The Impact of the COVID-19 Pandemic on the Demand for Density: Evidence from the U.S. Housing Market

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Abstract

We study the impact of the COVID-19 pandemic on the location demand for housing. We find that the pandemic has led to a shift in housing demand away from neighborhoods with high population density. The reduced demand for density is driven partially by the diminished need for living close to telework-compatible jobs and the declining value of access to consumption amenities. Neighborhoods with high pre-COVID-19 home values also see a greater drop in housing demand. We also find significant shift in housing demand away from large cities, though the magnitude is smaller.

Keywords: COVID-19, Pandemic, Density, Housing, Telework, Amenity

JEL Codes: R2, R3, I1

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1 Introduction

After the COVID-19 pandemic started, many office workers started to work from home (Bartik et al., 2020; Bick et al., 2020). Consumption amenities such as restaurants saw a sudden drop in visits (Cox et al., 2020). As a result, the desirability of dense neighborhoods and large cities, where jobs and consumption amenities are spatially concentrated, may have declined.

We find that the pandemic has indeed led to a strong shift in housing demand from central cities and dense neighborhoods to the suburbs and neighborhoods with lower population density. We use a number of local housing indicators such as inventory, home price, and rent to track the spatial difference in the change of housing demand, and document a strong divergence in growth trajectories in these indicators in central and dense neighborhoods versus suburban and remote neighborhoods.

We make several conjectures for the reasons behind the shift:

1. Dense neighborhoods tend to be close to job centers, which tend to have a greater share of telework-compatible jobs. With the rise of remote arrangements, the need for living in these neighborhoods could diminish.
2. Dense neighborhoods tend to have more consumption amenities. Because of the drop in visits to amenities during the pandemic, the value of living closer to premium locations could decline.
3. Dense neighborhoods tend to have higher costs of housing due to the lower housing supply elasticities (Baum-Snow and Han, 2020). As the need for living in these locations diminishes, the value of bearing such high housing costs to be in these locations could decrease.

We present empirical evidence that lends support to all of the conjectures. We find that home inventory growth is higher in neighborhoods with a greater share of telework-compatible jobs, a larger per-capita number of restaurants, and higher pre-COVID-19 home prices, indicating a spatial shift in demand from these neighborhoods. Home price and rent growth picks up some of the spatial variation, though with a smaller magnitude. We also find a shift in housing demand away from large and expensive cities, although the magnitude is smaller than the shift from central cities to the suburbs.

This paper contributes to the literature on how city structures change in the presence of the dispersion forces of diseases (Ambrus et al., 2020; Davis et al., 2021; Delventhal et al., 2021). Recent papers have

1 Appendix A1 presents a stylized model to capture the underlying mechanisms.
2 Table A1 confirms such correlations.
documented migration and bid-rent curve patterns consistent with our findings (Ramani and Bloom, 2021; Althoff et al., 2020; Gupta et al., 2021). We are the first to examine the pandemic’s effect on neighborhood-level spatial variation in housing demand and to test the underlying driving forces.

2 Data

For housing market outcomes, we use (i) monthly home sales, new listings, and inventory from Redfin Data Center since January 2016, (ii) the monthly repeated-transaction home price index (HPI) from CoreLogic, and (iii) monthly rent data—the Zillow Observed Rent Index (ZORI)—from Zillow Research.

We use the 2016 ZIP Code Business Patterns (ZCBP) and an industry-to-occupation crosswalk to calculate the number of jobs by occupation and ZIP Code. We then assign a telework indicator developed by Dingel and Neiman (2020) to each occupation, and compute the share of telework-compatible jobs within a 3-mile radius of each ZIP Code. We also compute the per-capita number of restaurants within a 3-mile radius of each ZIP Code.

We obtain local population characteristics from the 2013–2017 American Community Survey (Manson et al., 2020). We obtain county-level COVID-19 case rates from the Opportunity Insights Economic Tracker and weekly visit patterns data from SafeGraph Inc.

3 Empirical Analysis

Figures 1a, 1c, and 1e show the growth of inventory, home prices, and rents relative to the 2019 average for each month by distance to downtown for the 25 largest metropolitan statistical areas (MSAs). After the pandemic started in March 2020, the growth of home inventory in central cities far outpaced the growth in the suburbs. The strong diverging trends can be also observed in rental prices. Home price growth also exhibits a diverging trend between central cities and the suburbs, but the gap is smaller. The vast divergence in inventory and rent growth between central cities and the suburbs constitutes strong evidence that the demand for housing has shifted toward the suburbs. The smaller divergence in home price growth could be driven by the market expectation that the future demand for central locations could recover.

We also examine differential effects of the pandemic on housing demand across cities. Figures 1b, 1d, and 1f show the growth of inventory, home prices, and rents relative to the 2019 average for each month.

3https://opportunityinsights.org
by the size of MSAs—the 25 largest MSAs vs. others. The figures present evidence of a shift in housing demand from larger cities to smaller ones, but the magnitude is smaller compared with the shift from central cities and the suburbs.

3.1 Regression Analysis

To unpack the driving forces behind the large shift in housing demand within cities, we estimate the following regression at the ZIP Code (neighborhood) level:

$$\log(s_{ncmy}) = \beta_1 After_{my} \cdot x_{nc} + \beta_2 After_{my} \cdot \log(CaseRate_{nc})$$

$$+ After_{my} \cdot \lambda_c + \pi_{my} + \delta_{nm} + \gamma_{ny} + \epsilon_{ncmy},$$

where $s_{ncmy}$ is a local outcome, such as inventory, home prices (HPIs), and rents in $n$ within city $c$ in month $m$ of year $y$. $After_{my}$ indicates months after March 2020. $x_{nc}$ denotes a neighborhood characteristic of interest, such as density. We control for various characteristics interacted with $After_{my}$. $CaseRate_{nc}$ is the average case rate between April 2020 and February 2021 of the county that neighborhood $n$ belongs to. $After_{my} \cdot \lambda_c$ denotes city-specific effects of the pandemic, which absorbs differential lockdown effects across cities. $\pi_{my}$ denotes a time fixed effect. $\delta_{nm}$ denotes month-varying seasonality in neighborhood $n$. $\gamma_{ny}$ denotes year-varying local shocks. The coefficients of interest are $\beta_1$, which represent differential effects of the pandemic across various $x_{nc}$.

Table 1 presents the estimates of $\beta_1$ at the ZIP Code level. Panel A confirms the finding in Figure 1 that there is a reduced demand for central cities and dense neighborhoods. Panel B shows that neighborhoods with a greater share of telework-compatible jobs, more restaurants per capita, and higher pre-COVID-19 home prices witnessed a relative increase in inventory; there is also a relative decline in home and rental prices in such neighborhoods. The results confirm the conjectures presented in Section 1.

