DISCUSSION PAPER SERIES

DP16080

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FINANCIAL ECONOMICS

PUBLIC ECONOMICS

ISSN 0265-8003

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Discussion Paper DP16080
Published 28 April 2021
Submitted 26 April 2021

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JEL Classification: R23, R51, R12

Keywords: COVID-19, land values, bid-rent function, working from home

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Acknowledgements
The authors would like to thank Zillow, VenPath, Realtor, Pulsenomics, and Safegraph for providing data. We thank seminar participants at NYU Stern, Columbia GSB, Duke Fuqua Research Triangle, and the University of Wisconsin at Madison for comments.

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We show that the COVID-19 pandemic brought house price and rent declines in city centers, and price and rent increases away from the center, thereby flattening the bid-rent curve in most U.S. metropolitan areas. Across MSAs, the flattening of the bid-rent curve is larger when working from home is more prevalent, housing markets are more regulated, and supply is less elastic. Housing markets predict an urban revival with urban rent growth exceeding suburban rent growth for the foreseeable future, as working from home recedes.

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1 Introduction

Cities have historically been a major source of growth, development, and knowledge spillovers (Glaeser, 2011). In developing and developed countries alike, rising urbanization rates (United Nations, 2019) have led to increased demand for real estate in city centers and contributed to problems of housing affordability (Favilukis, Mabille, and Van Nieuwerburgh, 2019), especially in superstar cities (Gyourko, Mayer, and Sinai, 2013). The inelasticity of housing supply in urban centers means that a large fraction of economic growth in the last few decades has accrued to property owners, rather than improving the disposable income of local workers (Hornbeck and Moretti, 2018; Hsieh and Moretti, 2019).

This long-standing pattern reversed in 2020 as the COVID-19 pandemic led many residents to flee city centers in search of safer ground away from urban density. This urban flight was greatly facilitated by the ability, indeed the necessity, to work from home. Downtown Office hit historic lows in 2020 and remains low today, possibly turning many temporary suburbanites into permanent ones.[1] We document this migration pattern and show that it had a large impact on the demand for suburban relative to urban residential real estate.

An important question is whether real estate markets will return to their pre-pandemic state or be changed forever. There is much uncertainty circling around this question. Existing survey evidence indicates an increased willingness by employers to let employees work from home, and increasing desire to do so from employees, but without much evidence on lost productivity.[2] In this paper, we argue that by comparing the changes in

[1] According to JLL, U.S. office occupancy declined by a record 84 million square feet in 2020, propelling the vacancy rate to 17.1% at year-end. In addition, the sublease market grew by 50% in 2020, an increase of 47.6 million square feet (Jones Lang LaSalle, 2020).

[2] A survey of company leaders by Gartner found that 80% plan to allow employees to work remotely at least part of the time after the pandemic, and 47% will allow employees to work from home full-time. A PwC survey of 669 CEOs shows that 78% agree that remote collaboration is here to stay for the long-term. In a recent FlexJobs survey, 96% of respondents desire some form of remote work; 65% of respondents report wanting to be full-time remote employees post-pandemic, and 31% want a hybrid remote work environment. Bloom (2020) finds that 42% of the U.S. workforce was working remotely as of May 2020, and

house prices—which are forward looking—to the changes in rents in city centers and in the suburbs, we can glance an early answer to this difficult question.

We begin by documenting how urban agglomeration trends have shifted in the wake of the COVID-19 pandemic. The central object of interest is the bid-rent function, or the land price gradient, which relates house prices and rents to the distance from the city center. Prices and rents in the city center tend to be higher than in the suburbs, with the premium reflecting the scarcity of land available for development (including due to regulatory barriers), closer proximity to workplaces, urban amenities, and agglomeration effects. While bid-rent functions are typically downward sloping, we document striking changes in the slope of this relationship since the beginning of the COVID-19 pandemic. House prices far from the city center have risen faster than house prices in the center between December 2019 and December 2020. More starkly, rents in the suburbs rose strongly while rents in the center fell—in some metropolitan areas strongly—in 2020. The negative slope of the bid-rent function has become less negative. In other words, the pandemic has flattened the bid-rent curve.

Figure 1 illustrates this changing slope. Each observation is the slope of the bid-rent function for a particular month. Rents are on the left, house prices are on the right. The bid-rent slope values are calculated by pooling all ZIP codes for the largest 30 metropolitan areas in the U.S., and obtaining estimates of the relationship between log prices or log rents and log(1+distance) in a pooled regression with CBSA fixed effects and ZIP-level control variables. Distance from city hall is expressed in kilometers. The elasticity of house prices to distance changes from -0.127 pre-pandemic to -0.115 in December 2020. The change in slope for price means that house prices 50kms from the city center grew by 5.7 percentage points more than house prices in the center. For rents, the change in slope is much larger: from -0.04 to -0.004. The slope change for rents corresponds to suburban

Barrero, Bloom, and Davis (2020) estimates that the number of remote working days will increase four-fold in future years to 22%. Harrington and Emanuel (2020) finds positive productivity effects of working from home, consistent with Bloom, Liang, Roberts, and Ying (2015), but adverse selection into remote work.

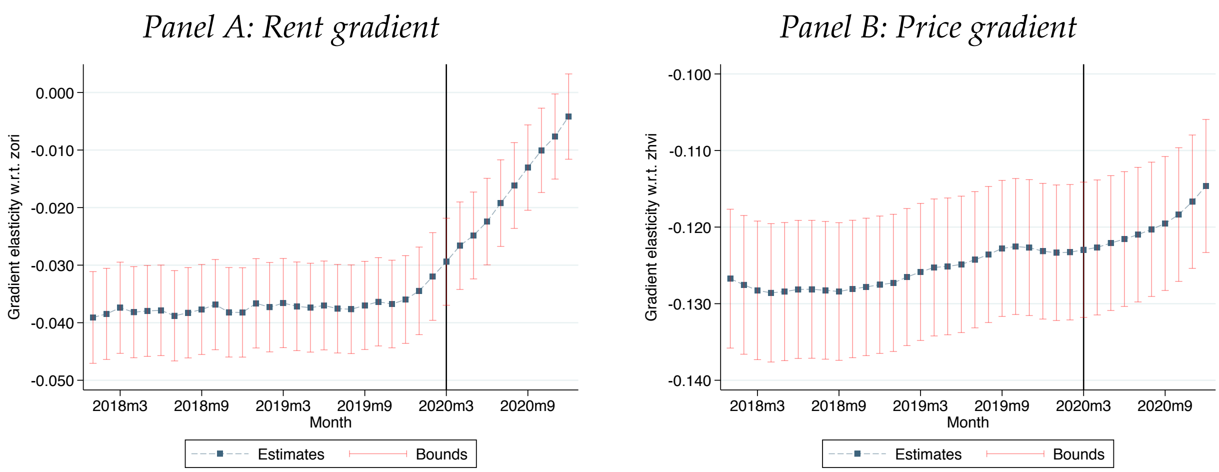

Figure 1. Rent and Price Gradients across top 30 MSAs

This plot shows coefficients from a repeated cross-sectional regression at the ZIP Code level as in equation 1 for the top 30 MSAs. We regress the distance from the city center (measured as the log of 1 + distance to City Hall in kms) against log rent (left) and log price (right). We include additional controls (log of annual gross income in 2017, median age of the head of household, proportion of Black households in 2019, and proportion of individuals who make over 150k in 2019), as well as MSA fixed effects, and run the specification separately each month. Price and rent data are drawn from Zillow.

rents appreciating by 9.9 percentage points more than in the city center.[3]

We also find large changes in housing quantities. Active listings, a measure of the housing inventory, displays large increases in the urban center and large decreases in the suburbs. A measure of housing liquidity shows that days-on-the-market increase in the urban core and falls sharply in the suburbs. There is a strong negative cross-sectional relationship between the house price change in a ZIP code on the one hand, and the change in inventory and days-on-the-market on the other hand. Since housing supply tends to be more elastic in the suburbs than in the urban core, part of the adjustment to higher demand is accommodated through increases in quantity. While the observed quantity adjustments are arguably limited over the nine months since the pandemic took hold, we expect them to be larger in the medium run. Shifting population to areas with higher supply elasticity will have important implications for housing affordability.

Next, we link these changes in prices and rents to migration data using high-frequency cell-phone location data. ZIP codes close to the center of the metro area lost population

[3]The main results, which use Zillow quality-adjusted house price data, are corroborated by using an alternative data source, Realtor, on asking prices.

while suburban ZIP codes gained people. We show that it is the places that experienced the strongest migration that experienced the largest price and rent changes. We also link migration to remote work using the Dingel and Neiman (2020) measure of occupational ability to work from home. This finding suggests that many workers with the capacity to leave cities did so, propelling housing values in suburban areas at the cost of urban ones.

We use a present-value model in the tradition of Campbell and Shiller (1989) to study what the relative changes in urban versus suburban house prices and rents teach us about the market's expectations on future rent growth in urban versus suburban locations. By studying differences between suburban and urban locations, we control for common drivers of house prices such as low interest rates. The much larger decline in rents than in prices in urban ZIP codes, and the equally large increase in prices and rents in the suburbs, implies that the price-rent ratio became more steeply downward sloping in distance from the center. If housing markets expect a gradual return to the pre-pandemic state, then the increase in the urban-minus-suburban price-rent ratio implies higher expected rent growth in the urban core than in the suburbs for the next several years. If urban-minus-suburban risk premia did not change, then that differential cumulative rent change is 7.5% points for the average MSA. If relative risk premia instead rose by 1% point, then the expected rent change becomes 15% points. If housing markets instead expect the pandemic to have brought permanent changes to housing markets, then the change in price-rent ratios implies that urban rents will expand by 0.5% points faster than suburban rents going forward, assuming that risk premia did not change. If urban risk premia instead changed by 1% point, we estimate urban rents will expand by 1.5% points.

A key quantitative question is where we are in between the fully transitory and fully permanent cases. We use unique survey data from Pulsenomics, which asked a panel of real estate professionals in February 2021 whether they thought that the change in working from home was permanent or transitory. Thirty-six percent thought the change was permanent, while the rest thought it was transitory. We use this probability to interpolate between the transitory and permanent cases of the present-value model to arrive at our best estimate of the expected future rent growth in urban relative to suburban areas. Housing markets price in an urban rent revival. Urban rent growth is expected to exceed suburban rent growth between 1.6% points and 3.4% points in 2021, before returning to levels about 0.1%–0.5% points above pre-pandemic levels.

In the last part of the paper, we study the cross-MSA variation in the change in the slope of the bid-rent function. We find that the changes are larger in MSAs that have a higher presence of jobs that can be done from home, and have lower housing supply elasticity stemming from higher physical or regulatory barriers to development. The strongest association is with the presence of remote workers, which we interpret as suggesting two important economic forces. Workers with jobs that can be done remotely are able to relocate their home location in the context of changing remote work policies. At the same time, these—largely high-skilled—workers may also change their preferences for urban amenities. We directly test for the role of changing amenities by examining pandemic lock-down measures, which result in the loss of many urban amenities (e.g., theater and restaurant closures). Though lockdown policies are also associated with stronger rent and price gradient changes, this association is not as strong.

To further disentangle the effect of working from home on the one hand and COVID-19 stringency measures and urban amenities on the other hand, we turn to the ZIP-code level. A specification with a MSA-fixed effect allows us to control for all MSA-specific characteristics, like amenities, as well as for amenities measured at the ZIP-level. ZIP codes within a MSA with higher exposure to work from home (WFH) see lower house price and rent growth even after accounting for other relevant ZIP-level variables. We interpret the residual association of WFH with real estate outcomes in this specification as largely reflecting the channel of workers re-optimizing location choices in the context of reduced commuting times both during the pandemic (rents) and in the future (prices). We find that WFH associates with rents more strongly than prices. This result is consistent with the earlier result on the predicted urban revival in rents, brought about by the partial reversal of remote work. Still, the effect on prices suggests at least some permanent or at least highly persistent changes in WFH practices, leaving a persistent imprint on the urban fabric.

Related Literature Our research builds on a large body of literature examining the role of urban land gradients in the context of agglomeration effects. Albouy, Ehrlich, and Shin (2018) estimates bid-rent functions across metropolitan areas in the United States. Albouy (2016) interprets the urban land premium in the context of local productivity, rents, and amenity values, building on the influential spatial equilibrium approach of Rosen (1979) and Roback (1982). Moretti (2013) argues that skilled workers have increasingly sorted into expensive urban areas, lowering the real skilled wage premium. A key finding from this literature is that productive spillovers and amenity values of cities account for the steep relationship between real estate prices and distance, the importance of which has been growing over time—particularly for skilled workers. We find strong and striking reversals of this trend during the COVID-19 period, especially for cities with the highest proportions of skilled workers, who can most often work remotely.

A large and growing literature investigates the effect of COVID-19. One strand of this research has examined the spatial implications of the pandemic on within-city changes in consumption resulting from migration, changing commutes, and changing risk attitudes (Althoff, Eckert, Ganapati, and Walsh, 2020; De Fraja, Matheson, and Rockey, 2020). A number of contemporaneous contributions have begun to assess the impact of COVID-19 on real estate markets. Delventhal, Kwon, and Parkhomenko (2021) propose a spatial equilibrium model with many locations, in which households can choose where to locate in response to increased remote working opportunities. Davis, Ghent, and Gregory (2021) likewise studies the effect of working from home on real estate prices. Liu and Su (2020) examines changes in real estate valuation as a function of density—whereas this study focuses on the urban bid-rent curve and what the conjunction of prices and rents tell us about future rent expectations. Ling, Wang, and Zhou (2020); Garcia, Rosenthal, and Strange (2021) study the impact of the pandemic on asset-level commercial real estate categories. Our focus is on residential real estate and changes in rents and prices resulting from household migration. Brueckner, Kahn, and Lin (2021) also examines changes in residential valuations; with a main focus on the spatial equilibrium implications of working from home across cities. Our work is complimentary in highlighting the intra-city consequences, as well as in estimating the persistence of the work-from-home shock.

