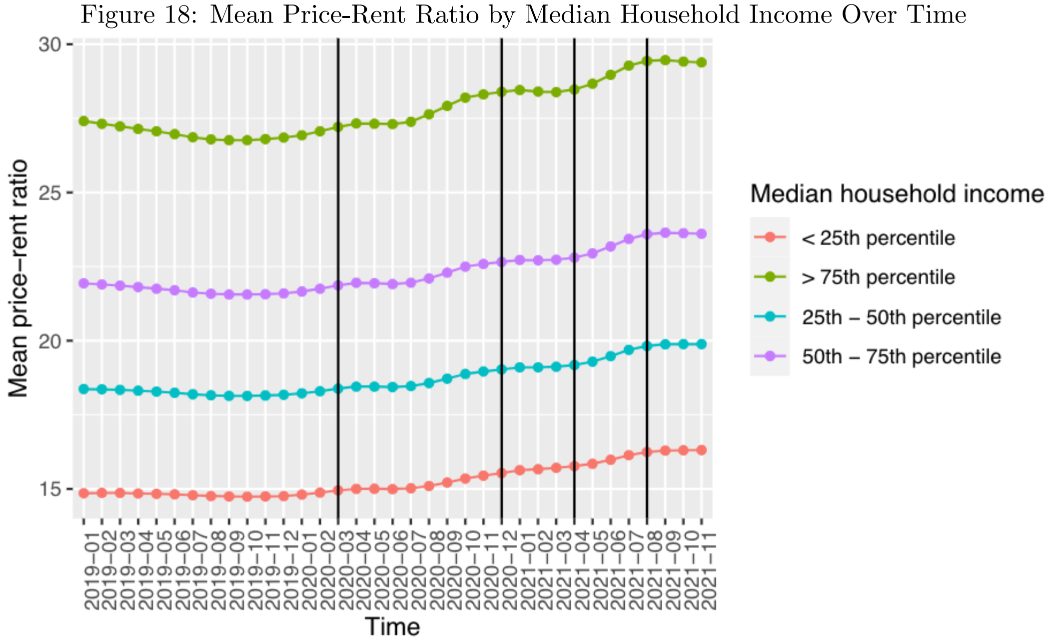
The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 17: Mean Rent Index by Median Household Income Over Time



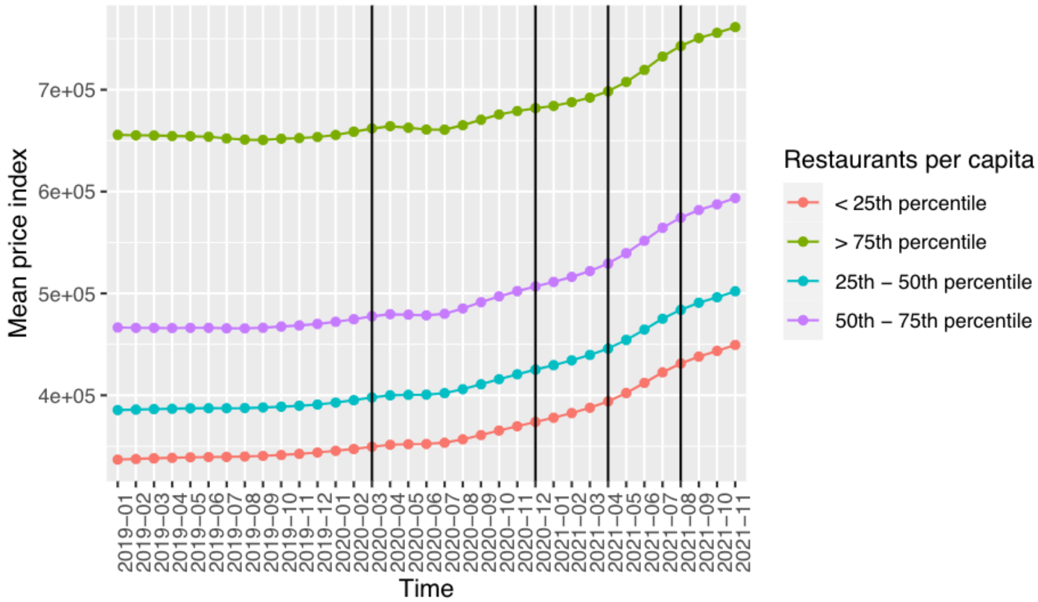
The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID–19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 18: Mean Price-Rent Ratio by Median Household Income Over Time