Appendix A3 presents MSA-level regression results, which suggest that housing demand has shifted away from cities with a greater share of telework jobs and higher pre-COVID-19 home values.

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4Appendix A2 presents county-level analysis.
5We treat 2020 and 2021 as the same year for neighborhood-year fixed effects, because 2021 is after the outbreak.
6Table A2 presents the estimates at the county level, which are consistent with results in Table 1.
7Table A3 presents the results with sales and new listings as outcome variables.
8Table A4 presents the estimates by month, which suggest that the changed demand for different neighborhood characteristics such as access to telework-compatible jobs and restaurants kicked in gradually.
Figure 1: Shift in Housing Demand Within and Across MSAs

Note: The figures present the growth of the housing market outcomes relative to the 2019 averages. Figures a, c, and e plot the changes at the ZIP Code level by distance to downtown for the 25 largest MSAs. Figures b, d, and f plot the changes at the MSA level by the size of MSA.
Table 1: Effects of COVID-19 across ZIP Codes

|                          | Log (Inventory) (1) | Log (HPI) (2) | Log (Rents) (3) |
|--------------------------|---------------------|---------------|-----------------|
| **Panel A: Baseline**    |                     |               |                 |
| After $\times$ Log (Distance to Downtown) | -0.0839***         | 0.000967      | 0.0101***       |
|                          | (0.0115)            | (0.000847)    | (0.00104)       |
| After $\times$ Log (Density) | 0.0304***          | -0.00325**    | -0.00715***     |
|                          | (0.00706)           | (0.00154)     | (0.00230)       |
| Observations             | 639,463             | 374,784       | 140,594         |

| **Panel B: Neighborhood Characteristics** |                     |               |                 |
| After $\times$ Log (Distance to Downtown) | -0.0387***         | -0.000720     | 0.00491***      |
|                          | (0.00795)           | (0.000901)    | (0.00116)       |
| After $\times$ Log (Density)          | 0.0135**           | -0.00194**    | -0.00644***     |
|                          | (0.00628)           | (0.000983)    | (0.00168)       |
| After $\times$ Log (Jobs per capita) | 0.0141             | 0.000927      | -0.00882***     |
|                          | (0.0123)            | (0.00128)     | (0.00188)       |
| After $\times$ Log (Share of Telework-compatible Jobs) | 0.103***        | -0.00495**    | -0.00291        |
|                          | (0.0252)            | (0.00203)     | (0.00350)       |
| After $\times$ Log (Restaurants per capita) | 0.0310**          | -0.00129      | 0.00545***      |
|                          | (0.0122)            | (0.00143)     | (0.00172)       |
| After $\times$ Log (Pre-COVID Home Value)  | 0.0973***          | -0.00757***   | -0.0150***      |
|                          | (0.0356)            | (0.00271)     | (0.00387)       |
| Observations             | 585,600             | 372,161       | 139,560         |

Note: The sample comprises all ZIP Codes between January 2016 and February 2021, except April 2020. The specifications is described in Section 3.1. We also control for After $\times$ Log (Income) and After $\times$ Log (Share of Whites). Observations are weighted by the ZIP Code’s population in columns 1–2, and the ZIP Code’s renter population in column 3. Standard errors are clustered at the MSA level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 
3.2 Changes in Traffic Patterns

To corroborate that there is a diminished value of visiting prime city locations for work or amenities, we show in Figure 2 that the number of visits to offices and restaurants plummeted after the pandemic, and the drop is greater for the establishments located in central cities.

![Figure 2: Visitor Traffic to Points-of-Interest](image)

(a) Office

(b) Restaurant

Note: The figures plot the average number of visits to offices (NAICS 51, 52, and 54) and restaurants (NAICS 722511) located by distance to downtown in the 25 largest MSAs, normalized by the first week of 2020, using data from SafeGraph Inc.

4 Conclusion

We find that the pandemic reduced the housing demand in central city neighborhoods and neighborhoods with higher population density. The decreased demand for density is partially driven by (i) the diminished need for living close to telework-compatible jobs, and (ii) the dwindling attraction of consumption amenities. Moreover, cities and neighborhoods with higher pre-COVID-19 home values witnessed a greater decline in housing demand.

Our findings suggest that COVID-19 has re-introduced disease transmission as a dispersion force in the urban spatial equilibrium, certainly in the short run. The smaller divergence in home price growth relative to that in inventory and rent growth between central cities and suburbs suggest the market anticipates that future demand for central locations could bound back to some degree in the long run.

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9 Figure A2 presents the number of visits to schools, parks, and gyms.
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Appendix

A1 Stylized Spatial Equilibrium Model

We present a simple stylized spatial equilibrium model to demonstrate the mechanisms through which the COVID-19 pandemic can affect the demand for dense locations. The model generates several predictions, which can be tested with data.

Assume that there are two locations: a central dense location \((j = 1)\) and a remote location \((j = 2)\). Residents choose either location to live in, based on commute time, amenity provision, and rents. To keep the framework simple to analyze, we assume that residents are ex ante homogeneous before they choose the residence location. Once a location is picked, each worker’s job may be telework-compatible or not with stochastic probabilities \(s_t\) and \(1 - s_t\), respectively.\(^{10}\)

Therefore, the ex-ante utility that each location \((j)\) gives a worker is as follows:

\[
U_j = -\theta E(c_j) + \gamma a_j - r_j,
\]

where \(E(c_j)\) is the ex ante expected commute time in location \(j\), which is the average commute time of telework-compatible jobs \((C^t)\) and non-telework-compatible jobs \((e^{nt})\), weighted by the probability that the worker’s job telework-compatible or not:

\[
E(c_j) = s^t c^t_j + (1 - s^t) c^{nt}_j.
\]

The utility associated with a location also depends on \(a_j\), the level of amenity provision at location \(j\). The amenity level is the average of the level of essential amenities \((a^e_j)\) and non-essential amenities \((a^{ne}_j)\), weighted by \(s^e\) and \(s^{ne}\) respectively, which can be considered as utility weights:

\[
a_j = s^e a^e_j + s^{ne} a^{ne}_j.
\]

Finally, \(r_j\) is the rent in location \(j\). We assume that housing is supplied inelastically. The inverse housing

\(^{10}\)To allow for a simple analytical comparative static exercise, we need to keep residents homogeneous when they choose locations.
supply equation is
\[ r_j = \alpha + \varepsilon_j \ln(N_j), \]
where \( N_j \) is the population in location \( j \). We assume that rent goes up as population increases, and \( \varepsilon_j \) is the inverse housing supply elasticity with respect to location demand/population. The more elastic housing supply is, the smaller \( \varepsilon_j \) is.