This research has begun to use high-frequency location data from cell phone pings to study patterns of consumption, commuting, and migration (Miyauchi, Nakajima, and Redding, 2021; Couture, Dingel, Green, Handbury, and Williams, 2021; Gupta, Van Nieuwerburgh, and Kontokosta, 2020). Coven, Gupta, and Yao (2020) shows that the pandemic led to large-scale migration. This migration is facilitated by increased work-from-home policies and shutdowns of city amenities—both of which raised the premium for housing characteristics found in suburbs and outlying areas such as increased space.

We also connect to asset pricing research that decomposes of stock price movements into transitory and long run shocks (Van Binsbergen, Brandt, and Koijen, 2012; Van Binsbergen, Hueskes, Koijen, and Vrugt, 2013). Gormsen and Koijen (2020) finds that stock markets priced in the risk of a severe and persistent economic contraction in March 2020 before revising that view later in 2020.

The rest of the paper is organized as follows. Section 2 describes our data sources. Section 3 describes our results on the price and rent gradient, as well as on migration. Section 4 uses a present-value model to extract market expectations about the future expected rent changes from the relative changes in price and rent gradients. Section 5 studies cross-sectional variation in the price and rent gradients to assess the underlying mechanism. The last section concludes.

2 Data

We focus on the largest 30 MSAs by population, presented in Table B.I in Appendix B. Our house price and rent data are at the ZIP code level derived from Zillow.[4] We use the Zillow House Value Index (ZHVI), which adjusts for house characteristics using machine learning techniques, as well as the Zillow Observed Rental Index (ZORI), which is a constant-quality rental price index capturing asking rents. Housing units include both single-family and multi-family units for both the price and the rent data series.

We also use data from the listing agent Realtor. We obtain ZIP code-level variables at the monthly level for all the ZIP codes in the U.S. Specifically, we use median listing price, median listing price per square foot, active listing counts, and median days a property is on the market.

We measure mobility using data from VenPath, a holistic global provider of compliant smartphone data. We obtain information from approximately 120 million smart phone devices containing information on geographical location for users. We combine information from both background pings (location data provided while applications are running) as well as foreground pings (while users are actively using an application) to determine user residence and migration over the period February 1 to July 13, 2020.

Additionally, we obtain the following ZIP code level variables; the proportion of households with yearly income higher than 150 thousand dollars, the proportion of Black residents, and median household income from the Census Bureau, and the count of bars and restaurants from Safegraph. These variables serve as control variables in our analysis and are shown in Table B.II in the Appendix.

Finally, we draw on a rich set of MSA-level variables from prior research to investigate the MSA-level factors that drive the changes in urban land gradients. We use the Dingel and Neiman (2020) measure of the fraction of local jobs which can potentially be performed remotely. We measure constraints on local housing development through sev-

[4]The data are publicly available from `https://www.zillow.com/research/data/`.

eral measures commonly used in the literature. The Wharton regulatory index (Gyourko, Saiz, and Summers, 2008) captures constraints on urban construction. We also measure physical constraints on housing using the Lutz and Sand (2019) measure of land unavailability, which is an extension of the Saiz (2010a) measure. These physical constraints allow us to measure the elasticity of the local housing stock. We also measure the stringency of local lock-downs following Hale, Atav, Hallas, Kira, Phillips, Petherick, and Pott (2020).

3 Results

We begin by showing descriptive evidence of price and rent changes across ZIP codes. The figure in the main text are for the largest 30 metropolitan areas. The figures in the Appendix zoom in on several MSAs, an in particular on New York City and San Francisco.

3.1 Raw Price and Rent Growth

We first highlight the geography of changes in prices and rents for New York and San Francisco in Figure 2. We observe strong rent decreases in the urban core (Manhattan, centered around Grand Central Terminal) and rent increases in the suburbs, with particularly high values in the Hamptons on the far east of the map. The pattern for price changes is similar, but less extreme. For San Francisco, we also see dramatic decreases in rents and prices in the downtown ZIP codes, and increases in more distant regions such as Oakland.

3.2 Bid-Rent Function

We next examine changes in prices and rents at the ZIP-code level across a broad sample of the 30 largest MSAs in the U.S. Figure 3 highlights the relationship between rents (Panel A) and prices (Panel B) against distance from the city center, comparing pre-

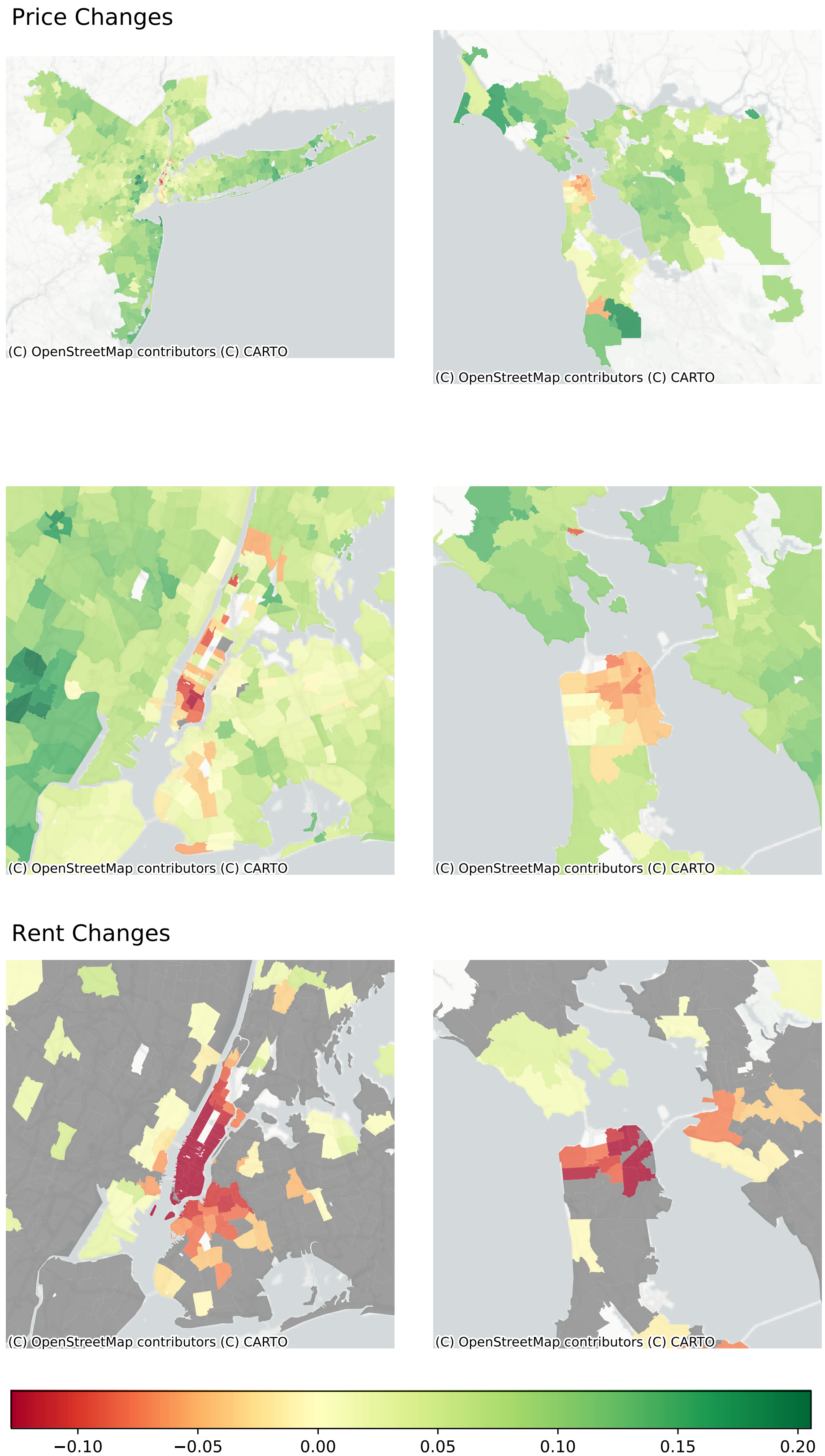

Figure 2. Price and Rent Growth, NYC and SF

This map shows year-over-year changes in prices (top four panels) and rents (bottom two panels) for the New York and San Francisco MSAs at the ZIP code level over the period Dec 2019–Dec 2020. The bottom two rows zoom in on the city center. Darker green colors indicate larger increases, while darker red colors indicate larger decreases.

and post-pandemic patterns. We observe flatter gradients for both prices and rents, with larger changes in the slope of the bid-rent curve for rents than in the curve for prices.

A flattening bid-rent function implies that rent or price changes are higher in the suburbs than in the center. An alternative way of seeing this pattern is to examine the changes in rents (Panel C) and changes in prices (Panel D), for each ZIP code, against distance to the center of the city. We observe strongly decreasing rent values in urban cores, and strongly rising rents in suburban ZIP codes. For house prices, urban ZIP codes do not feature strong declines. Rather, prices rise faster in suburban areas.

The change in prices and rents plotted against the pre-pandemic levels show strong reversals of value in the most expensive ZIP Codes (Panels E and F of Figure 3). These findings highlight that price and rent reversals have been largest in areas which previously enjoyed large urban premiums.

Appendix Figures A1 and A2 highlight similar patterns for several large cities of New York, San Francisco, Chicago, Boston, and Los Angeles.

3.3 Estimating the Bid-Rent Function

Next, we formally estimate the slope of the bid-rent function using the following empirical specification:

$$\ln p_{ijt} = \alpha_{jt} + \delta_{jt}\big[\ln(1 + D(\mathbf{z}^z_{ij}, \mathbf{z}^m_j))\big] + \beta X_{ij} + e_{ijt}, \qquad e_{ijt} \sim \text{i.i.d.}\mathcal{N}(0, \sigma_e^2). \tag{1}$$

The unit of observation is a ZIP code-month. Here p_{ijt} refers to the price or rent in ZIP code i of MSA j at time t, and $D(\mathbf{z}^z_{ij}, \mathbf{z}^m_j)$ is the distance in kilometers between the centroid of ZIP code i and the center of the MSA j, where $i \in j$.[5] We control for MSA fixed effects, time fixed effects, and ZIP-code level control variables (X_{ij}). The ZIP-code controls are: log of annual gross income in 2017, median age of the head of household, proportion of

[5]We define the center of the MSA as City Hall, as in Albouy, Ehrlich, and Shin (2018), except for New York City, in which we define Grand Central as the center.

Figure 3. Changes in Prices and Rents

The top two figures show the bid-rent function for the top 30 MSAs: the relationship between distance from the city center (the log of 1 + the distance in kilometers from City Hall) and the log of rents (Panel A) and prices (Panel B). Lighter points indicate ZIP codes, while darker points indicate averages by 5% distance bins (binscatter). Subsequent figures show changes in rents (Panels C & E) and prices (Panels D & F) against distance and the pre-pandemic levels of rents and prices.