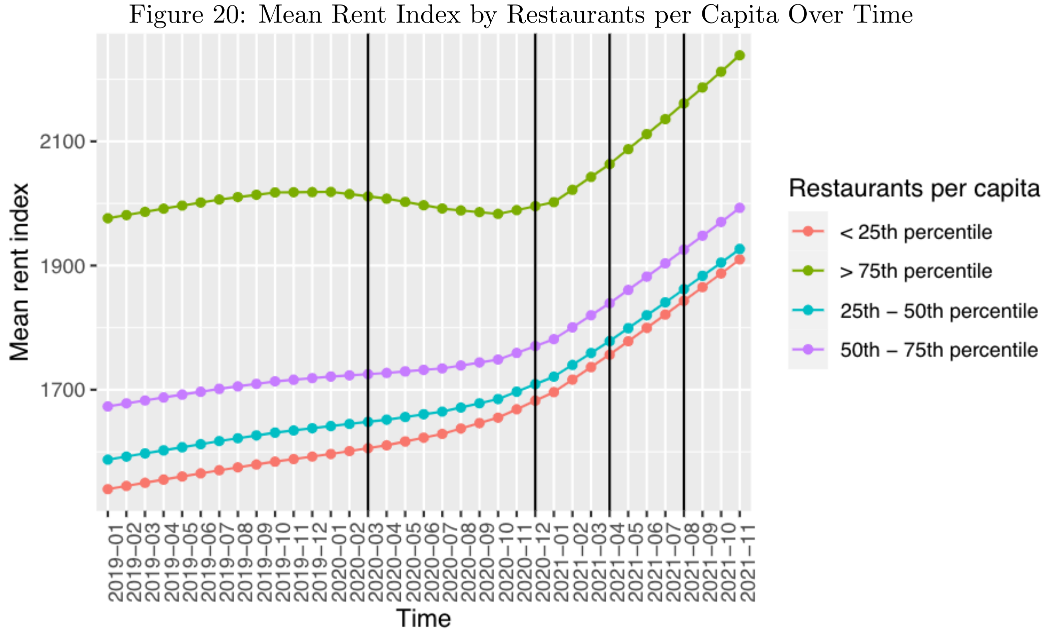
The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID–19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 19: Mean Price Index by Restaurants per Capita Over Time



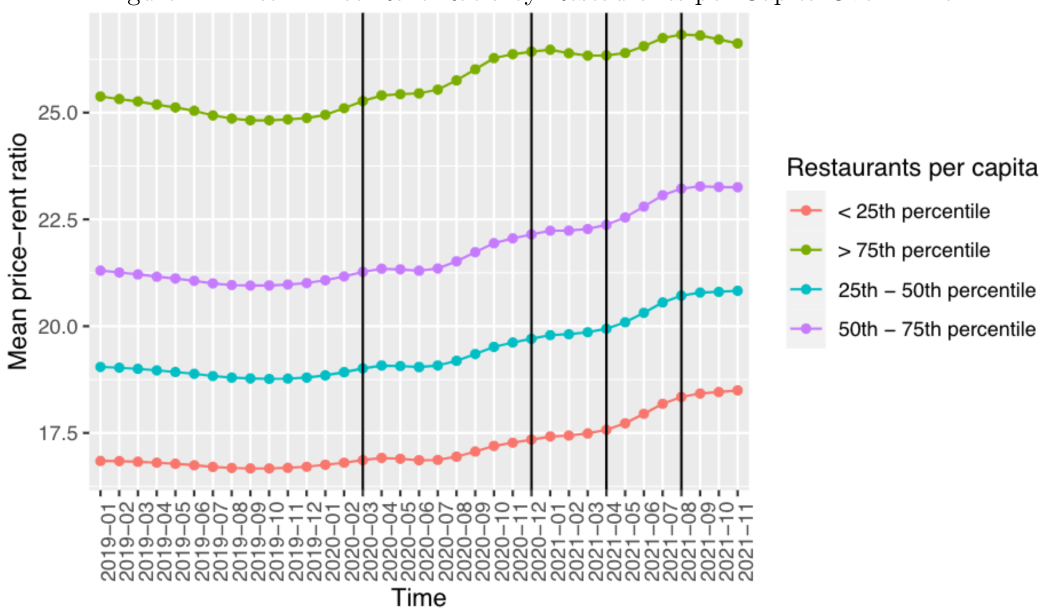
The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 20: Mean Rent Index by Restaurants per Capita Over Time