### A1.1 Spatial Equilibrium

In spatial equilibrium, the housing market clears, and different locations’ population (\( N_1 \) and \( N_2 \)) and rent levels (\( r_1 \) and \( r_2 \)) are determined by the housing market clearing condition. Under the simplifying assumption of homogeneous residents, the utility levels are equalized across the two locations as \( \bar{U} \). Hence, the spatial equilibrium is implicitly characterized by

\[
\bar{U} = -\theta \left( s^t c^t_j + (1 - s^t) c^nt_j \right) + \gamma \left( s^e a^e_j + s^{ne} a^{ne}_j \right) - \alpha - \varepsilon_j \ln(N_j), \quad \forall j = 1, 2. \quad (2)
\]

To put this equation in the perspective of dense and remote locations, we assume that prior to the pandemic, the expected commute time for both types of jobs is shorter when living in the dense location than living in the remote location: \( c^t_1 < c^t_2 \) and \( c^nt_1 < c^nt_2 \), and the non-essential amenities such as eateries and cafes are richer in the dense location: \( a^{ne}_1 > a^{ne}_2 \). For essential amenities, we assume that they are equally provisioned in dense and remote locations: \( a^e_1 = a^e_2 \).

With a lower cost of commuting and better provision of amenities, the dense location would have attracted a larger population than the remote location. However, the larger population would drive up rents and press down the utility of living in the dense location. In equilibrium, the population distribution (\( N_1 \) and \( N_2 \)) is determined such that the equilibrium utility levels of both locations are equalized. Without the loss of generality, we normalize the total population to 1: \( N_1 + N_2 = 1 \). Equation (2) provides us with an analytical framework to solve for the effect of the pandemic on the equilibrium location demand.

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¹¹Since the dense location is better both in terms of commuting time and amenities, if we assume that the inverse housing supply elasticities are the same (e.g., same provision of buildable land and construction cost), then the dense location will have a larger population and higher density.
A1.2 The Effects of COVID-19 on Location Demand

Once the COVID-19 pandemic hits, assume that workers with telework-compatible jobs have commute time of zero regardless of their locations: $c_t^1 = c_t^2 = 0$. Moreover, assume that essential amenities are operational and are unchanged, but access to non-essential amenities becomes zero: $\hat{a}_1^{ne} = \hat{a}_2^{ne} = 0$. Under these assumptions, we use the implicit function theorem to derive the model-implied impact of changes in commute time and amenities on location demand.\(^{12}\)

The impact of the change in commute time for telework-compatible jobs on location demand is

$$\frac{\partial N_1}{\partial (c_t^1 - c_t^2)} = -\frac{\theta s^t}{\frac{1}{N_1} + \frac{\varepsilon^2}{N_2}}.$$ 

Since the difference in commute time increases from a negative number $c_t^1 - c_t^2$ to 0 after the pandemic, the change in the location demand for the dense location due to the change in commute time for telework-compatible jobs is

$$-\theta s^t \Delta (c_t^1 - c_t^2) \varepsilon^1 N_1 + \varepsilon^2 N_2 < 0,$$

The impact of the change in the provision of amenities on location demand is

$$\frac{\partial N_1}{\partial (a_{ne}^1 - a_{ne}^2)} = \frac{\gamma s^{ne}}{\frac{1}{N_1} + \frac{\varepsilon^2}{N_2}}.$$ 

Since the difference in non-essential amenities decreases from a positive number $a_{ne}^1 - a_{ne}^2$ to 0 after the pandemic, the change in location demand for the dense location due to the change in amenity provision is

$$\frac{\gamma s^{ne} \Delta (a_{ne}^1 - a_{ne}^2)}{\frac{1}{N_1} + \frac{\varepsilon^2}{N_2}} < 0.$$

Therefore, the model-predicted change in location demand for the dense location is

$$\Delta N_1 = -\theta s^t \Delta (c_t^1 - c_t^2) \frac{\varepsilon^1}{N_1} + \frac{\varepsilon^2}{N_2}$$

$$\frac{\gamma s^{ne} \Delta (a_{ne}^1 - a_{ne}^2)}{\frac{1}{N_1} + \frac{\varepsilon^2}{N_2}} < 0.$$ 

The model predicts that the demand for the dense location would decrease after the pandemic due to the remote work arrangement of workers who are in telework-compatible jobs and the loss of the advantage of non-essential amenity provision in the dense location. Moreover, the model suggests that the decrease in the demand for the dense location is greater if

\(^{12}\)The differentiation procedure is simple. First, we take the difference of the equation \(2\). Since utility must equalize across location at all time, the utility is always zero. Then, we can apply the implicit function theorem on the utility difference.
1. the likelihood of working in telework-compatible jobs is larger;

2. the dense location has a relatively larger provision of non-essential amenities; or

3. the dense location has a higher initial rent.

These predictions crystallize the intuitions of the conjectures 1–3 in the introduction. In Section 3, we test the conjectures by empirically showing that the demand for housing decreases disproportionately in neighborhoods where there is (i) a greater share of telework-compatible jobs, (ii) a greater initial provision of non-essential amenities such as restaurants, and (iii) a higher initial rent.

A2 County-level Analysis

We conduct analysis at the county level because county-level data are more sensitive to timing—Redfin Data Center provides monthly data at the county level. At the ZIP Code level, variables on home sales and new listings are constructed with pooled three-month lagged data, which may lead to a downward bias in the magnitude of the estimates.

Panel A of Table A2 presents the estimates of $\beta_1$. We find that home sales declined more in counties with higher population density and higher pre-COVID-19 home value (column 1). The pandemic has also spurred more new listings in denser neighborhoods (column 2). As a result, home inventory increased more in denser and more expensive counties (column 3). The results suggest that the pandemic has shifted housing purchases toward less dense and cheaper counties, and induced homeowners in denser locations to sell their homes. Moreover, we find that home prices increased less in more expensive neighborhoods (column 4), and rental prices declined more in denser and more expensive neighborhoods (column 5). The finding suggests that renters in the dense and expensive neighborhoods may seek to buy their own homes in less dense and cheaper neighborhoods.