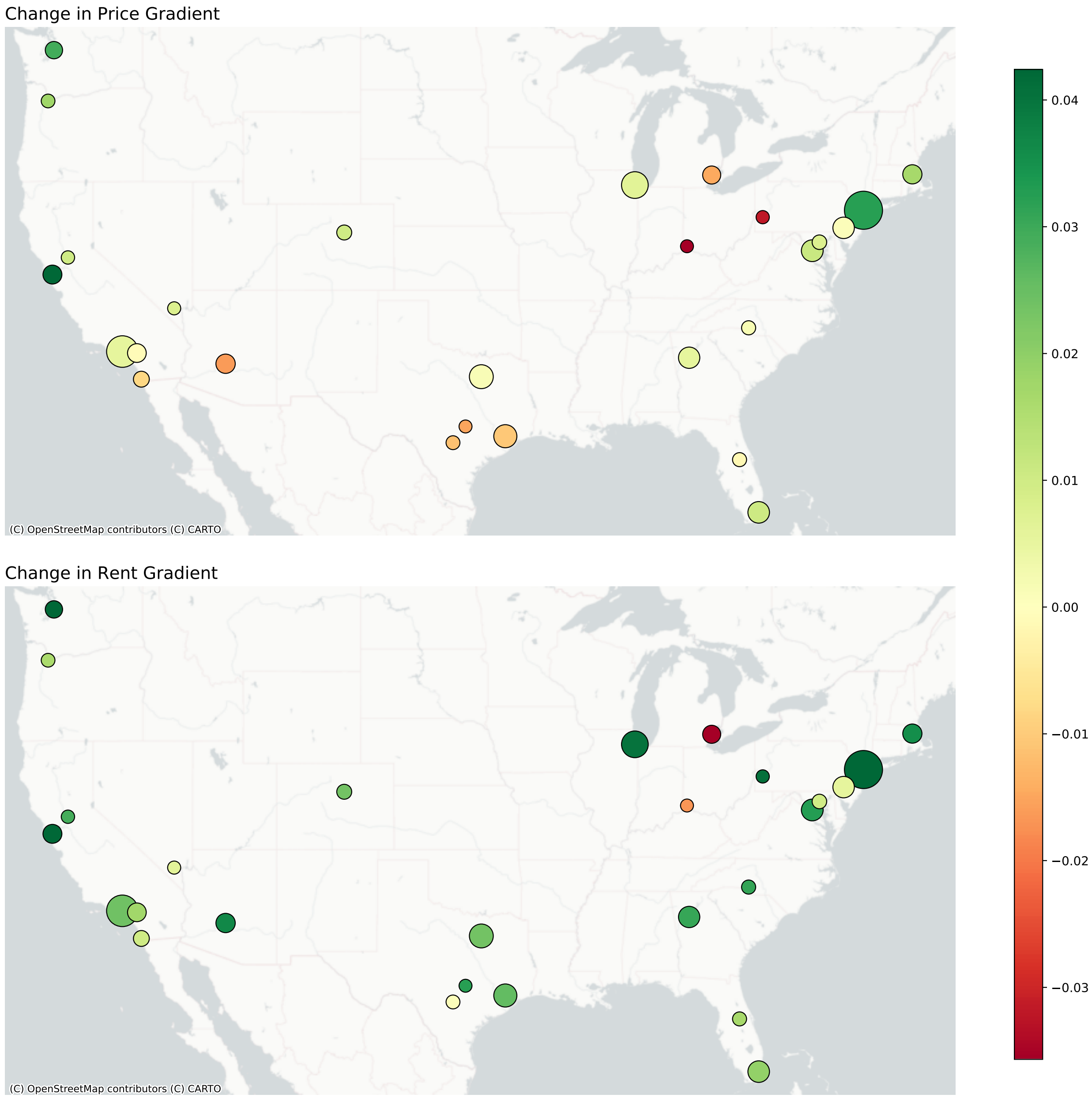

Figure 4. MSA level Changes in Price and Rent Gradients

This map plots the change in price and rent gradients across the U.S. over the period Dec 2019–Dec 2020. For each MSA, we estimate the price and rent gradient as in equation 1, and plot the resulting change at the MSA-level. Higher values correspond to a flatter bid-rent curve. The size of the circle corresponds to the magnitude of the change.

Black households in 2019, and proportion of individuals who earn over $150k in 2019. The controls are all measured pre-pandemic (based on the latest available data) and do not vary over time during our estimation window.

The coefficient of interest is δ_{jt} which measures the elasticity of prices or rents to distance between the ZIP code and the center of the MSA. We refer to it as the price or rent gradient. Historically, δ_{jt} is negative, as prices and rents decrease as we move away from the city center. Our main statistic of interest is $\delta_{jt+1} - \delta_{jt}$, shown in Figure 1. Properties away from the city center have become more valuable over the course of 2020, *flattening the bid-rent curve*, and resulting in a positive estimate for $\delta_{jt+1} - \delta_{jt}$. Figure 4 shows the change in price and rent gradient across the US.

3.4 Listing Prices

As an alternative to Zillow prices and to explore homeowners' listing behavior, we also study list prices from Realtor. Panels A and B of Figure 5 show that listing price prices (median and median price per sq. ft.) are increasing with distance from the city center, consistent with the evidence from transactions prices. This result confirms a greater increases in prices in the suburbs than in the urban core.[6]

3.5 Quantity Adjustments

Next we assess two measures of housing quantities, which are often interpreted as measures of liquidity. Active listings measures the number of housing units that are currently for sale. There was a large increase in the housing inventory in the urban core between December 2019 and December 2020 and a large decline in inventory in the suburbs (Panel C of Figure 5). Buyers depleted large fractions of the available housing inventory in the suburbs during the pandemic, even after taking into account that a strong sellers'

[6] Appendix Figure A5 shows the changes in the log median listing price for New York and San Francisco metropolitan areas (Panel A), and changes in the log of median listing price per square foot (Panel B).

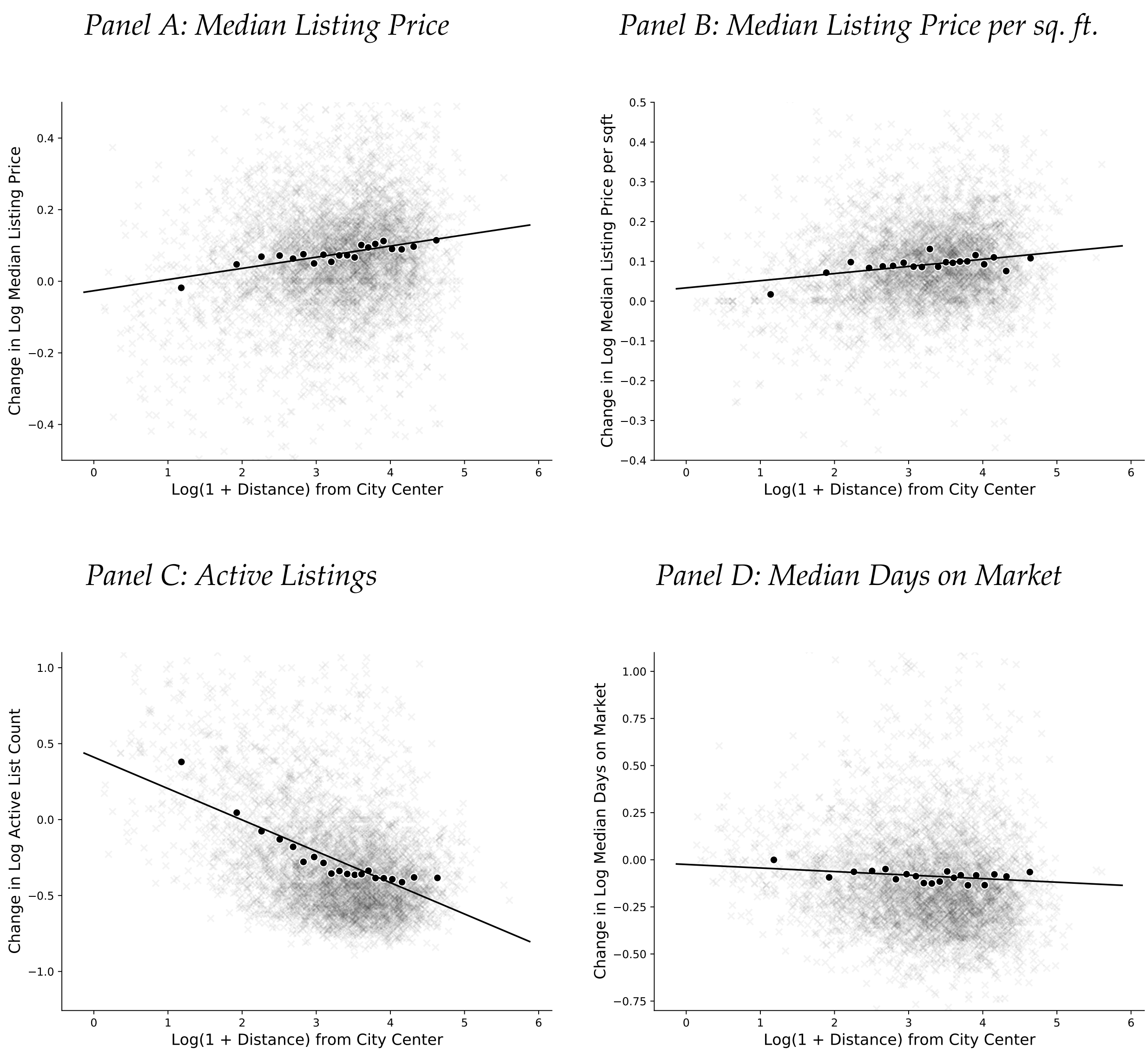

Figure 5. Changes in Listing Prices and Market Inventory

The relationship between changes in listing prices, measured as either the median listing price (Panel A) or the median listing price per sq. ft. (Panel B) with respect to distance. Changes in two measures of market inventory, active listings (Panel C) and median days on market (Panel D) against distance from the center of the city the top 30 MSAs in the US. Each observation is a ZIP Code and represents the change in the market inventory or listing price measure from Dec 2019 to Dec 2020.

market may have prompted additional suburban homeowners to put their house up for sale over the course of 2020.

The second measure we study is median days-on-the-market (DOM), a common metric used in the housing search literature (Han and Strange, 2015) to quantify how long it takes to sell a house. DOM rose in the urban core and fell in the suburbs (Figure 5, Panel

D). Housing liquidity improved dramatically in the suburbs and deteriorated meaningfully in the center.[7]

There is a strong negative cross-sectional relationship between house price changes and changes in active listings across all ZIP codes of the top-30 metropolitan areas in the U.S. (Figure 6). ZIP codes in the suburbs are in the top left corner of this graph while ZIP codes in the urban core are in the bottom right corner.

Panel A: Price change against active listing changes

Panel B: Price and median days on market changes

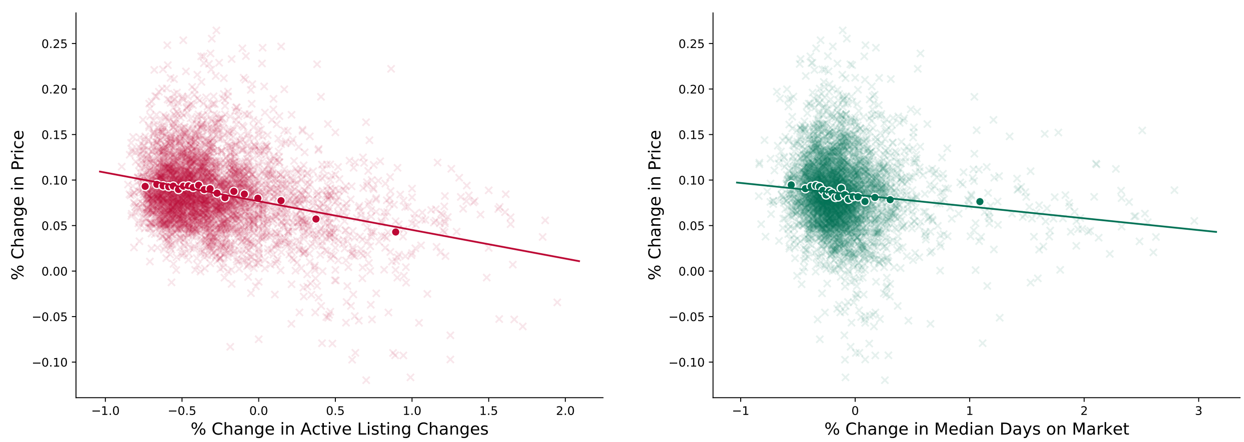

Figure 6. Price change against Changes in Inventory

Changes in prices against changes in two measures of inventories. Panel A plots the relationship between the percentage change in house prices from Dec 2019–Dec 2020 against the percentage change in active listings over this period. Panel B plots the same change in house prices against the percentage change in days on market over the same period.

3.6 Migration

These large changes in real estate markets correspond to substantial revaluations of urban premia in the context of the pandemic shock of COVID-19. In this section, we connect these changes to the migration pattern of individuals over this time period, and the role of remote work in facilitating these moves.

[7] Appendix Figure A6 shows similar results for New York and San Francisco.

To measure home residence, we use mobile phone geolocation data provided by VenPath. We measure individual night-time residence based on frequency of pings at night hours.[8] We observe a large migration elasticity with respect to distance to the city center. Residents near the center of the city start to leave after March, and populations rise in the suburbs (Figure 7, Panel A). We examine a number of other major metro areas in Figure A7, finding a considerable suburban exodus across many superstar cities.

We connect these population changes to remote work in Panel B of Figure 7, using a ZIP level measure of the fraction of jobs which could potentially be done remotely by Dingel and Neiman (2020). We find a strong association between population flight and the share of the population in the ZIP that is able to work remotely, suggesting that workers with flexibility in their work location were particularly likely to leave their home ZIP codes during the pandemic.

This migration away from the center of cities began in the wake of the pandemic, boosted by several factors both temporary and permanent. Initially, there was considerable concern that densely populated metropolitan areas presented additional risk for disease transmission. Additionally, the ensuing lock-downs lowered the value of local amenities. Work-from-home policies enabled many workers to work remotely rather than commute to work. While these policies were initially temporary, many employers have signaled the possibility of long-lasting remote work policies, either towards a fully-remote workforce or towards hybrid forms of remote work several days a week for a large share of employees. These partial remote policies may explain the permanent relocation of individuals to the outskirts of metropolitan areas, as workers anticipate less frequent commutes. We return to this discussion in the last section of the paper.

We also connect migration patterns to changes in rents (Panel C) and prices (Panel D). We find a particularly strong association of migration and changes in rent, but still

[8] We require three or more pings from 5pm–8am in a given census tract to designate a user as a possible resident in a night, and require at least five associations of individuals with night-time pings to assign a residence.