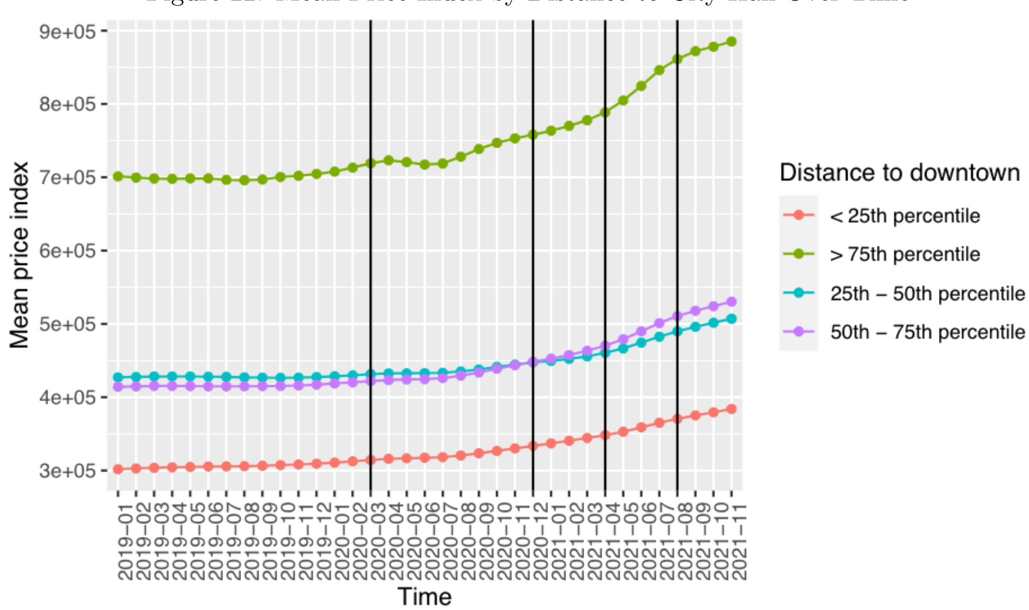
The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 21: Mean Price-Rent Ratio by Restaurants per Capita Over Time



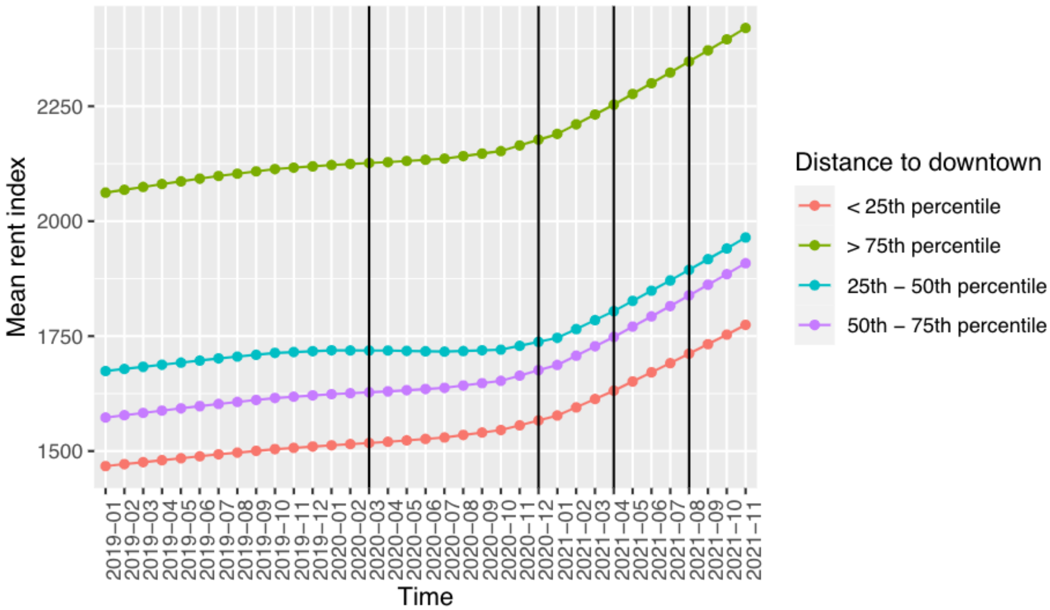
The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 22: Mean Price Index by Distance to City Hall Over Time