Decreased demand for density persists despite an aggregate recovery in sales  One might speculate that the overall effects of the pandemic are mainly driven by the immediate aftermath of the outbreak, and the reduced demand for density may rebound as the housing market recovers. We examine this by estimating the effect of the pandemic by month after the outbreak.

\[ \frac{\partial \Delta \Delta N_1}{\partial (c_1 - c_2)} < 0, \quad \frac{\partial \Delta N_1}{\partial (a_1 - a_2)} > 0. \]
Panel B of Table A2 presents different effects of the pandemic over time by replacing $After_{my}$ with a series of dummies for the post-pandemic months. We find that the heterogeneous effects of the pandemic on sales by density and pre-COVID-19 home value were very strong in the initial periods of the pandemic, but such effects dwindled over time (column 1). In contrast, although the heterogeneous effects on new listings were not pronounced at the beginning, the differences became more remarkable as the pandemic progressed (column 2). The initial heterogeneous effects on home sales but not new listings could be because the would-be buyers of homes in dense and expensive neighborhoods could easily put off their plans if they lost their interest of homes in these neighborhoods. However, the would-be sellers in these locations may have to postpone their selling activities even if they were willing to sell because of the restrictions of lockdown policies. Over time, as more home owners in denser neighborhoods put up their homes on sale, the heterogeneous effects on new listings became more pronounced. As selling activities increased, the heterogeneous effects on sales became increasingly muted. As a result, we find that the heterogeneous effects on inventory strengthened in the summer of 2020 and remained significant and stable afterward (column 3), implying that the shift in housing demand did not fizzle over time. Although the difference in the effect on home prices across neighborhoods by pre-COVID-19 home value was much smaller, the difference has strengthened over time (column 4). Similarly, the difference in the effect on rents across neighborhoods by density and pre-COVID-19 home value has also increased over time (column 5). In short, the results suggest that the reduced demand for dense neighborhoods not only persisted through the aggregate recovery since June, but also appeared to have strengthened.

### A3 MSA-level Analysis

To examine the shift in housing demand across MSAs/cities, we estimate the following equation:

$$\log(s_{cmy}) = \alpha_1 After_{my} \cdot x_c + \alpha_2 After_{my} \cdot \log(CaseRate_c) + \pi_{my} + \delta_{cm} + \gamma_{cy} + \epsilon_{cmy},$$

(3)

where $s_{cmy}$ is a housing market outcome of city $c$ in month $m$ of year $y$; $x_c$ is a city characteristic; $CaseRate_c$ is the average case rate of city $c$ between April 2020 and February 2021; $\delta_{cm}$ is a city × month fixed effect; $\gamma_{cy}$ is a city × year fixed effect. Other variables are defined as in Equation 1. The coefficient of
interest is $\alpha_1$, which estimates the differential effects of the pandemic across $x_c$.

Table A6 presents the estimates of $\alpha_1$. We find that inventory increased more in more expensive cities and cities with a greater share of telework-compatible jobs, which seems unsurprising—work-from-home arrangements allow many workers to relocate in less expensive cities different from the city where they work. We also find a relative decrease in home and rental prices in cities with higher pre-COVID-19 home values.

Table A7 shows the effects by month. The results suggest that the lower demand for large cities and cities with more telework-compatible workers has persisted during the period of analysis.

## A4 Telework-compatibility by Su (2020)

In the main analysis, we use the telework-compatibility indicator developed by Dingel and Neiman (2020). As a robustness check, we use an alternative telework indicator developed by Su (2020). Su uses a similar method to select telework-compatible occupations as Dingel and Neiman, with a slightly different and simpler set of criteria. Specifically, Su assigns each occupation as either telework-compatible or not telework-compatible, based on five work context indices provided by O*NET. An occupation is remote-compatible if five criteria are all met:

1. Work involves frequent use of email;
2. Work does not require physical proximity with other people closer than arm’s length.
3. Work involves sitting at least half of the time.
4. Work does not involve significant kneeling, crouching, stooping or crawling.
5. Work does not involve significant bending, or twisting of the body.

The detailed selection criteria are listed as follows:

1. Work context variable “Electronic Mail” $\geq 87.5$. According to the scale of the index, an index of 75 means using email at least once a week and not every day. An index of 100 means using email every day. “Frequent use of email” is likely close to every day. However, since O*NET is estimated statistically from national surveys, Su takes an average between 75 and 100 as the cutoff value to allow some room for statistical error.
2. Work context variable “Physical Proximity” ≥ 75. An index of 75 means physical proximity of an arm’s length.

3. Work context variable “Spend Time Kneeling, Crouching, Stooping, or Crawling” < 50.

4. Work context variable “Spend Time Bending or Twisting the Body” < 50.

The occupation code used is occ2010 defined in the IPUMS USA data. O*NET occupation codes are linked to occ2010 with a SOC-occ2010 crosswalk.

The regression results using Su is shown in Table A5. The magnitude of the coefficient on the log share of telework-compatible jobs does not vary much by either definition of telework-compatibility.
Figure A1: Growth of Sales and New Listings Within and Across MSAs

Note: The figures present the growth of log home sales and new listings for each month in 2020 and 2021 relative to 2019. Figures a and c plot the changes at the ZIP Code level by distance to downtown for the most populous 25 MSAs. Note that ZIP Code level sales and new listings are reported as the three-month moving average led by the month shown. This explains that the lack of sharp changes shown in the MSA-level plots. Figures b and d plot the changes at the MSA-level by the size of MSA.
Figure A2: Visitor Traffic to Point-of-Interest by Type and Distance to Downtown

Note: These figures plot the average number of visits to business establishments located within 5 miles of downtown, 5–20 miles from downtown, and more than 20 miles from downtown by month, normalized by the number of visits in January 2020.
Table A1: Relationship Between Population Density and Other Neighborhood Characteristics

|                                   | Log (Density) |
|-----------------------------------|---------------|
|                                   | (1)           | (2)           | (3)           | (4)           |
| Log (Distance to Downtown)        | -0.673***     | -0.732***     | -0.849***     | -0.379***     |
|                                   | (0.0204)      | (0.0198)      | (0.0185)      | (0.0204)      |
| Log (Transits per capita)         | 0.340***      |               | 0.216***      |               |
|                                   | (0.0144)      |               | (0.0132)      |               |
| Log (Jobs per capita)             |               | -0.183***     | -0.285***     |               |
|                                   |               | (0.0285)      | (0.0289)      |               |
| Log (Share of Telework-Compatible Jobs) | 0.246***     |               | 0.358***      |               |
|                                   | (0.0565)      |               | (0.0571)      |               |
| Log (Restaurants per capita)      | 0.502***      |               | 0.561***      |               |
|                                   | (0.0283)      |               | (0.0291)      |               |
| Log (Pre-COVID Home Value)        |               | 0.432***      | 0.221***      |               |
|                                   |               | (0.0345)      | (0.0306)      |               |
| Log (Income)                      |               | -0.573***     | -0.327***     |               |
|                                   |               | (0.0478)      | (0.0464)      |               |
| Log (Share of Whites)             |               | -0.231***     | -0.217***     |               |
|                                   |               | (0.0182)      | (0.0161)      |               |
| Observations                      | 7,744         | 9,204         | 9,095         | 7,446         |