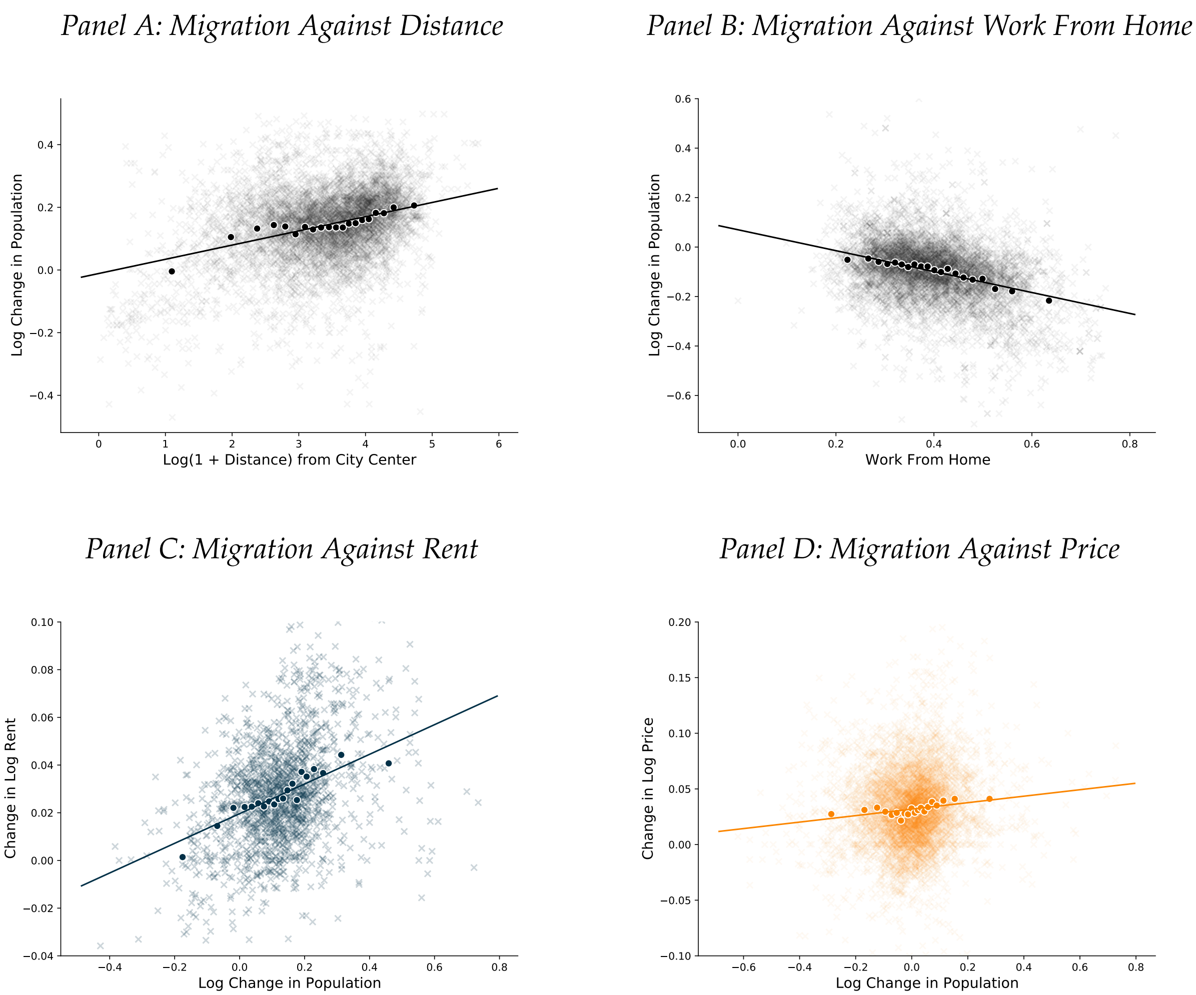

Figure 7. Associations of Intracity Migration

Shows the change in population from February to March as measured in VenPath against log(1 + distance) to the city center (Panel A) and Dingel and Neiman (2020) Work From Home metric for the top 30 MSAs (Panel B). The binscatter line is estimated by weighing the ZIP codes by their population. Shows change in population plotted against changes in rents at the ZIP level (Panel D) and changes in prices (Panel D) for the top 30 MSAs.

meaningful shocks to prices, suggesting that the housing markets may be affected for the long-run. While these results establish large changes in location decisions for individuals through the pandemic, a major point of uncertainty is the persistence of these trends in the future. We address this question in the next section by combining evidence on rents, prices, and survey expectations to infer the persistence of the COVID-19 shock on the urban environment from real estate markets.

4 Beliefs About Future Rent Growth

In this section, we investigate what housing markets tell us about future rent growth expectations following the COVID-19 shock. To do so, we combine the observed changes in the price and rent gradients with a present-value model to build expectations about the relative rent growth rate in suburbs versus the urban core over the next several years.

4.1 Observed Price-Rent Ratios

In the subsequent analysis we use price-rent ratios. Because the Zillow data are quality-adjusted, it is reasonable to interpret the price-rent ratio in a ZIP code as pertaining to the same typical property that is either for rent or for sale. For our purposes, it is enough that the change over time in the price-rent ratio is comparable across ZIP codes within an MSA.

We first calculate the price-rent ratio for each ZIP-month over the period of January 2014 (when the rent data starts) until December 2019. We then average over these 72 months. This average acts as a proxy for the long-run equilibrium price-rent ratio before the pandemic. Price-rent ratios are high in the city center and decrease with distance to the center. The "Pre-Pandemic" line in Figure A9 illustrates this pattern for the New York MSA.

We also compute the price-rent ratio in the fourth quarter of 2020, averaging the price-rent ratios of October, November, and December 2020.[9] The "Post-Pandemic" line in Figure A9 shows the price-rent ratio at the end of 2020 in New York. In the suburbs, rents and prices rose by about the same amount over the course of 2020, leaving the price-rent ratio unchanged. In the urban core, rents fell much more than prices, resulting in a large increase in the price-rent ratio. Thus, the price-rent ratio curve became steeper during the pandemic. Put differently, it became cheaper to rent than to own in the core and relatively more expensive to rent in the periphery.

Another way to see this is to plot the average 12-month rental growth rate over the January 2014 to December 2019 period as a function of distance from the center. Panel A of Figure 8 shows that rental growth was similar in the core and in the suburbs of New York City pre-pandemic. This pattern changes dramatically during the pandemic, with steeply falling rents in the core and steeply rising rents in the suburbs. Panel B shows a strong reversal in house price growth as a function of distance before and after the pandemic.

Panel A: Rent Growth *Panel B: Price Growth*

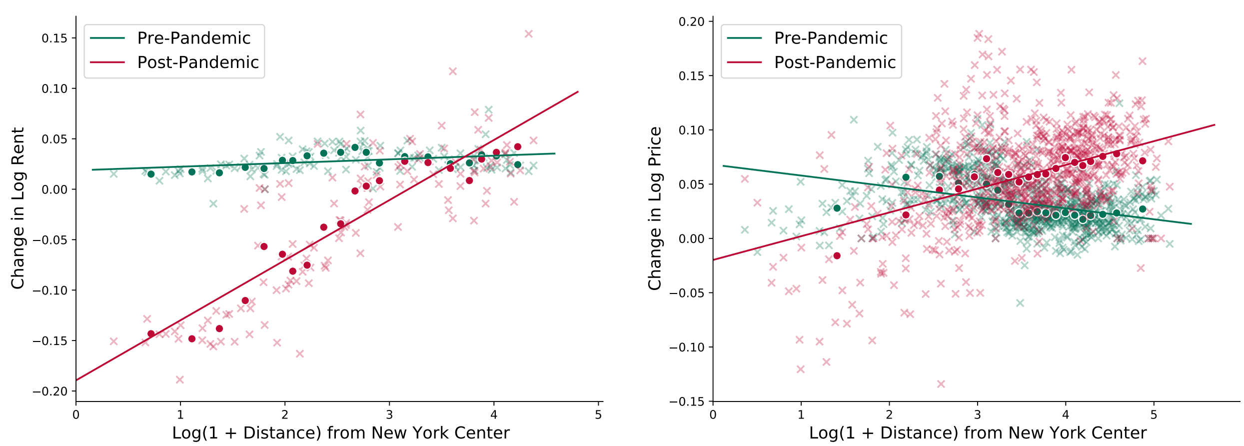

Figure 8. Changes in Rent and Price Growth Rates

The changes in rental growth rates (Panel A) and price growth rates (Panel B) over the pre-pandemic period (Jan 2014–Dec 2019) compared with the period during pandemic (Jan 2020–Dec 2020) across distance from the center of New York (log of 1 + distance to Grand Central in kilometers).

[9] As long as the price-rent ratio in one of the months is available, the ZIP code is included in the analysis.

We compute price-rent ratios and average rental growth rates for each ZIP code in each of the largest 30 MSAs.

4.2 Present-Value Model

We briefly review the the present-value model of Campbell and Shiller (1989), a standard tool in asset pricing. Campbell, Davis, Gallin, and Martin (2009) were the first to apply the present value model to real estate. They studied a variance decomposition of the aggregate residential house price-rent ratio in the U.S. Van Nieuwerburgh (2019) applied the model to REITs, publicly traded vehicles owning (mostly commercial) real estate.

Let P_t be the price of a risky asset, in our case the house, D_{t+1} its (stochastic) cash-flow, in our case the rent, and R_{t+1} the cum-dividend return:

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t}.$$

We can log-linearize the definition of the cum-dividend return to obtain:

$$r_{t+1} = k + \Delta d_{t+1} + \rho\, pd_{t+1} - pd_t,$$

where all lowercase letters denote natural logarithms and $pd_t = p_t - d_t = -dp_t$. The constants k and ρ are functions of the long-term average log price-rent ratio. Specifically,

$$\rho = \frac{\exp(\overline{pd})}{1 + \exp(\overline{pd})}, \qquad k = \log(1 + \exp(\overline{pd})) - \rho \overline{pd}. \tag{2}$$

By iterating forward on the return equation, adding an expectation operator on each side, and imposing a transversality condition (i.e., ruling out rational bubbles), we obtain the present-value model of Campbell and Shiller (1989):

$$pd_t = \frac{k}{1-\rho} + E_t\left[\sum_{j=1}^{+\infty} \rho^{j-1} \Delta d_{t+j}\right] - E_t\left[\sum_{j=1}^{+\infty} \rho^{j-1} r_{t+j}\right]. \tag{3}$$

A high price-rent ratio must reflect either the market's expectation of higher future rent growth, or lower future returns on housing (i.e., future price declines), or a combination of the two.

This equation also holds unconditionally:

$$\overline{pd} = \frac{k}{1-\rho} + \frac{\bar{g}}{1-\rho} - \frac{\bar{x}}{1-\rho}, \tag{4}$$

where $\bar{g} = E[\Delta d_t]$ and $\bar{x} = E[r_t]$ are the unconditional expected rent growth and expected return, respectively. Equation (4) can be rewritten to deliver the well-known Gordon Growth model (in logs) by plugging in for k:

$$\log\left(1 + \exp \overline{pd}\right) - \overline{pd} = \bar{x} - \bar{g}. \tag{5}$$

The left-hand side variable is approximately equal to the long-run rental yield $\overline{D/P}$.

Subtracting equation (4) from (3), we obtain:

$$pd_t - \overline{pd} = E_t\left[\sum_{j=1}^{+\infty} \rho^{j-1} \left(\Delta d_{t+j} - \bar{g}\right)\right] - E_t\left[\sum_{j=1}^{+\infty} \rho^{j-1} \left(r_{t+j} - \bar{x}\right)\right]. \tag{6}$$

Price-rent ratios exceed their long-run average, or equivalently rental yields are below their long-run average, when rent growth expectations are above their long-run average or expected returns are below the long-run expected return.

Expected Rent Growth In what follows, we assume that expected rent growth follows an autoregressive process. We denote expected rent growth by g_t:

$$g_t \equiv E_t[\Delta d_{t+1}]$$

and assume an AR(1) for g_t:

$$g_t = (1 - \rho_g)\overline{g} + \rho_g g_{t-1} + \varepsilon_t^g \tag{7}$$

Under this assumption, the rent growth term in equation (6) can be written as a function of the current period's expected rent growth in excess of the long-run mean:

$$E_t \left[\sum_{j=1}^{+\infty} \rho^{j-1} \left(\Delta d_{t+j} - \overline{g} \right) \right] = \frac{1}{1 - \rho\rho_g} (g_t - \overline{g}). \tag{8}$$

Expected Returns Similarly, we define expected returns by x_t

$$x_t \equiv E_t[r_{t+1}]$$

and assume an AR(1) for x_t following Lettau and Van Nieuwerburgh (2008); Binsbergen and Koijen (2010); Koijen and van Nieuwerburgh (2011):

$$x_t = (1 - \rho_x)\overline{x} + \rho_x x_{t-1} + \varepsilon_t^x \tag{9}$$

Under this assumption, the return term in equation (6) can be written as a function of the current period's expected return in excess of the long-run mean:

$$E_t \left[\sum_{j=1}^{+\infty} \rho^{j-1} \left(r_{t+j} - \overline{x} \right) \right] = \frac{1}{1 - \rho\rho_x} (x_t - \overline{x}). \tag{10}$$

Implied Dividend Growth Expectations With equations (8) and (10) in hand, we can restate equation (6)

$$pd_t - \overline{pd} = A(g_t - \overline{g}) - B(x_t - \overline{x}). \tag{11}$$

where $A = \frac{1}{1-\rho\rho_g}$ and $B = \frac{1}{1-\rho\rho_x}$.

From equation (11), we can back out the current-period expectations about future rent growth:

$$g_t = \overline{g} + (1 - \rho\rho_g)\left(pd_t - \overline{pd}\right) + \frac{1-\rho\rho_g}{1-\rho\rho_x}\left(x_t - \overline{x}\right). \tag{12}$$

Current beliefs about rent growth depend on long-run expected rent growth (first term), the deviation of the price-rent ratio from its long-run mean (second term), and the deviation of expected returns from their long-run mean (third term). Long-run expected dividend growth $\overline{g}$ is obtained from equation (4) given $\overline{pd}$ and $\overline{x}$.