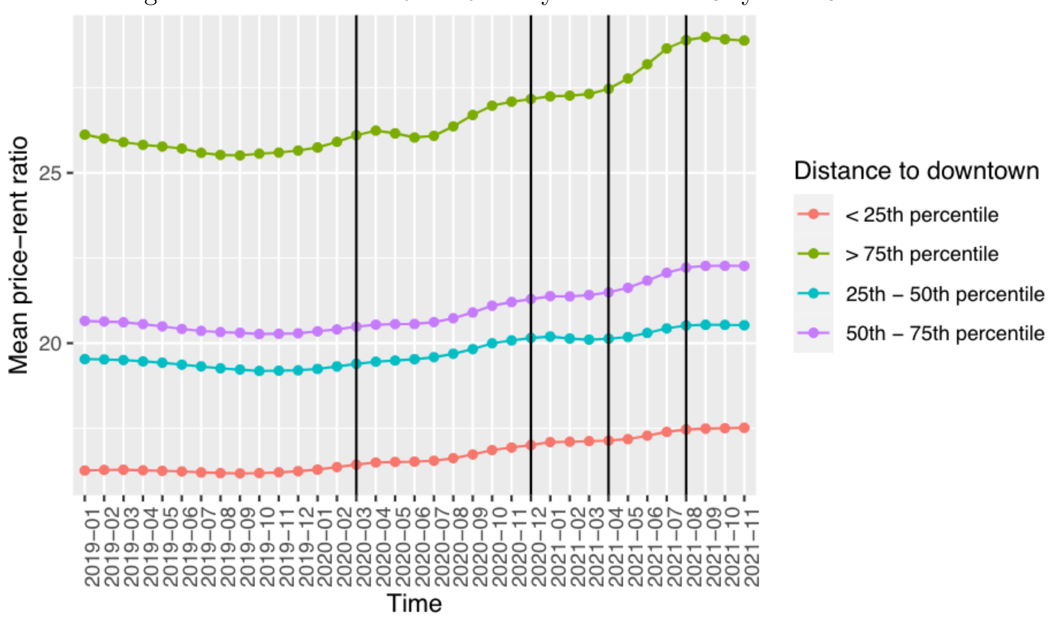
The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 23: Mean Rent Index by Distance to City Hall Over Time



The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Figure 24: Mean Price-Rent Ratio by Distance to City Hall Over Time



The vertical lines indicate when pandemic disruption began in the United States,when the FDA approved the 1st COVID−19 vaccine, when any American adult could receive the vaccine, and the peak of the Delta wave.

Table 2: Effects of the COVID-19 Pandemic Across ZIP Codes - Baseline Model

	(1)	(2)	(3)
	Log(Price Index)	Log(Rent Index)	Log(Price-Rent Ratio)
Population density (per sq mi)	0.00000278**	0.00000133***	0.00000144
	(0.00000111)	(0.000000398)	(0.000000905)
Public transportation usage (%)	0.0119***	0.00327***	0.00865***
	(0.00152)	(0.000609)	(0.00152)
Share of whites (%)	0.00575***	0.000629**	0.00512***
	(0.000577)	(0.000290)	(0.000485)
Median household income	0.00000852***	0.00000416***	0.00000436***
	(0.000000661)	(0.000000296)	(0.000000509)
Restaurants per capita	4.771***	3.160***	1.611
	(1.646)	(0.749)	(1.271)
Distance to downtown	-0.142***	-0.0234	-0.118*
	(0.0470)	(0.0339)	(0.0609)
Average case rate (per 100k population)	0.000253	0.000585***	-0.000333**
	(0.000158)	(0.0000957)	(0.000135)
Observations	61565	61565	61565