Note: The sample comprises all ZIP Codes. All columns include MSA fixed effects. Observations are weighted by the ZIP Code’s population. Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.
## Table A2: Heterogeneous Effects of COVID-19 across Counties

|                          | Log (Sales) (1) | Log (New Listings) (2) | Log (Inventory) (3) | Log (HPI) (4) | Log (Rents) (5) |
|--------------------------|----------------|------------------------|---------------------|--------------|---------------|
| **Panel A: Average Effects** |                |                        |                     |              |               |
| After $\times$ Log (Density) | -0.0111**     | 0.0156***              | 0.0455***           | -0.000411    | -0.00497**    |
|                          | (0.00505)      | (0.00393)              | (0.00926)           | (0.000775)   | (0.00203)     |
| After $\times$ Log (Pre-COVID Home Value) | -0.186***     | 0.00475                | 0.181**             | -0.0169***   | -0.0560***    |
|                          | (0.0427)       | (0.0489)               | (0.0837)            | (0.00257)    | (0.00573)     |
| Observations             | 72,540         | 72,540                 | 72,540              | 50,034       | 16,417        |
| **Panel B: Effects by Months** |                |                        |                     |              |               |
| Apr–Jun $\times$ Log (Density) | -0.0317***    | -0.00683               | 0.00948**           | 0.000687     | -0.00210      |
|                          | (0.00500)      | (0.00588)              | (0.00471)           | (0.000591)   | (0.00130)     |
| Jul–Sep $\times$ Log (Density) | -0.00793      | 0.0359***              | 0.0571***           | -0.000647    | -0.00556***   |
|                          | (0.00784)      | (0.00504)              | (0.0104)            | (0.000950)   | (0.00180)     |
| Oct–Dec $\times$ Log (Density) | 0.00624       | 0.0179***              | 0.0700***           | -0.00127     | -0.00724**    |
|                          | (0.00547)      | (0.00541)              | (0.0145)            | (0.00143)    | (0.00335)     |
| Jan–Feb $\times$ Log (Density) | -0.00813      | 0.00283                | 0.0572***           | -0.00561***  | -0.0161***    |
|                          | (0.00601)      | (0.00639)              | (0.0178)            | (0.00165)    | (0.00536)     |
| Apr–Jun $\times$ Log (Pre-COVID Home Value) | -0.128***     | -0.158*                | 0.0586*             | 0.000162     | -0.0230***    |
|                          | (0.0316)       | (0.0918)               | (0.0324)            | (0.00240)    | (0.00406)     |
| Jul–Sep $\times$ Log (Pre-COVID Home Value) | -0.266**      | 0.146***               | 0.243**             | -0.0137***   | -0.0531***    |
|                          | (0.112)        | (0.0313)               | (0.101)             | (0.00376)    | (0.00540)     |
| Oct–Dec $\times$ Log (Pre-COVID Home Value) | -0.164***     | 0.0264                 | 0.243**             | -0.0372***   | -0.0914***    |
|                          | (0.0432)       | (0.0298)               | (0.120)             | (0.00409)    | (0.00973)     |
| Jan–Feb $\times$ Log (Pre-COVID Home Value) | -0.0452       | 0.0938***              | 0.285*              | -0.0685***   | -0.102***     |
|                          | (0.0312)       | (0.0190)               | (0.160)             | (0.00596)    | (0.0163)      |
Observations 72,540 72,540 72,540 50,034 16,415

Note: The sample comprises all counties between January 2016 and February 2021. The dependent variable includes log sales, log new listings, log inventory, log HPI, and log rents. In Panel A, After is a dummy variable that is equal to 1 if the observation is after March 2020, and 0 otherwise. In Panel B, the month dummies are indicators of the corresponding month of 2020. Pre-COVID Home Value is the mean of monthly median house sales value in 2019. All specifications in Panel A include year × month, After × MSA, county × year, and county × month fixed effects, After × log income level, After × fraction of whites, and After × log average case rate. (After is replaced with post-COVID-19 month dummies in Panel B.) Observations are weighted by the county’s population in columns 1–4 and the county’s renter population in column 5. Standard errors are clustered at the MSA level: *** p < 0.01, ** p < 0.05, *p < 0.1.
|                                                                 | Log (Sales)   | Log (New Listings) |
|-----------------------------------------------------------------|--------------|-------------------|
|                                                                 | (1)          | (2)               |
| After × Log (Distance to Downtown)                              | 0.00794      | -0.00997*         |
|                                                                 | (0.00515)    | (0.00544)         |
| After × Log (Density)                                           | -0.0204**    | 0.00463           |
|                                                                 | (0.00994)    | (0.00529)         |
| After × Log (Jobs per capita)                                   | -0.000903    | 0.00357           |
|                                                                 | (0.00737)    | (0.00838)         |
| After × Log (Share of Telework-compatible Jobs)                 | 0.00257      | 0.0274            |
|                                                                 | (0.0189)     | (0.0208)          |
| After × Log (Restaurants per capita)                            | -0.000217    | 0.0111            |
|                                                                 | (0.00601)    | (0.00782)         |
| After × Log (Pre-COVID Home Value)                              | -0.0627**    | 0.00426           |
|                                                                 | (0.0302)     | (0.0302)          |
| After × Log (Income)                                            | 0.0736***    | 0.0484**          |
|                                                                 | (0.0225)     | (0.0226)          |
| After × Log (Share of Whites)                                   | 0.0250***    | 0.0509***         |
|                                                                 | (0.00359)    | (0.00513)         |
| Observations                                                   | 585,600      | 585,600           |

Note: The sample comprises all ZIP Codes between January 2016 and February 2021, except April 2020. The dependent variable includes log sales and log new listings. After is a dummy variable that is equal to 1 if the observation is after March 2020, and 0 otherwise. All specifications include year × month, MSA × After, ZIP Code × year, and ZIP Code × month fixed effects, and After × log average case rate. Observations are weighted by the ZIP Code’s population. Note that ZIP Code level sales and new listings are reported as the three-month moving average led by the month shown. Standard errors are clustered at the MSA level: *** \( p < 0.01 \), ** \( p < 0.05 \), * \( p < 0.1 \).
Table A4: Heterogeneous Effects of COVID-19 across ZIP Codes: Effects by Month