4.3 Case 1: Pandemic is Transitory

We assume that ZIP codes were at their long-run averages $\left(\overline{x}^{ij}, \overline{g}^{ij}\right)$ prior to the pandemic, in December 2019. They imply $\overline{pd}^{ij}$ per equation (5). In a first set of calculations, we assume that following the COVID-19 shock, expected rent growth and expected returns (and hence the mean pd ratio) will gradually return to those pre-pandemic averages. Under these assumptions, we can ask what the observed changes in the price-rent ratios between December 2019 and December 2020 imply about the market's expectations about rent growth in urban relative to suburban ZIP codes over the next several years.

If pd_t is measured as of December 2020, then equation (11) measures the percentage change in the price-rent ratio post versus pre-pandemic. Let $i = u$ denote a ZIP code in the urban core and let $i = s$ denote a ZIP code in the suburbs. Then the difference-in-difference of the price-rent ratio between post- and pre-pandemic and between suburban and urban ZIP codes in the same MSA is given by:

$$
\begin{aligned}
\Delta pd^j &= \left[A^{uj}\left(g_t^{uj}-\overline{g}^{uj}\right)-A^{sj}\left(g_t^{sj}-\overline{g}^{sj}\right)\right]-\left[B^{uj}\left(x_t^{uj}-\overline{x}^{uj}\right)-B^{sj}\left(x_t^{sj}-\overline{x}^{sj}\right)\right] \quad (13)\\
\Delta pd^j &\equiv \left(pd_t^{uj}-\overline{pd}^{uj}\right)-\left(pd_t^{sj}-\overline{pd}^{sj}\right)
\end{aligned}
$$

where the second line defines Δpd^j for an MSA j.

We observe Δpd^j, but there are two unknowns on the right-hand side. Hence, there is a fundamental identification problem which is well understood in the asset pricing literature. One either needs additional data on return expectations or on expected cash flow growth, for example from survey data, or one needs to make an identifying assumption. We follow the second route.

Assumption 1. Expected returns and expected rent growth have the same persistence across geographies: $\rho_x^{ij}=\rho_x$ and $\rho_g^{ij}=\rho_g$. We also assume that $\rho^{ij}=\rho^j$.

This assumption implies that A^{ij} and B^{ij} only depend on the MSA j.[10]

Under Assumption 1, we can use the present-value relationship to back out the market's expectation in terms of expected rent growth in urban minus suburban ZIP codes:

$$
g_t^{uj}-g_t^{sj}=\overline{g}^{uj}-\overline{g}^{sj}+(1-\rho^j\rho_g)\Delta pd^j+\frac{1-\rho^j\rho_g}{1-\rho^j\rho_x}\Delta x^j. \quad (14)
$$

where

$$
\Delta x^j \equiv (x_t^{uj}-\overline{x}^{uj})-(x_t^{sj}-\overline{x}^{sj})
$$

Equation (14) gives the expected rent growth differential over the next twelve months, measured as of December 2020, i.e., between December 2020 and December 2021. But since expected rent growth follows an AR(1), there will be further changes in 2022, 2023,

[10]This is an approximation. The mean log price-rent ratio, $\overline{pd}^{ij}$, and hence ρ^{ij} depends on (i,j) because of heterogeneity in $\left(\overline{x}^{ij},\overline{g}^{ij}\right)$. We construct the population-weighted mean of $\overline{pd}^{ij}$ across all zip codes in the MSA, call it $\overline{pd}^j$, and then form ρ^j from $\overline{pd}^j$ using equation (2).

etc. The expected discounted cumulative rent changes over all future years are given by:

$$\frac{g_t^{uj} - g_t^{sj}}{1 - \rho^j \rho_g} = \frac{\overline{g}^{uj} - \overline{g}^{sj}}{1 - \rho^j \rho_g} + \Delta pd^j + \frac{\Delta x^j}{1 - \rho^j \rho_x}. \tag{15}$$

Δx^j measures to what degree the pandemic changed the risk premium on urban versus suburban housing. Estimating time-varying risk premia is hard, even in liquid markets with long-time series of data. It is neigh impossible for illiquid assets like homes over short periods of time like the 12-month period we are interested in. As such, the best we can do is define our assumptions and understand their impact. We consider two alternative assumptions on Δx^j.

Assumption 2. Expected returns did not change differentially in urban and suburban areas in the same MSA in the pandemic: $\Delta x^j = 0$.

This assumption allows for expected returns to be different in urban and suburban ZIP codes and for expected returns to change in the pandemic. It only precludes that this change was different for suburban and urban areas. Expected returns can be written as the interest rate plus a risk premium. Since the dynamics of interest rates (and mortgage rates more generally) are common across space, this assumption is one on the dynamics of urban-suburban risk premia.

Expected returns in suburban areas are typically higher than in urban areas pre-pandemic. The second assumption we make is that the annual urban risk premium increases by one percentage point relative to the suburban risk premium:

Assumption 3. $\Delta x^j = 0.01, \ \forall j$.

Alternatively, it would be possible to consider a different change or a change that varied by MSA.

4.4 Case 2: Pandemic is Permanent

The opposite extreme from assuming that everything will go back to the December 2019 state is to assume that the situation as of December 2020 is the new permanent state.

In that case, we can use equation (5) to back out what the market expects the new long-term expected urban minus suburban rent growth to be, denoting the new post-pandemic steady state by hatted variables:

$$\widehat{g}^{uj} - \widehat{g}^{sj} = \left(\widehat{pd}^{uj} - \widehat{pd}^{sj}\right) - \left(\log\left(1 + e^{\widehat{pd}^{uj}}\right) - \log\left(1 + e^{\widehat{pd}^{sj}}\right)\right) + \widehat{x}^{uj} - \widehat{x}^{sj}. \tag{16}$$

The first two terms can be computed directly from the observed price-rent ratios in December 2020. The last term requires a further assumption.

We consider the same two assumptions on post-pandemic urban minus suburban expected returns (or equivalently risk premia) as in the transitory case. The first one is that urban minus suburban risk premia differences remain unchanged pre- versus post-pandemic.

Assumption 4. $\widehat{x}^{uj} - \widehat{x}^{sj} = \overline{x}^{uj} - \overline{x}^{sj},\ \forall j$. We refer to this as $\Delta\overline{x}^{j} = 0$.

The second assumption is that urban risk premia rise relative to suburban risk premia by a constant amount of 1% point.

Assumption 5. $\widehat{x}^{uj} - \widehat{x}^{sj} = \overline{x}^{uj} - \overline{x}^{sj} + 0.01,\ \forall j$. We refer to this as $\Delta\overline{x}^{j} = 0.01$.

The difference in comparison to the transitory case is that, now, the relative risk premium change is permanent.

4.5 Case 3: Combining Transitory and Permanent Cases

Let p be the probability that the changes in the urban-minus-suburban expected rent growth and expected return are transitory, and $1 - p$ be the probability that the changes are permanent. In the subsequent section we incorporate survey evidence on p.

Denote $\widetilde{g}_t^{uj}$ and $\widetilde{g}_t^{sj}$ as the urban and suburban expected rent growth combining the transitory and permanent cases:

$$\widetilde{g}_t^{uj} - \widetilde{g}_t^{sj} = p\left(g_t^{uj} - g_t^{sj}\right) + (1-p)\left(\widehat{g}_t^{uj} - \widehat{g}_t^{sj}\right) \tag{17}$$

The first term comes from equation (14), while the second term uses equation (16).

Similarly, let $\widetilde{pd}_t^{uj}$ and $\widetilde{pd}_t^{sj}$ denote the combined log price-rent ratios for the urban and suburban areas, respectively. The difference $\widetilde{pd}_t^{uj} - \widetilde{pd}_t^{sj}$ is the weighted average of the transitory and permanent cases:

$$\widetilde{pd}_t^{uj} - \widetilde{pd}_t^{sj} = p\left(pd_t^{uj} - pd_t^{sj}\right) + (1-p)\left(\widehat{pd}_t^{uj} - \widehat{pd}_t^{sj}\right) \tag{18}$$

The first term is calculated under assumptions 2 and 3 from equation (11), while the second term consists of the observed price-rent ratios in December 2020, which are considered to be the new long-run levels in the permanent case.

4.6 Results: Implied Urban-Suburban Rent Growth Expectations

We report results for each of the 30 largest MSAs in which rent data is available for at least some of the suburban areas (Table I).

We define the urban ZIP codes to be all ZIP codes less than 10 kilometers from the MSA centroid (city hall), and the suburbs to be the ZIP codes more than 40 kilometers from the MSA centroid. For each ZIP code, we compute the price-rent ratio in each month from January 2014 (the start of ZORI data) until December 2019, and compute the time-series average. Similarly, we compute the time-series mean of the average annual rental growth rate for each ZIP code over the 2014–2019 period. We then compute population-weighted averages among the urban and suburban ZIP codes (columns 1–4). For presentation purposes, the mean price-rent ratio is reported in levels (rather than logs) and average rent growth is multiplied by 100 (expressed in percentage points). We use equation (5) to compute the expected annual returns in columns (5) and (6). These expected returns are also multiplied by 100 (annual percentage points). Expected returns are between 5% and 14%. Typically, though not always, expected returns are higher in the suburbs. The numbers in columns (1–6) reflect the pre-pandemic steady state.

Columns (7) and (8) report the price-rent ratio (in levels) for the pandemic. We report the mean, computed over October, November, and December of 2020 (or over as many of these three months as are available in the data).

Column (9) reports Δpd, the log change in the urban-minus-suburban price-rent ratio during the pandemic versus before the pandemic. Most of the reported values are positive, indicating that price-rent ratios went up in urban relative to suburban areas. What this implies depends on the model in question.

4.6.1 Pandemic is Transitory

In the model in which the pandemic is purely transitory, the positive Δpd implies that urban rent growth is expected to exceed suburban rent growth: $g_t^u - g_t^s > 0$. After the steep decline in urban rents, urban rent growth is expected to rebound to restore the price-rent ratio to pre-pandemic level. The large increase in suburban rents will also revert, leading to slower expected rent growth in the suburbs. Columns (10–11) report the urban minus suburban cumulative rent differential, computed from equation (15) under assumptions 2 and 3, respectively.

To implement equation (15), we need values for (ρ_g, ρ_x, ρ^j). We set $\rho_g = 0.747$. This is the estimated 12-month persistence of annual rent growth rates in the U.S. between 1982 and 2020. It implies a half-life of expected rent shocks of approximately 2.5 years. Note that the AR(1) assumption on expected rents means that a 1% point change in current period expected rent translates into a $(1 - \rho^j \rho_g)^{-1} \approx 3.5\%$ point cumulative change in rents over the current and all future periods (assuming a typical value for ρ^j). We set

$\rho_x = 0.917$ based on the observed persistence of aggregate annual price-dividend ratios.[11] We compute ρ^j from equation (2), using the population-weighted mean price-rent ratio for all ZIP codes in the MSA pre-pandemic.

If there is no differential change in urban versus suburban risk premia (column 10), urban rent growth is expected to exceed suburban rent growth by 4.5% points in New York over the next several years cumulatively. However, if the urban risk premium temporarily rises by 1% point relative to the suburban risk premium, and that difference then slowly reverts back to 0, then urban rent growth will exceed suburban rent growth by 12.6% cumulatively (column 11). The corresponding numbers for San Francisco are similar at 3.5% (column 10) and 12.3% (column 11).

Los Angeles is expected to see much larger cumulative urban-suburban rent growth between 18.7% (column 10) and 27.3% (column 11). This is because the change in the urban-minus-suburban price-rent ratio is much larger (12.8%). Restoring the pre-pandemic urban-suburban price-rent multiples requires large catch-up growth in urban rents. The same is true for Philadelphia, Sacramento, and Charlotte.

Miami, St Louis, and Baltimore are at the other end of the spectrum with low urban-suburban rent growth expectations (column 10). Baltimore is unusual in that it has higher price-rent ratios, lower rent growth, and higher risk premia in the urban core than in the suburbs before the pandemic. If the suburban risk premium falls relative to the urban one by 1% point (column 11), urban rent growth must exceed suburban growth by 7.8% to restore the old price-rent ratios.

Figure A10 shows that expected rent growth is a declining function of distance from the city center.

[11] We compute the log price-rent ratio for the United States from January 1987 until December 2020 as the log of the Case-Shiller Core Logic National House Price Index minus the log of the CPI Rent of Primary Residence series. We then take the 12-month autocorrelation.

4.6.2 Pandemic is Permanent

In the model where the pandemic is permanent, the interpretation of the price-rent ratio change Δpd^j is quite different. Columns (12) and (13) report the expected urban minus suburban rent growth, as given by equation (16) under assumptions 3 and 4, respectively. These columns report an annual growth rate differential (not a cumulative change), but that change is now expected to be permanent.