Standard errors in parentheses

Includes MSA and time fixed effects. Standard errors clustered at the MSA level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effects of the COVID-19 Pandemic Across ZIP Codes - Pandemic Concern

	(1) Log(Price Index)	(2) Log(Rent Index)	(3) Log(Price-Rent Ratio)
Population density (per sq mi)	0.00000278**	0.00000133***	0.00000144
	(0.00000111)	(0.000000398)	(0.000000905)
Public transportation usage (%)	0.0119***	0.00327***	0.00865***
	(0.00152)	(0.000609)	(0.00152)
Share of whites (%)	0.00575***	0.000629**	0.00512***
	(0.000577)	(0.000290)	(0.000485)
Median household income	0.00000852***	0.00000416***	0.00000436***
	(0.000000661)	(0.000000296)	(0.000000509)
Restaurants per capita	4.771***	3.160***	1.611
	(1.646)	(0.749)	(1.271)
Distance to downtown	-0.142***	-0.0234	-0.118*
	(0.0470)	(0.0339)	(0.0609)
Average case rate (per 100k population)	0.000253	0.000585***	-0.000333**
	(0.000158)	(0.0000957)	(0.000135)
Share worried about getting COVID (%)	0.0118***	0.0111***	0.000653
	(0.00138)	(0.00107)	(0.000787)
Pandemic indicator (0 = pre-pandemic, 1 = post-pandemic)	-0.173***	-0.233***	0.0595**
	(0.0384)	(0.0294)	(0.0296)
Observations	61565	61565	61565

Standard errors in parentheses

Includes MSA and time fixed effects. Standard errors clustered at the MSA level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effects of the COVID-19 Pandemic Across ZIP Codes - Pandemic Duration Expectations

	(1) Log(Price Index)	(2) Log(Rent Index)	(3) Log(Price-Rent Ratio)
Population density (per sq mi)	0.00000278**	0.00000133***	0.00000144
	(0.00000111)	(0.000000398)	(0.000000905)
Public transportation usage (%)	0.0119***	0.00327***	0.00865***
	(0.00152)	(0.000609)	(0.00152)
Share of whites (%)	0.00575***	0.000629**	0.00512***
	(0.000577)	(0.000290)	(0.000485)
Median household income	0.00000852***	0.00000416***	0.00000436***
	(0.000000661)	(0.000000296)	(0.000000509)
Restaurants per capita	4.771***	3.160***	1.611
	(1.646)	(0.749)	(1.271)
Distance to downtown	-0.142***	-0.0234	-0.118*
	(0.0470)	(0.0339)	(0.0609)
Average case rate (per 100k population)	0.000253	0.000585***	-0.000333**
	(0.000158)	(0.0000957)	(0.000135)
Share who believe pandemic will end in a few months or less (%)	-0.00196***	-0.00186***	-0.000109
	(0.000229)	(0.000178)	(0.000131)
Pandemic indicator (0 = pre-pandemic, 1 = post-pandemic)	0.293***	0.207***	0.0853***
	(0.0235)	(0.0186)	(0.0100)
Observations	61565	61565	61565

Standard errors in parentheses

Includes MSA and time fixed effects. Standard errors clustered at the MSA level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effects of the COVID-19 Pandemic Across ZIP Codes - Pandemic Outlook

	(1) Log(Price Index)	(2) Log(Rent Index)	(3) Log(Price-Rent Ratio)
Population density (per sq mi)	0.00000278**	0.00000133***	0.00000144
	(0.00000111)	(0.000000398)	(0.000000905)
Public transportation usage (%)	0.0119***	0.00327***	0.00865***
	(0.00152)	(0.000609)	(0.00152)
Share of whites (%)	0.00575***	0.000629**	0.00512***
	(0.000577)	(0.000290)	(0.000485)
Median household income	0.00000852***	0.00000416***	0.00000436***
	(0.000000661)	(0.000000296)	(0.000000509)
Restaurants per capita	4.771***	3.160***	1.611
	(1.646)	(0.749)	(1.271)
Distance to downtown	-0.142***	-0.0234	-0.118*
	(0.0470)	(0.0339)	(0.0609)
Average case rate (per 100k population)	0.000253	0.000585***	-0.000333**
	(0.000158)	(0.0000957)	(0.000135)
Share who believe pandemic is improving - worsening (%)	-0.000319***	-0.000301***	-0.0000176
	(0.0000372)	(0.0000288)	(0.0000213)
Pandemic indicator (0 = pre-pandemic, 1 = post-pandemic)	0.262***	0.178***	0.0836***
	(0.0208)	(0.0165)	(0.00961)
Observations	61565	61565	61565