|                                      | Log (Sales)          | Log (New Listings) | Log (Inventory) | Log (HPI)   | Log (Rents)  |
|--------------------------------------|----------------------|--------------------|----------------|-------------|--------------|
|                                      | (1)                  | (2)                | (3)            | (4)         | (5)          |
| May–Jun × Log (Distance to Downtown) | 0.00952*             | -0.00147           | -0.00504       | -0.000333   | 0.00228***   |
|                                      | (0.00545)            | (0.00556)          | (0.00590)      | (0.000895)  | (0.000523)   |
| Jul–Sep × Log (Distance to Downtown) | 0.0130***            | -0.0222***         | -0.0417***     | -0.00109    | 0.00446***   |
|                                      | (0.00419)            | (0.00795)          | (0.0105)       | (0.000773)  | (0.00105)    |
| Oct–Dec × Log (Distance to Downtown) | 0.00189              | -0.00337           | -0.0583***     | -0.00605    | 0.00716***   |
|                                      | (0.00861)            | (0.00548)          | (0.0106)       | (0.00137)   | (0.00169)    |
| Jan–Feb × Log (Distance to Downtown) | -0.00541             | -0.00507           | -0.0721***     | 0.000536    | 0.0100***    |
|                                      | (0.00944)            | (0.00577)          | (0.0151)       | (0.00147)   | (0.00304)    |
| May–Jun × Log (Density)              | -0.0209***           | -0.0103            | 0.00616        | -0.000365   | -0.00265***  |
|                                      | (0.00532)            | (0.0107)           | (0.00523)      | (0.000591)  | (0.000699)   |
| Jul–Sep × Log (Density)              | -0.0243***           | 0.00355            | 0.0147**       | -0.00200**  | -0.00570***  |
|                                      | (0.00890)            | (0.00394)          | (0.00622)      | (0.00101)   | (0.00150)    |
| Oct–Dec × Log (Density)              | -0.0161              | 0.0157***          | 0.0172**       | -0.00294**  | -0.00963***  |
|                                      | (0.0148)             | (0.00480)          | (0.00829)      | (0.00139)   | (0.00248)    |
| Jan–Feb × Log (Density)              | -0.0187*             | 0.00697*           | -0.0102        | -0.00377**  | -0.0133***   |
|                                      | (0.00991)            | (0.00405)          | (0.0111)       | (0.00186)   | (0.00380)    |
| May–Jun × Log (Jobs per capita)      | 0.00526              | 0.0158*            | 0.0195***      | 0.000561    | -0.00433***  |
|                                      | (0.00647)            | (0.00858)          | (0.00711)      | (0.00102)   | (0.000850)   |
| Jul–Sep × Log (Jobs per capita)      | -0.00587             | 0.00851            | 0.0164         | 0.000924    | -0.00794***  |
|                                      | (0.00879)            | (0.00945)          | (0.0143)       | (0.00116)   | (0.00166)    |
| Oct–Dec × Log (Jobs per capita)      | -4.84e-05            | -0.00955           | 0.00808        | 0.00118     | -0.0127***   |
|                                      | (0.00844)            | (0.00977)          | (0.0156)       | (0.00185)   | (0.00273)    |
| Jan–Feb × Log (Jobs per capita)      | -0.00384             | 0.00382            | 0.00520        | 0.00247     | -0.0139***   |
|                                      | (0.00917)            | (0.00947)          | (0.0178)       | (0.00182)   | (0.00360)    |
| Period       | Log (Share of Telework-compatible Jobs) | Log (Restaurants per capita) | Log (Pre-COVID Home Value) | Log (Income) |
|--------------|----------------------------------------|------------------------------|-----------------------------|--------------|
| May–Jun 2020 | -0.0609***                             | -0.0336                      | 0.0349**                    | -0.00275     |
|              | (0.0155)                               | (0.0337)                     | (0.0138)                    | (0.00174)    |
| Jul–Sep 2020 | 0.00456                                 | 0.0281                       | 0.101***                    | -0.00485**   |
|              | (0.0201)                               | (0.0212)                     | (0.0302)                    | (0.00214)    |
| Oct–Dec 2020 | 0.0429*                                 | 0.0674***                    | 0.150***                    | -0.00651**   |
|              | (0.0252)                               | (0.0200)                     | (0.0333)                    | (0.00283)    |
| Jan–Feb 2021 | 0.0352**                               | 0.0349*                      | 0.151***                    | -0.0158***   |
|              | (0.0172)                               | (0.0202)                     | (0.0373)                    | (0.00317)    |
| May–Jun 2021 | -0.0149**                               | -0.00916                     | 0.00176                     | -0.000235    |
|              | (0.00635)                              | (0.00848)                    | (0.00777)                   | (0.00117)    |
| Jul–Sep 2021 | 0.00290                                 | 0.0125                       | 0.0297**                    | -0.000916    |
|              | (0.00732)                              | (0.00821)                    | (0.0137)                    | (0.00117)    |
| Oct–Dec 2021 | 0.00647                                 | 0.0232**                     | 0.0543***                   | -0.00236     |
|              | (0.00697)                              | (0.0103)                     | (0.0159)                    | (0.00217)    |
| Jan–Feb 2022 | 0.0188**                               | 0.0160                       | 0.0720***                   | -0.00601***  |
|              | (0.00804)                              | (0.0103)                     | (0.0175)                    | (0.00172)    |
| May–Jun 2022 | -0.0687***                             | -0.0484                      | 0.0510**                    | -0.00289**   |
|              | (0.00788)                              | (0.0406)                     | (0.0247)                    | (0.00124)    |
| Jul–Sep 2022 | -0.0563*                               | 0.0602**                     | 0.119***                    | -0.00439     |
|              | (0.0292)                               | (0.0279)                     | (0.0363)                    | (0.00284)    |
| Oct–Dec 2022 | -0.0652                                | -0.0166                      | 0.106**                     | -0.0139***   |
|              | (0.0496)                               | (0.0275)                     | (0.0437)                    | (0.00433)    |
| Jan–Feb 2023 | -0.0445                                | -0.00782                     | 0.150***                    | -0.0265***   |
|              | (0.0294)                               | (0.0152)                     | (0.0507)                    | (0.00731)    |
| May–Jun 2023 | 0.0316***                              | 0.0634*                      | -0.0620***                  | 0.00402***   |
|              | (0.0112)                               | (0.0360)                     | (0.0219)                    | (0.00142)    |
| Jul–Sep 2023 | 0.0477***                              | 0.0305                       | -0.143***                   | 0.00514**    |
|              | (0.00387)                              | (0.00138)                    | (0.00138)                   | (0.00387)    |
| Month       | Log (Income)  | Log (Income)  | Log (Income) | Log (Income) | Log (Income) |
|-------------|---------------|---------------|--------------|--------------|--------------|
| Oct–Dec     | 0.128***      | 0.0562***     | -0.240***    | 0.0123***    | 0.00591      |
|             | (0.0447)      | (0.0197)      | (0.0427)     | (0.00267)    | (0.00407)    |
| Jan–Feb     | 0.0357        | -0.0520***    | -0.367***    | 0.00308      | -0.00553     |
|             | (0.0335)      | (0.0151)      | (0.0515)     | (0.00557)    | (0.00671)    |
| May–Jun     | -0.000968     | 0.00199       | -0.00386     | 0.000788     | -0.00101*    |
|             | (0.00510)     | (0.00563)     | (0.00366)    | (0.00109)    | (0.000575)   |
| Jul–Sep     | 0.0163***     | 0.0609***     | 0.0435***    | 0.00248**    | -0.00145     |
|             | (0.00529)     | (0.00699)     | (0.00675)    | (0.00107)    | (0.00105)    |
| Oct–Dec     | 0.0511***     | 0.0735***     | 0.0695***    | 0.00464***   | -0.00244     |
|             | (0.00399)     | (0.00574)     | (0.0112)     | (0.00131)    | (0.00169)    |
| Jan–Feb     | 0.0625***     | 0.0576***     | 0.0511***    | 0.00561***   | -0.00262     |
|             | (0.00454)     | (0.00489)     | (0.0116)     | (0.00140)    | (0.00220)    |