If risk premia do not change, New York's price-rent ratio in December 2020 implies permanently lower annual rent growth of -0.23% in urban than in suburban ZIP codes. However, if the urban-suburban risk premium rises permanently by 1% point (thereby shrinking it from -2% pre-pandemic to -1% post-pandemic), urban rent growth is expected to exceed suburban growth by 0.77% annually. The numbers in columns (12) and (13) differ by exactly 1% point, the assumed difference in urban-suburban risk premia between the two columns. Column (13) can be compared to column (11), after dividing column (11) by about 3.5 (more precisely, multiplying it by $1 - \rho^j \rho_g$). Both numbers then express an annual expected rent growth under the assumption that risk premia in urban areas go up by 1% point relative to suburban areas. For New York, the temporary model implies 3.65% higher rent growth in urban ZIP codes while the permanent model implies 0.77% higher growth. However, in the temporary model, both the expected rent growth and the expected return will revert to pre-pandemic levels while in the permanent model they will not. Both models suggest that the market expects the rent in urban ZIP codes in New York to grow more strongly than in the suburbs in the future.

In LA, the permanent model indicates urban rent growth that will exceed suburban growth by 2% (column 12) or 3% (column 13). We find similar rent growth differences for Atlanta, and even stronger rent growth differences for Charlotte. Miami, Seattle, and San Diego see the lowest urban growth differentials.

Table I. Backing Out Expected Rents

#	MSA	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
		Pre-pandemic						Pandemic			Transitory Change		Permanent Change	
#	MSA	$\overline{PD}^{uj}$	$\overline{PD}^{sj}$	$\overline{g}^{uj}$	$\overline{g}^{sj}$	$\overline{x}^{uj}$	$\overline{x}^{sj}$	PD_t^{uj}	PD_t^{sj}	Δpd^j	$(g_t^{uj} - g_t^{sj})/(1-\rho^j\rho_g)$		$\hat{g}^{uj} - \hat{g}^{sj}$	
											$\Delta x^j = 0$	$\Delta x^j = 0.01$	$\Delta \overline{x}^j = 0$	$\Delta \overline{x}^j = 0.01$
1	New York-Newark-Jersey City, NY-NJ-PA	24.85	17.47	2.50	2.91	6.44	8.47	27.06	17.93	5.99	4.56	12.64	-0.23	0.77
2	Los Angeles-Long Beach-Anaheim, CA	29.55	24.48	5.76	4.12	9.09	8.13	34.95	25.47	12.82	18.65	27.25	1.99	2.99
3	Chicago-Naperville-Elgin, IL-IN-WI	17.40	11.34	2.88	2.79	8.47	11.24	18.73	11.94	2.18	2.48	9.51	0.07	1.07
4	Dallas-Fort Worth-Arlington, TX	15.18	12.62	4.27	4.02	10.65	11.65	17.51	13.76	5.55	6.37	13.12	0.46	1.46
5	Houston-The Woodlands-Sugar Land, TX	20.52	14.05	0.99	1.83	5.74	8.71	22.18	14.46	4.87	2.10	8.89	-0.69	0.31
6	Washington-Arlington-Alexandria, DC-VA-MD-WV	23.91	17.74	2.94	1.99	7.04	7.47	26.71	18.75	5.59	8.88	16.78	1.09	2.09
7	Miami-Fort Lauderdale-Pompano Beach, FL	16.26	11.93	2.79	4.00	8.75	12.05	18.08	12.96	2.29	-1.66	5.04	-1.25	-0.25
8	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	10.60	14.85	3.11	2.43	12.12	8.95	12.88	15.75	13.61	15.82	22.63	1.85	2.85
9	Atlanta-Sandy Springs-Alpharetta, GA	16.26	13.66	6.21	4.58	12.18	11.64	18.40	14.39	7.13	12.49	19.31	1.96	2.96
10	Phoenix-Mesa-Chandler, AZ	14.98	15.84	7.31	6.26	13.78	12.38	16.82	16.34	8.47	12.03	19.37	1.56	2.56
11	Boston-Cambridge-Newton, MA-NH	21.30	17.08	3.88	4.64	8.47	10.33	24.40	18.65	4.83	2.19	10.15	-0.65	0.35
12	San Francisco-Oakland-Berkeley, CA	33.56	26.38	4.02	4.68	6.95	8.40	39.07	28.94	5.92	3.55	12.33	-0.58	0.42
15	Seattle-Tacoma-Bellevue, WA	30.71	16.04	5.59	6.46	8.79	12.51	36.29	18.67	1.50	-1.56	6.60	-1.22	-0.22
17	San Diego-Chula Vista-Carlsbad, CA	21.46	22.13	5.56	4.95	10.11	9.37	23.72	23.66	3.36	5.51	13.73	0.76	1.76
18	Tampa-St Petersburg-Clearwater, FL	11.51	9.46	5.03	4.89	13.36	14.95	14.39	11.26	4.82	5.27	11.71	0.20	1.20
19	Denver-Aurora-Lakewood, CO	21.68	18.58	5.68	5.03	10.18	10.27	24.34	19.72	5.63	7.87	15.65	0.84	1.84
20	St Louis, MO-IL	13.77	12.93	3.11	2.67	10.12	10.12	14.70	14.01	-1.44	-0.02	6.26	0.32	1.32
21	Baltimore-Columbia-Towson, MD	8.84	14.93	1.43	1.57	12.15	8.05	9.47	15.74	1.64	1.21	7.80	0.23	1.23
22	Charlotte-Concord-Gastonia, NC-SC	15.06	13.25	6.07	3.14	12.50	10.42	18.36	14.06	13.91	23.55	30.46	3.65	4.65
23	Orlando-Kissimmee-Sanford, FL	12.99	11.85	5.45	4.31	12.87	12.41	15.01	12.98	5.34	9.08	15.84	1.43	2.43
24	San Antonio-New Braunfels, TX	11.63	13.94	3.99	2.46	12.24	9.39	13.27	15.13	5.09	10.05	16.63	1.99	2.99
26	Sacramento-Roseville-Folsom, CA	17.91	22.18	7.09	7.99	12.53	12.40	19.32	19.97	18.08	14.96	22.80	-0.04	0.96
29	Austin-Round Rock-Georgetown, TX	21.07	14.47	4.16	3.11	8.80	9.80	25.30	16.32	6.26	9.82	17.28	1.07	2.07
	MSA Population Weighted Average									6.45	7.47	14.96	0.54	1.54

4.6.3 Headline Result: Combining Transitory and Permanent Cases

The Pulsenomics survey held in February of 2021 reports that 64% survey respondents believe that working from home represents a temporary shift for the housing market, while 36% believe the shift is permanent. The sample consists of 102 real estate experts from banking, consulting, and academia.[12]

We use this survey evidence to estimate the probability parameter that the change in the housing market is transitory: $p = 0.64$. Using the experts' view on the transitory versus permanent nature of the working from home shift, we can then compute the expected rental growth rate from equation (17).

Figure 9 summarizes our results for the population-weighted average MSA. We show the evolution of the urban-minus-suburban expected rent growth differential. The red line is for the purely transitory case ($p = 1$), the blue line for the purely permanent case ($p = 0$), and the orange line for the probability-weighted average ($p = 0.64$). The left panel shows the results assuming no change in urban-minus-suburban risk premia ($\Delta x = 0$), while the right panel shows the case of $\Delta x = 0.01$.

The prediction of an increase in urban relative to suburban rents—an urban rent revival—is robust, as all predicted lines are above zero. In the transitory cases, annual expected rent growth increases strongly initially, about 2% points in the left panel and 4% points in the right panel, and then slowly reverts back down to pre-pandemic levels. In case the pandemic change is permanent, the rent growth differential jumps up post-pandemic and remains there. The jump is 0.5% in the left and 1.5% in the right panel. For the combination of transitory and permanent cases, the trajectory of expected rent growth naturally

[12]Pulsenomics surveys these experts about their house price expectations every quarter. Each survey has additional one-off topics. The question in the 2021.Q1 survey used here is on the topic of shifting housing preferences: "The pandemic and rise of remote work have altered housing needs and preferences, though it is uncertain if these changes will prove to be permanent or temporary. For each of the following, would you say that consumer preferences have shifted permanently, temporarily, or not at all? Full-time work from home in favor of full-time work from company office." In addition to the working from home question, which we use, there is also a question on "suburban lifestyle in favor of urban lifestyle." This question received the following responses: 46% permanent and 54% transitory (includes 8% no change).

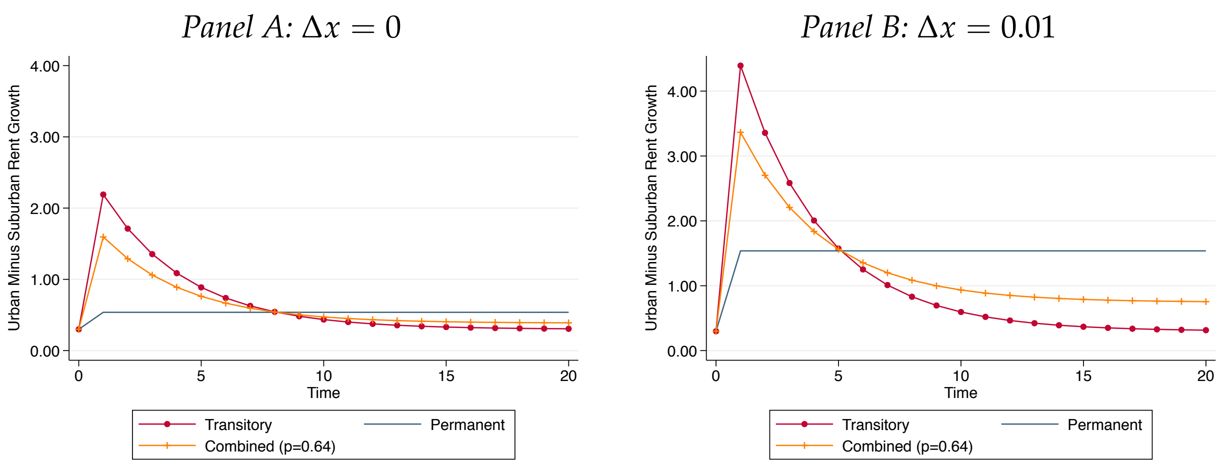

Figure 9. Evolution of Rent Growth when Pandemic is Transitory and Permanent along with a Combination of Two Regimes

The evolution of urban minus suburban rent growth pre and post pandemic in the cases in which the pandemic is transitory (red) permanent (blue), and combining both regimes (orange). We plot the population weighted average of the MSAs. We consider two cases as in Table I: (1) $\Delta x = 0$, and (2) $\Delta x = 0.01$.

lies in between the two extreme cases, and suggests a small long-run increase in urban rent growth. Table 10 reports the combination model's prediction for expected urban-minus-suburban rent growth across MSAs. Specifically, it plots the change in expected rent growth relative to the pre-pandemic level. The reported number is a cumulative discounted change over many years. The two sets of bars correspond to the two different assumptions on expected returns. There is substantial variation in predicted urban rent growth revival, with large values for Los Angeles, Sacramento, Charlotte, Philadelphia, and Phoenix.

Finally, we show the evolution of the (population-weighted average) urban-minus-suburban price-rent ratio (Figure 11). The initial increase in the transitory case is the same in the left and in the right panel because it is dictated by the 2020.Q4 data. From that point forward, the dynamics in the price dividend ratio are governed by the dynamics of expected rent growth and expected returns. We see a gradual decline in urban relative to suburban price-rent ratios in the left panel as expected rent growth mean-reverts. In the right panel, expected returns also mean-revert (at a slower pace because $\rho_x > \rho_g$), which leads to richer dynamics that exhibit under-shooting after year four. In the permanent

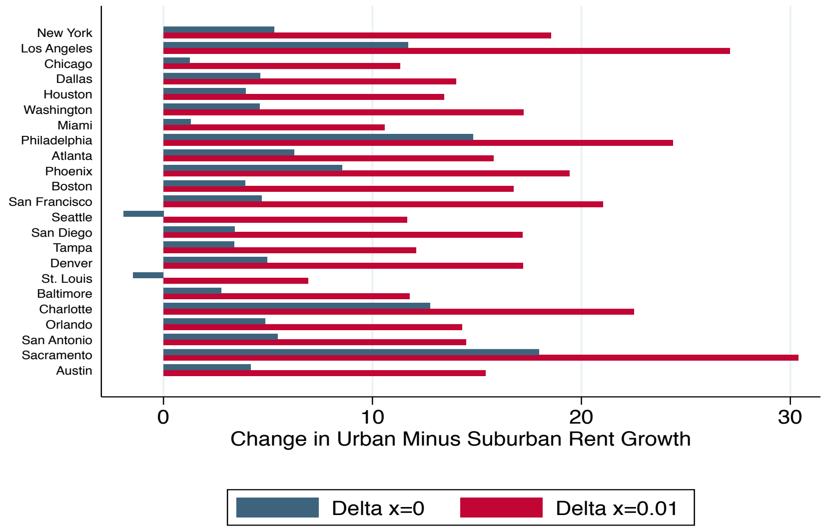

Figure 10. Change in Urban Minus Suburban Rent Growth Relative to Pre-Pandemic for Combination of Transitory and Permanent Regime

The change in urban minus suburban rent growth are shown relative to the pre-pandemic level for the combined regime across our sample of Top 30 MSAs. The combined case is calculated using weights as $p = 0.64$ for the transitory regime, and $1 - p = 0.36$ for the permanent regime, as reported by the Pulsenomics survey. We consider two cases as in Table I: (1) $\Delta x = 0$, and (2) $\Delta x = 0.01$.

case, the price-rent ratio remains at its 2020.Q4 level permanently. For our preferred combination case, we obtain urban price-rent ratios that remain about 3% points above the pre-pandemic levels in the long-run. Owning in the city center becomes permanently more expensive than renting.