Standard errors in parentheses

Includes MSA and time fixed effects. Standard errors clustered at the MSA level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effects of the COVID-19 Pandemic Across ZIP Codes - Effects by Pandemic Concern

	(1) Log(Price Index)	(2) Log(Rent Index)	(3) Log(Price-Rent Ratio)
Population density (per sq mi)	0.00000313**	0.00000160***	0.00000153
	(0.00000121)	(0.000000441)	(0.000000928)
Public transportation usage (%)	0.0124***	0.00386***	0.00853***
	(0.00156)	(0.000600)	(0.00153)
Share of whites (%)	0.00577***	0.000602**	0.00517***
	(0.000606)	(0.000288)	(0.000488)
Median household income	0.00000877***	0.00000439***	0.00000438***
	(0.000000680)	(0.000000310)	(0.000000511)
Restaurants per capita	5.221***	3.699***	1.521
	(1.708)	(0.791)	(1.282)
Distance to downtown	-0.143***	-0.0224	-0.120**
	(0.0468)	(0.0328)	(0.0602)
Average case rate (per 100k population)	0.000722	0.00146***	-0.000739
	(0.000502)	(0.000398)	(0.000590)
Share worried about getting COVID (%)	0.0133***	0.0126***	0.000671
	(0.00130)	(0.00113)	(0.000785)
Pandemic indicator (0 = pre-pandemic, 1 = post-pandemic)	-0.181***	-0.245***	0.0637**
	(0.0359)	(0.0312)	(0.0313)
Worried x Population density	-1.42e-08***	-1.07e-08***	-3.58e-09
	(5.31e-09)	(3.01e-09)	(3.49e-09)
Worried x Public transportation usage	-0.0000188***	-0.0000239***	0.00000510
	(0.00000585)	(0.00000410)	(0.00000798)
Worried x Share of whites	-0.000000751	0.00000113	-0.00000188
	(0.00000320)	(0.00000353)	(0.00000277)
Worried x Household income	-1.02e-08***	-9.24e-09***	-9.82e-10
	(1.89e-09)	(1.60e-09)	(1.62e-09)
Worried x Restaurants per capita	-0.0180***	-0.0216***	0.00360
	(0.00362)	(0.00395)	(0.00236)
Worried x Distance to downtown	0.0000451	-0.0000420	0.0000872
	(0.000109)	(0.000133)	(0.000105)
Worried x Average case rate	-0.0000133	-0.0000225***	0.00000921
	(0.0000100)	(0.00000731)	(0.0000124)
Observations	61565	61565	61565

Standard errors in parentheses

Includes MSA and time fixed effects. Standard errors clustered at the MSA level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Effects of the COVID-19 Pandemic Across ZIP Codes - Effects by Pandemic Duration Expectations