| Observations | 585,600 | 585,600 | 585,600 | 372,161 | 139,588 |

Note: The sample comprises all ZIP Codes between January 2016 and February 2021, except April 2020. The dependent variable includes log sales, log new listings, log inventory, log HPI, and log rents. The month dummies are indicators of the corresponding month of 2020 or 2021. All specifications include year × month, MSA × post-COVID-19 month dummies, ZIP Code × year, and ZIP Code × month fixed effects, and post-COVID-19 month dummies × log average case rate. Observations are weighted by the ZIP Code’s population in columns 1–4 and the ZIP Code’s renter population in column 5. Note that ZIP Code level sales and new listings are reported as the three-month moving average led by the month shown. Standard errors are clustered at the MSA level: *** p < 0.01, ** p < 0.05, *p < 0.1.
| After × Log (Distance to Downtown) | Log (Sales) | Log (New Listings) | Log (Inventory) | Log (HPI) | Log (Rents) |
|----------------------------------|------------|--------------------|-----------------|-----------|-------------|
|                                  | 0.00788    | -0.0100*           | -0.0390***      | -0.000699 | 0.00493***  |
|                                  | (0.00524)  | (0.00548)          | (0.00799)       | (0.00904) | (0.00116)   |
| After × Log (Density)            | -0.0204**  | 0.00470            | 0.0138**        | -0.00196**| 0.00647***  |
|                                  | (0.00988)  | (0.00525)          | (0.00629)       | (0.00984) | (0.00168)   |
| After × Log (Jobs per capita)    | -0.000503  | 0.00340            | 0.0136          | 0.000892  | -0.00902*** |
|                                  | (0.00715)  | (0.00862)          | (0.0125)        | (0.0128)  | (0.00207)   |
| After × Log (Share of Telework-compatible Jobs) | 0.000894  | 0.0268             | 0.0999***       | -0.00462**| -0.00218    |
|                                  | (0.0172)   | (0.0208)           | (0.0249)        | (0.0205)  | (0.00381)   |
| After × Log (Restaurants per capita) | -0.000528 | 0.0113             | 0.0318**        | -0.00128  | 0.00561***  |
|                                  | (0.00589)  | (0.00804)          | (0.0124)        | (0.0143)  | (0.00190)   |
| After × Log (Pre-COVID Home Value) | -0.0626** | 0.00466            | 0.0988***       | -0.00766***| -0.0151***  |
|                                  | (0.0299)   | (0.0300)           | (0.0353)        | (0.00270) | (0.00386)   |
| After × Log (Income)             | 0.0737***  | 0.0481**           | -0.160***       | 0.00757***| 0.00442     |
|                                  | (0.0225)   | (0.0224)           | (0.0330)        | (0.00187) | (0.00284)   |
| After × Log (Share of Whites)    | 0.0250***  | 0.0507***          | 0.0406***       | 0.00290***| -0.00174    |
|                                  | (0.00361)  | (0.00510)          | (0.00712)       | (0.00111) | (0.00111)   |
| Observations                     | 585,600    | 585,600            | 585,600         | 372,161   | 139,560     |

Note: The sample comprises all ZIP Codes between January 2016 and February 2021, except April 2020. The dependent variable includes log sales, log new listings, log inventory, log HPI, and log rents. After is a dummy variable that is equal to 1 if the observation is after March 2020. The number of jobs per capita and the share of jobs within 3 miles of a ZIP Code are estimated using data from Su (2020). All specifications include year × month, MSA × After, ZIP Code × year, and ZIP Code × month fixed effects, and After × log average case rate. Observations are weighted by the ZIP Code’s population in columns 1–4 and the ZIP Code’s renter population in column 5. Note that ZIP Code level sales and new listings are reported as the three-month moving average led by the month shown. Standard errors are clustered at the MSA level: *** p < 0.01, ** p < 0.05, *p < 0.1.
Table A6: Heterogeneous Effects of the COVID-19 Pandemic across MSAs

|                                | Log (Sales) | Log (New Listings) | Log (Inventory) | Log (HPI) | Log (Rents) |
|--------------------------------|-------------|--------------------|-----------------|-----------|-------------|
|                                | (1)         | (2)                | (3)             | (4)       | (5)         |
| **After × Log (Population)**   | -0.0241***  | -0.00191           | 0.00521         | -0.000678 | -0.00758*** |
|                                | (0.00757)   | (0.00764)          | (0.0147)        | (0.00168) | (0.00231)   |
| **After × Log (Share of Teleworkers)** | 0.0784      | 0.0530             | 0.350**         | -0.0200   | -0.00857    |
|                                | (0.0710)    | (0.0747)           | (0.166)         | (0.0148)  | (0.0255)    |
| **After × Log (Restaurants per capita)** | -0.000138   | 0.0510*            | 0.0408          | 0.00385   | -0.0307**   |
|                                | (0.0280)    | (0.0295)           | (0.0693)        | (0.00534) | (0.0131)    |
| **After × Log (Pre-COVID Home Value)** | -0.0495**   | 0.0397*            | 0.152***        | -0.0112***| -0.0211***  |
|                                | (0.0231)    | (0.0237)           | (0.0514)        | (0.00416) | (0.00612)   |
| **After × Log (Income)**       | 0.132**     | 0.0468             | -0.285**        | 0.0335*** | -0.0130     |
|                                | (0.0610)    | (0.0557)           | (0.127)         | (0.0121)  | (0.0216)    |
| **After × Log (Share of Whites)** | -0.0310*    | -0.0228            | -0.000598       | 0.00415   | -0.0113     |
|                                | (0.0179)    | (0.0234)           | (0.0407)        | (0.00393) | (0.00695)   |
| **Observations**               | 10,168      | 10,168             | 10,168          | 9,486     | 5,309       |