5 Mechanisms

This section explores potential drivers of the changing price and rent gradient, exploiting variation across MSAs.

5.1 MSA-Level Analysis

Having established the change in price and rent gradient at the metropolitan level, in this section we examine the main driving factors behind the changes in the bid-rent function in the cross-section. We focus on three key variables: the fraction of the popula-

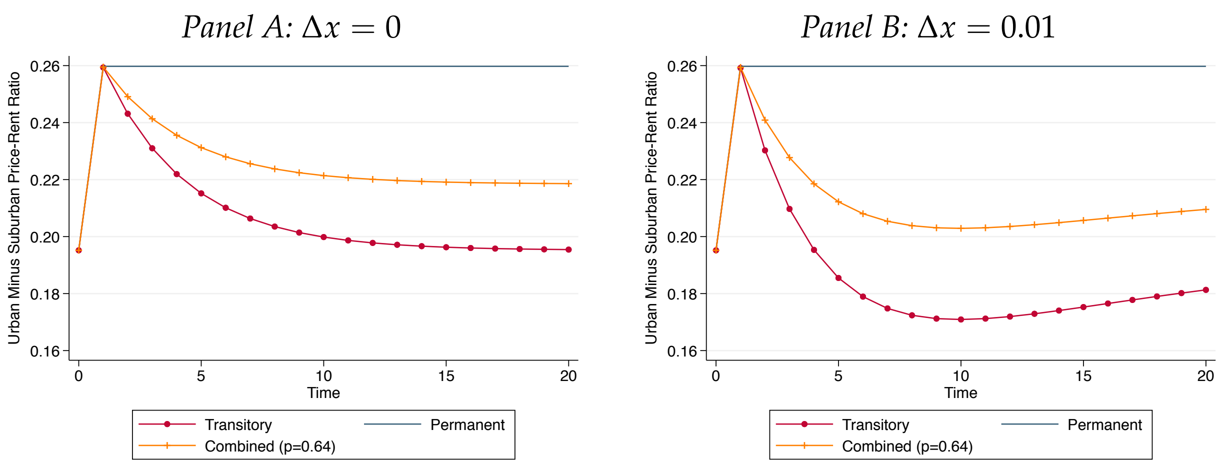

Figure 11. Evolution of Price-Rent Ratio when Pandemic is Transitory and Permanent along with a Combination of Two Regimes

The evolution of urban minus suburban price-rent ratio pre- and post-pandemic in scenarios in which the pandemic is transitory, permanent, and combining both regimes. We plot the population weighted average of the MSAs. We consider two cases as in Table I: (1) $\Delta x = 0$, and (2) $\Delta x = 0.01$.

tion with occupations that can be done remotely (Dingel and Neiman, 2020), COVID-19 lockdown restrictions from Hale, Atav, Hallas, Kira, Phillips, Petherick, and Pott (2020),[13] and a measure of housing inelasticity (the first principal component of the Saiz (2010b) supply elasticity measure, the Gyourko, Saiz, and Summers (2008) land use regulatory index, and the Lutz and Sand (2019) measure of land availability). Appendix Table A.I explores a larger list of other possible covariates; given our limited sample of MSAs we focus on a smaller set of important covariates for the main analysis.

We regress the change in the price gradient for each of the top-30 MSAs on several MSA-level characteristics (Table II). Table III presents the results for the change in the rent gradient. Column (1) shows that variation in remote work (Dingel and Neiman, 2020) across MSAs alone explains 22.8% of variation in price gradient changes and 27.0% of variation in rent gradient changes, and is a strong economic predictor of changes in these gradients. A 10 percentage point increase in the fraction of jobs in an MSA which can be done remotely changes the price gradient by 2.15 percentage points and the rent

[13] We associate each MSA with the preponderant state in the area to assign lockdown policies; for instance the NYC MSA with New York State.

gradient by 3.26 percentage points. These are substantial increases which reflect large revaluations of suburban vs. urban real estate in areas with more remote work.

The larger positive coefficient on WFH for rents as compared to prices indicates a greater reversal in rent gradients versus price gradients across MSAs. As rents reflect short-term expectations, and prices capture future long-term expectations of real estate markets, this evidence supports the urban revival results in Section 4.6. A transitory component in WFH, consistent with the Pulsenomics survey evidence, suggests an expected future reduction in work from home practices relative to the high 2020 WFH levels. At the same time, the impact on price gradients suggests that some of the effect is expected to be permanent.

While this specification shows the importance of the WFH shock in accounting for the cross-section of urban real estate repricing, we acknowledge that this is a composite shock reflecting two important channels. One channel is that workers with the capacity to work remotely saw this latent capacity realized over the course of the pandemic, as many employers moved to a remote working model. Survey data suggest that many employers and employees expect remote work to continue in the future, at least on a hybrid basis enabling workers to work remotely some number of days in the week.[14] Facing a looser commuting constraint, this unbundling of work and residence enables remote workers to re-optimize their housing choices. Many choose to live in cheaper and less dense areas in the suburban fringes of cities.

At the same time, the class of remote workers generally consists of educated and skilled workers, who have historically also preferred cities for reasons of urban amenities (Couture, Gaubert, Handbury, and Hurst, 2019; Guerrieri, Hartley, and Hurst, 2013). If these workers have experienced a shift in their preference for urban amenities, the resulting reallocation will also lower urban gradients—even if these workers still anticipate regular commuting in the future. At the MSA-level, we do not seek to disentangle these

[14]Survey evidence in Barrero, Bloom, and Davis (2020) indicates a persistence in remote working policies.

two complementary channels for urban revaluation. Here, our focus is on documenting the nature of these urban changes, highlighting the cross-sectional predictors, and examining the persistence of these trends.

Table II. Explaining the Variation in Price Gradient Changes

	(1)	(2)	(3)	(4)	(5)
Work from Home	0.215***			0.151*	0.215***
	(0.0747)			(0.0751)	(0.0683)
Stringency Measure		0.107**		0.00776	
		(0.0464)		(0.0513)	
Supply Inelasticity Index			0.0372***	0.0290**	
			(0.0109)	(0.0126)	
Orthogonalized Stringency Index					0.0663
					(0.0445)
Orthogonalized Supply Inelasticity					0.0290**
					(0.0126)
Constant	-0.0750**	-0.0447**	-0.0161**	-0.0708**	-0.0750***
	(0.0277)	(0.0213)	(0.00642)	(0.0280)	(0.0253)
Observations	30	30	30	30	30
R^2	0.228	0.160	0.293	0.400	0.400
Adjusted R^2	0.200	0.130	0.268	0.331	0.331

Standard errors in parentheses

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

The work from home measure is from Dingel and Neiman (2020), stringency measure is from Hale, Atav, Hallas, Kira, Phillips, Petherick, and Pott (2020), and the supply inelasticity index is the first principal component of the Wharton regulatory and land use restrictions index (Gyourko, Saiz, and Summers, 2008), housing supply elasticity measure (Saiz, 2010a), and the land unavailability measure (Lutz and Sand, 2019). Column (5) orthogonalizes the land inelasticity and stringency measures against the WFH variable.

We are able to measure one possible component of amenity revaluation in column (2), which measures COVID restrictions. These correspond to government-imposed restrictions in private activity, which directly affected the ability of residents to take advantage of local amenities. We also examine housing supply inelasticity in the subsequent column.These variables are normalized to be the same range (0–1) as the WFH measure to enable comparability. These two indicators are both important individually, suggesting that MSAs which feature more strict COVID restrictions see more revaluation towards suburban properties. At the same time, cities which are more inelastic—where urban premia reflect supply constraints—also see urban revaluation, suggesting that affordability constraints in superstar cities may drive interest in suburban lifestyles. However, these variables are strongly correlated, making it difficult to draw strong conclusions from the univariate analysis.

We combine all three variables under two sets of assumptions in columns (4) and (5). In column (4) we include all three variables in conjunction. These three variables combined explain 40% variation in price gradient changes and 31.4% variation in rent gradient changes across MSAs. The WFH measure remains large and economically significant for both rent and price gradient changes, showing the importance of remote work in explaining the reversal of the price and rent gradients. Individuals highly value the importance of remote work leading to increases in suburban valuation. The stringency measure itself becomes small and insignificant for both prices and rents. Supply inelasticity remains significant for prices—suggesting that affordability concerns in space-constrained metros may be more important for permanent moves rather than temporary ones.

A natural concern is that the work from home measure might be correlated with the stringency and supply inelasticity index. In column (5), we orthogonalize the stringency and supply inelasticity index to the WFH measure. The effect of remote work is naturally larger in Column (5) as compared to Column (4) as the coefficient soaks up the common variation which was earlier attributed to other measures. The orthogonalized supply inelasticity remains significant for prices.

In Appendix Figure A11, we decompose these effects for each MSA based on our estimates from column (5) for rents and prices. While MSAs broadly see changes in urban valuation due to remote work policies, there is considerable variation in the cross-section due to the frequency of remote work. Many superstar metro areas like New York, San Francisco, Washington, and Seattle feature high amounts of remote work, and correspondingly see large changes in the valuation of urban properties. By contrast, other metro areas like Orlando, Detroit, and Pittsburgh have far less remote work. Some metros

Table III. Explaining the Variation in Rent Gradient Changes

	(1)	(2)	(3)	(4)	(5)
Work from Home	0.326***			0.267**	0.326***
	(0.101)			(0.112)	(0.102)
Stringency Measure		0.145**		0.0623	
		(0.0651)		(0.0766)	
Supply Inelasticity Index			0.0300*	0.00862	
			(0.0172)	(0.0188)	
Orthogonalized Stringency Index					0.0797
					(0.0664)
Orthogonalized Supply Inelasticity					0.00862
					(0.0188)
Constant	-0.100**	-0.0461	0.00391	-0.111**	-0.100**
	(0.0375)	(0.0300)	(0.0101)	(0.0418)	(0.0378)
Observations	30	30	30	30	30
R^2	0.270	0.151	0.098	0.314	0.314
Adjusted R^2	0.244	0.121	0.066	0.235	0.235

Standard errors in parentheses

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

The work from home measure is from Dingel and Neiman (2020), stringency measure is from Hale, Atav, Hallas, Kira, Phillips, Petherick, and Pott (2020), and the supply inelasticity index is the first principal component of the Wharton regulatory and land use restrictions index (Gyourko, Saiz, and Summers, 2008), housing supply elasticity measure (Saiz, 2010a), and the land unavailability measure (Lutz and Sand, 2019). Column (5) orthogonalizes the land inelasticity and stringency measures against the WFH variable.

like Charlotte, Austin, and San Antonio see a partial offset of the WFH effect due to more elastic housing supply. In these areas, the relative ease of building means that greater real estate demand results in higher quantities, rather than higher prices.

5.2 ZIP-Level Analysis

In Table IV, we break down the patterns at a higher level of granularity at the ZIP-level within our sample of MSAs. We regress rent changes from Dec 2019–Dec 2020 against a variety of ZIP-level covariates in Panel A. Panel B repeats the estimation for price changes. In particular, we measure the fraction of remote workers at the ZIP-code level, and find that this variable remains strongly predictive of real estate changes, even after controlling for MSA-fixed effects and other potentially important covariates[15].

For rents, a 10% point increase in the fraction of remote work in a ZIP code is associated with a 1.8–2.9% point decrease in rent growth, depending on the specification. The number of restaurants and bars, a measure of the pre-pandemic amenity value of a ZIP code, also predicts declines in rents, but not prices—consistent with a temporary urban revaluation based on the diminished attractiveness of local nightlife.

The WFH measure also is an important driver of ZIP-level variation in house price growth within the MSA (Panel B), with a 10% point increase in remote workers decreasing local house price growth by between 0.7–1.4% points. The estimates for the impact of remote work remain economically and statistically significant after controlling for ZIP-level covariates. The nature of our controls enables us to make stronger statements about the nature of the WFH shock at the ZIP-level. This specification controls for MSA-fixed effects, which should account for changes in the revaluation of MSA-wide amenities. Additionally, we also control for local amenities (visits to restaurants and bars) at the ZIP level.

Because these two variables should account for a substantial component of the association of local amenities and real estate valuation, the residual association of WFH and real estate outcomes likely reflects the importance of the remote worker reallocation channel. This reflects the ability of workers with remote jobs to change desired real estate demand. In principle, the disconnection of living and working could have either pro-urban or pro-suburban tilts. Some workers may use the flexibility of work to actually relocate towards cities, while other workers will use flexibility to head towards cheaper suburban areas. On net, the nature of urban revaluation is for remote workers to leave expensive urban areas for less expensive suburban locations within their MSAs.

[15]Results do not change when the orthogonalized work from home measure to log of income is used. In the case of New York City, where the count of COVID-19 cases and deaths are available at the ZIP-code level, we find that the effect is not driven by these COVID variables and the work from home measure remains significant.