	(1) Log(Price Index)	(2) Log(Rent Index)	(3) Log(Price-Rent Ratio)
Population density (per sq mi)	0.00000300**	0.00000148***	0.00000152*
	(0.00000116)	(0.000000429)	(0.000000915)
Public transportation usage (%)	0.0123***	0.00367***	0.00863***
	(0.00156)	(0.000634)	(0.00153)
Share of whites (%)	0.00578***	0.000623**	0.00516***
	(0.000587)	(0.000288)	(0.000485)
Median household income	0.00000864***	0.00000426***	0.00000437***
	(0.000000669)	(0.000000303)	(0.000000509)
Restaurants per capita	4.973***	3.390***	1.582
	(1.675)	(0.771)	(1.276)
Distance to downtown	-0.143***	-0.0236	-0.119*
	(0.0468)	(0.0331)	(0.0605)
Average case rate (per 100k population)	-0.000462**	0.000104	-0.000567***
	(0.000223)	(0.000188)	(0.000171)
Share who believe pandemic will end in a few months or less (%)	-0.00171***	-0.00157***	-0.000141
	(0.000294)	(0.000240)	(0.000232)
Pandemic indicator (0 = pre-pandemic, 1 = post-pandemic)	0.304***	0.215***	0.0892***
	(0.0226)	(0.0182)	(0.0101)
Few months or less x Population density	-1.33e-08***	-8.57e-09***	-4.70e-09*
	(4.59e-09)	(2.53e-09)	(2.68e-09)
Few months or less x Public transportation usage	-0.0000222**	-0.0000235***	0.00000128
	(0.00000972)	(0.00000335)	(0.00000718)
Few months or less x Share of whites	-0.00000168	0.000000415	-0.00000210
	(0.00000218)	(0.00000225)	(0.00000170)
Few months or less x Household income	-6.55e-09***	-5.78e-09***	-7.64e-10
	(1.40e-09)	(9.22e-10)	(1.20e-09)
Few months or less x Restaurants per capita	-0.0119***	-0.0134***	0.00151
	(0.00248)	(0.00254)	(0.00156)
Few months or less x Distance to downtown	0.0000993	0.0000392	0.0000601
	(0.0000793)	(0.0000834)	(0.0000771)
Few months or less x Average case rate	0.0000428***	0.0000305***	0.0000124***
	(0.00000989)	(0.00000818)	(0.00000404)
Observations	61565	61565	61565

Standard errors in parentheses

Includes MSA and time fixed effects. Standard errors clustered at the MSA level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Effects of the COVID-19 Pandemic Across ZIP Codes - Effects by Pandemic Outlook

	(1) Log(Price Index)	(2) Log(Rent Index)	(3) Log(Price-Rent Ratio)
Population density (per sq mi)	0.00000278**	0.00000133***	0.00000145
	(0.00000111)	(0.000000398)	(0.000000906)
Public transportation usage (%)	0.0119***	0.00328***	0.00865***
	(0.00152)	(0.000609)	(0.00152)
Share of whites (%)	0.00575***	0.000627**	0.00512***
	(0.000578)	(0.000290)	(0.000485)
Median household income	0.00000852***	0.00000416***	0.00000436***
	(0.000000661)	(0.000000295)	(0.000000509)
Restaurants per capita	4.775***	3.162***	1.613
	(1.646)	(0.749)	(1.271)
Distance to downtown	-0.142***	-0.0234	-0.118*
	(0.0470)	(0.0338)	(0.0609)
Average case rate (per 100k population)	0.000251	0.000617***	-0.000366**
	(0.000206)	(0.000139)	(0.000163)
Pandemic indicator (0 = pre-pandemic, 1 = post-pandemic)	0.262***	0.178***	0.0842***
	(0.0208)	(0.0163)	(0.0101)
Share who believe pandemic is improving - worsening (%)	0.0000386	-0.0000599	0.0000985
	(0.000106)	(0.0000970)	(0.0000697)
Outlook x Population density	-3.38e-09*	5.24e-10	-3.91e-09**
	(1.99e-09)	(7.78e-10)	(1.69e-09)
Outlook x Public transportation usage	-0.00000607***	-0.0000109***	0.00000478
	(0.00000195)	(0.00000149)	(0.00000293)
Outlook x Share of whites	0.000000274	0.00000113	-0.000000858
	(0.000000796)	(0.000000917)	(0.000000878)
Outlook x Household income	-2.56e-09***	-2.09e-09***	-4.68e-10
	(4.51e-10)	(5.43e-10)	(4.80e-10)
Outlook x Restaurants per capita	-0.00542***	-0.00227***	-0.00315***
	(0.000945)	(0.000678)	(0.000712)
Outlook x Distance to downtown	0.00000563	-0.00000855	0.0000142
	(0.0000433)	(0.0000316)	(0.0000332)
Outlook x Average case rate	-0.00000353	-0.00000242	-0.00000110
	(0.00000314)	(0.00000396)	(0.00000204)
Observations	61565	61565	61565

Standard errors in parentheses

Includes MSA and time fixed effects. Standard errors clustered at the MSA level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$