Note: The sample comprises all MSAs between January 2016 and February 2021. The dependent variable includes log sales, log new listings, log inventory, log HPI, and log rents. After is a dummy variable that is equal to 1 if the observation is after March 2020. All specifications include year × month, MSA × year, and MSA × month fixed effects, and After × log average case rate. Observations are weighted by the MSA’s population in columns 1–4 and the MSA’s renter population in column 5. Standard errors are clustered at the MSA level: *** p < 0.01, ** p < 0.05, * p < 0.1.
Table A7: Heterogeneous Effects of the COVID-19 Pandemic across MSAs: Effects by Month

|                      | Log (Sales) | Log (New Listings) | Log (Inventory) | Log (HPI) | Log (Rents) |
|----------------------|-------------|--------------------|----------------|-----------|-------------|
|                      | (1)         | (2)                | (3)            | (4)       | (5)         |
| Apr–Jun × Log (Population) | -0.0540*** | -0.0582***         | -0.0218**      | -0.000183 | 0.000575    |
|                      | (0.0178)    | (0.0210)           | (0.00865)      | (0.00125) | (0.00141)   |
| Jul–Sep × Log (Population) | -0.0262*   | 0.0452***          | 0.0103         | -0.000199 | -0.0195**   |
|                      | (0.0151)    | (0.0163)           | (0.0175)       | (0.00125) | (0.00772)   |
| Oct–Dec × Log (Population) | 0.00781    | 0.00735            | 0.0271         | -0.00165  | -0.00387*   |
|                      | (0.00730)   | (0.0104)           | (0.0246)       | (0.00287) | (0.00222)   |
| Jan–Feb × Log (Population) | 0.00498    | 0.0138             | 0.0294         | -0.00260  | -0.0104**   |
|                      | (0.00988)   | (0.0179)           | (0.0271)       | (0.00387) | (0.00396)   |
| Apr–Jun × Log (Share of Teleworks) | 0.382**    | 0.596***           | 0.361***       | 0.00477   | -0.0161     |
|                      | (0.156)     | (0.166)            | (0.0799)       | (0.0105)  | (0.0119)    |
| Jul–Sep × Log (Share of Teleworks) | 0.0292     | -0.239*            | 0.420**        | -0.0157   | 0.0549      |
|                      | (0.124)     | (0.139)            | (0.205)        | (0.0144)  | (0.0580)    |
| Oct–Dec × Log (Share of Teleworks) | -0.176**  | -0.198             | 0.270          | -0.0489*  | -0.0651**   |
|                      | (0.0855)    | (0.122)            | (0.262)        | (0.0252)  | (0.0303)    |
| Jan–Feb × Log (Share of Teleworks) | -0.141     | 0.0152             | 0.219          | -0.0265   | -0.0683     |
|                      | (0.104)     | (0.175)            | (0.324)        | (0.0312)  | (0.0663)    |
| Apr–Jun × Log (Restaurants per capita) | 0.0470     | -0.120             | -0.159***      | -0.00166  | 0.00370     |
|                      | (0.0783)    | (0.0804)           | (0.0362)       | (0.00372) | (0.00579)   |
| Jul–Sep × Log (Restaurants per capita) | -0.0844    | 0.159*             | 0.0698         | 0.00260   | -0.0736**   |
|                      | (0.0579)    | (0.0859)           | (0.0917)       | (0.00552) | (0.0360)    |
| Oct–Dec × Log (Restaurants per capita) | 0.0370     | 0.113***           | 0.212*         | 0.0106    | -0.0224*    |
|                      | (0.0577)    | (0.0415)           | (0.115)        | (0.00887) | (0.0120)    |
| Jan–Feb × Log (Restaurants per capita) | 0.0805     | 0.0263             | 0.206          | -0.0223** | -0.0715**   |
|                      | (0.0583)    | (0.0794)           | (0.165)        | (0.0109)  | (0.0303)    |
| Period     | Interaction | Coefficient 1 | Coefficient 2 | Coefficient 3 | Coefficient 4 | Coefficient 5 |
|------------|-------------|---------------|---------------|---------------|---------------|---------------|
| Apr–Jun | Log (Pre-COVID Home Value) | -0.135*** | 0.0511 | 0.165*** | -0.00954*** | -0.0106*** |
|           |             | (0.0506) | (0.0423) | (0.0205) | (0.00316) | (0.00342) |
| Jul–Sep | Log (Pre-COVID Home Value) | -0.0207 | 0.00573 | 0.166*** | -0.0120*** | -0.0225 |
|           |             | (0.0354) | (0.0380) | (0.0611) | (0.00416) | (0.0170) |
| Oct–Dec | Log (Pre-COVID Home Value) | 0.00723 | 0.0623 | 0.124 | -0.0120* | -0.0301*** |
|           |             | (0.0272) | (0.0432) | (0.0828) | (0.00708) | (0.00749) |
| Jan–Feb | Log (Pre-COVID Home Value) | 0.0417 | 0.0953* | 0.124 | 0.0341*** | -0.00701 |
|           |             | (0.0305) | (0.0486) | (0.0951) | (0.0107) | (0.0127) |
| Apr–Jun | Log (Income) | 0.0884 | -0.364*** | -0.369*** | 0.00921 | -0.00441 |
|           |             | (0.129) | (0.102) | (0.0581) | (0.00839) | (0.00952) |
| Jul–Sep | Log (Income) | 0.119 | 0.215** | -0.342** | 0.0266** | -0.0375 |
|           |             | (0.0925) | (0.101) | (0.160) | (0.0118) | (0.0543) |
| Oct–Dec | Log (Income) | 0.189** | 0.289** | -0.142 | 0.0647*** | 0.00371 |
|           |             | (0.0784) | (0.114) | (0.195) | (0.0210) | (0.0236) |
| Jan–Feb | Log (Income) | 0.103 | 0.00149 | 0.0508 | -0.0288 | -0.0658 |
|           |             | (0.0841) | (0.136) | (0.249) | (0.0301) | (0.0453) |
| Apr–Jun | Log (Share of Whites) | -0.0472 | -0.0764 | 0.0258 | -0.00321 | 0.000227 |
|           |             | (0.0367) | (0.0584) | (0.0206) | (0.00283) | (0.00334) |
| Jul–Sep | Log (Share of Whites) | -0.0447 | 0.0498 | 0.0250 | 0.00405 | -0.0316* |
|           |             | (0.0301) | (0.0325) | (0.0485) | (0.00367) | (0.0185) |
| Oct–Dec | Log (Share of Whites) | -0.00119 | -0.0419 | -0.0526 | 0.0116* | -0.00233 |
|           |             | (0.0217) | (0.0383) | (0.0646) | (0.00607) | (0.00838) |
| Jan–Feb | Log (Share of Whites) | -0.0491* | -0.0825 | -0.165** | 0.0390*** | 0.0110 |
|           |             | (0.0286) | (0.0530) | (0.0739) | (0.00743) | (0.0135) |
| Observations | | 10,168 | 10,168 | 10,168 | 9,486 | 5,309 |
Note: The sample comprises all MSAs between January 2016 and February 2021. The dependent variable includes log sales, log new listings, log inventory, log HPI, and log rents. The month dummies are indicators of the corresponding month of 2020 or 2021. All specifications include year × month, MSA × year, and MSA × month fixed effects, and post-COVID-19 month dummies × log average case rate. Observations are weighted by the MSA’s population in columns 1–4 and the MSA’s renter population in column 5. Standard errors are clustered at the MSA level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 