Table IV. Intra-city Rent and Price Changes

Panel A: ZIP-Level Rent Changes

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Distance)	0.0292***		0.0247***	0.0252***	0.0240***	0.0233***
	(5.95)		(5.33)	(6.29)	(5.49)	(6.82)
Work from Home		-0.274***	-0.287***	-0.225***	-0.182***	-0.227***
		(-9.12)	(-9.22)	(-12.79)	(-6.17)	(-9.68)
Log(2017 Income)					-0.00237	-0.000886
					(-0.43)	(-0.18)
Median Age					0.000136	0.000212
					(0.25)	(0.70)
Percent of Black Households					0.00667	0.0223*
					(0.29)	(2.03)
Share of High Income Households					-0.0663**	0.0264
					(-2.14)	(1.34)
Log(Restaurants & Bars)					-0.0144***	-0.00865***
					(-5.36)	(-4.52)
Constant	-0.0688***	0.136***	0.0672***	0.0392***	0.120*	0.0773
	(-4.68)	(10.57)	(4.14)	(3.19)	(1.88)	(1.68)
MSA fixed effects	✓	✓		✓		✓
Observations	1697	1697	1697	1697	1697	1697
R squared	0.566	0.527	0.475	0.671	0.524	0.690
Adj. R squared	0.559	0.519	0.474	0.665	0.522	0.683

Panel B: ZIP-Level Price Changes

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Distance)	0.00283		-0.00130	-0.000480	0.00412	0.00705
	(0.64)		(-0.30)	(-0.10)	(0.94)	(1.57)
Work from Home		-0.136***	-0.120***	-0.138***	-0.0663**	-0.0927***
		(-7.12)	(-5.75)	(-9.19)	(-2.64)	(-4.85)
Log(2017 Income)					0.00144	0.000773
					(0.65)	(0.29)
Median Age					-0.0000367	-0.000253
					(-0.10)	(-1.45)
Percent of Black Households					0.0195*	0.0396***
					(1.83)	(5.78)
Share of High Income Households					-0.0583**	-0.0278
					(-2.72)	(-1.41)
Log(Restaurants & Bars)					0.000626	0.00114
					(0.63)	(0.88)
Constant	0.0694***	0.133***	0.131***	0.135***	0.0830***	0.0910***
	(4.62)	(17.55)	(8.20)	(8.01)	(3.66)	(4.55)
MSA fixed effects	✓	✓		✓		✓
Observations	6387	6387	6387	6387	5760	5760
R squared	0.180	0.240	0.055	0.240	0.110	0.329
Adj. R squared	0.176	0.236	0.055	0.236	0.108	0.325

t statistics in parentheses

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

Prices and rents are from Zillow, work from home is computed at the ZIP level following Dingel and Neiman (2020), log of income, median age, percentage of black households, and share of high income households are obtained from the Census, and log of restaurants and bars from Safegraph.

The comparison of WFH effects across rents and prices also points to the persistence of urban revaluation. Changes in rents reflect short-run changes in real estate markets; rents have to adjust (possibly drastically) to ensure that current supply and demand line up for rental properties. Changes in prices, however, also include a long-run expectations component as people purchase property in anticipation of changes in future rents. We find that WFH is more strongly associated with rent changes than price changes. This suggests that a large component of WFH associated urban flight is temporary, reflecting changes in urban amenities during the pandemic as well as particularly flexible remote working policies during this period. This also points to an expected—partial—reversal of the effects of WFH on real estate values, since urban real estate (which capitalizes future rents) has held up much better than rents. Still, WFH is associated with large changes in prices at the ZIP-level, pointing to the role of persistently changed (expectations) about future remote work policies and commuting patterns.

6 Conclusion

A central paradox of the internet age has been that digital tools enable greater collaboration at further distances, yet have led to even more concentrated economic activity into a handful of dense urban areas. We document that the COVID-19 pandemic, and the migration flows it has prompted, has partially reversed this trend. The reversal in the premium for urban real estate is particularly strong for rents but also present in house prices. Combining a present-value model with professional forecaster data on the permanency of working from home, we find that housing markets paint an optimistic picture of urban revival, indicating higher rent growth in urban versus suburban areas for the foreseeable future. These shifts in economic activity appear to be related to practices around working from home, suggesting that they may persist to the extent that employers allow remote working practices beyond the pandemic.

A key benefit to workers of this changing economic geography is being able to access the larger and more elastic housing stock at the periphery of cities, thereby alleviating rent burden. However, the results also point to potential problems for local government finances in the wake of the pandemic. Urban centers may confront dwindling populations and lower tax revenue from property and sales in the short and medium run. More dispersed economic activity may offer greater opportunities for areas previously left behind, but potentially at the cost of agglomeration economies built in urban areas. Overall our results suggest important challenges and opportunities in the context of a radically reshaped urban landscape.

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A Appendix

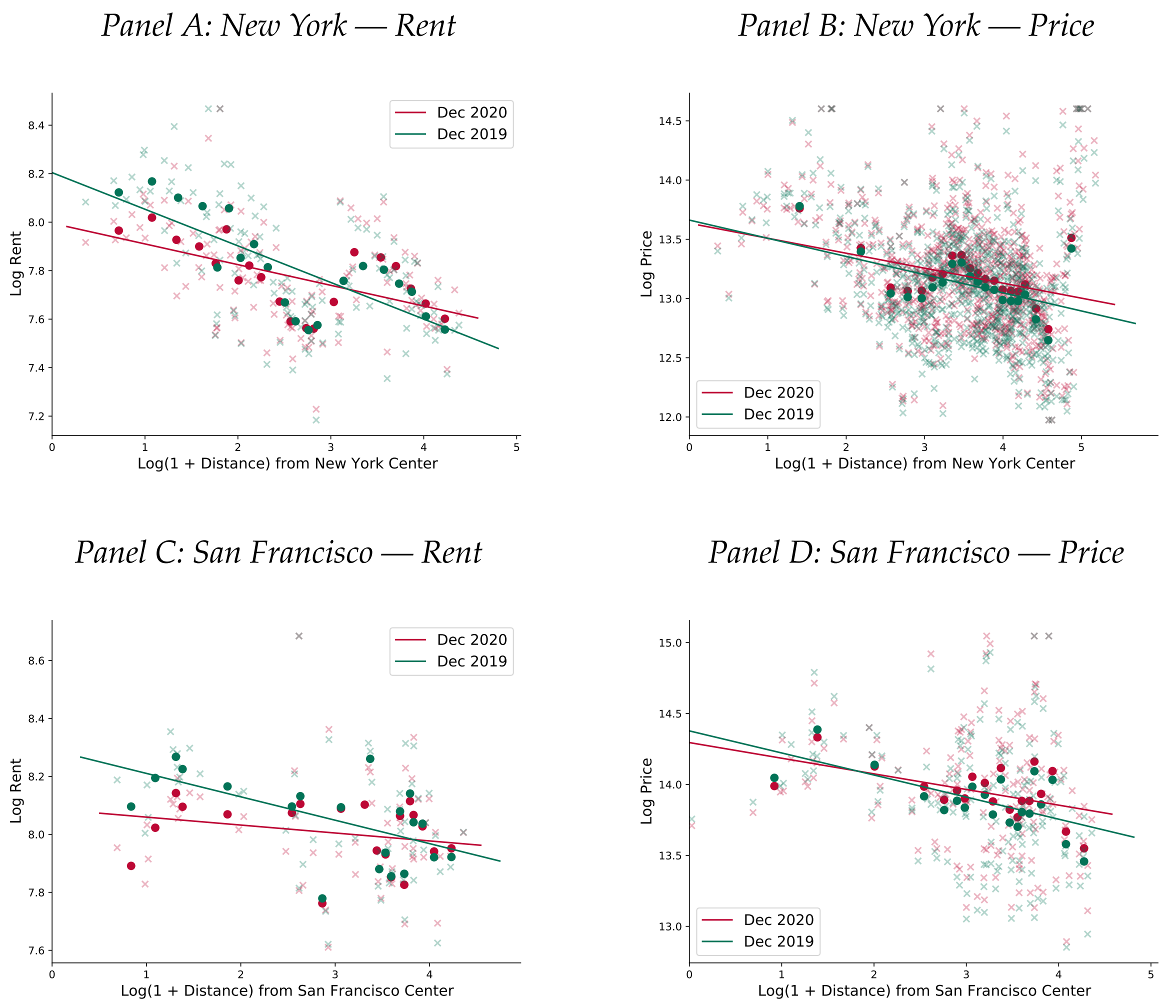


Figure A1. Bid-rent Functions for San Francisco and New York

The bid-rent function for the San Francisco-Oakland-Berkeley CA and New York-Newark-Jersey City NY-NJ-PA MSAs. Panels on the left show the relationship between distance from the city center (the log of 1 + the distance in kilometers from City Hall) and the log of rents measured at the ZIP code level. Panels on the right repeats the exercise for prices. Both plots show this relationship prior to the pandemic (Dec 2019, in green) as well as afterwards (Dec 2020, in red).

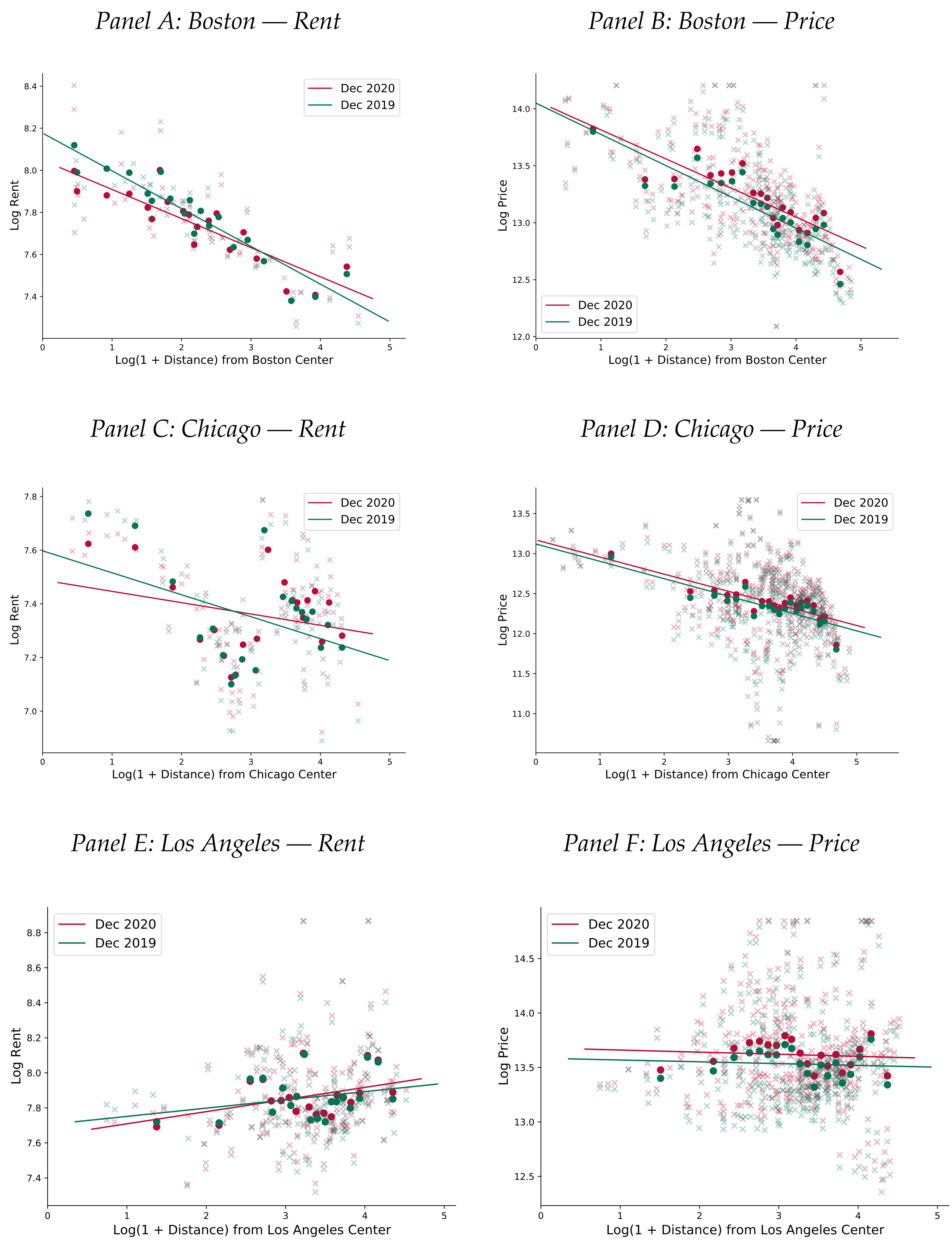
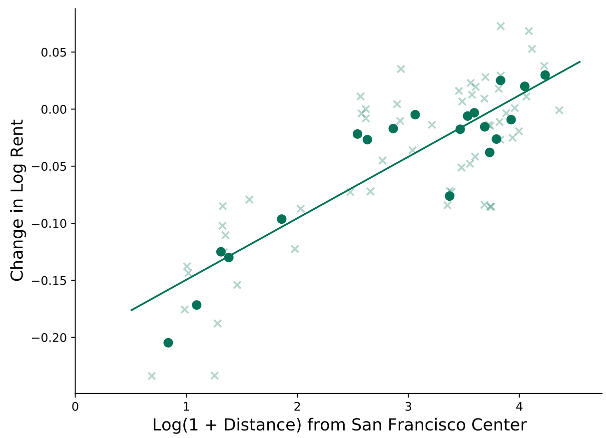


Figure A2. Bid-rent Functions for Boston, Chicago, Los Angeles

The bid-rent function for the Boston-Cambridge-Newton MA-NH, Chicago-Naperville-Elgin IL-IN-WI and Los Angeles-Long Beach-Anaheim CA MSAs. Panel A on the left shows the relationship between distance from the city center (the log of 1 + the distance in kilometers from City Hall) and the log of rents measured at the ZIP code level. Panel B on the right show the same function for prices. Both plots show this relationship prior to the pandemic (Dec 2019, in green) as well as afterwards (Dec 2020, in red).

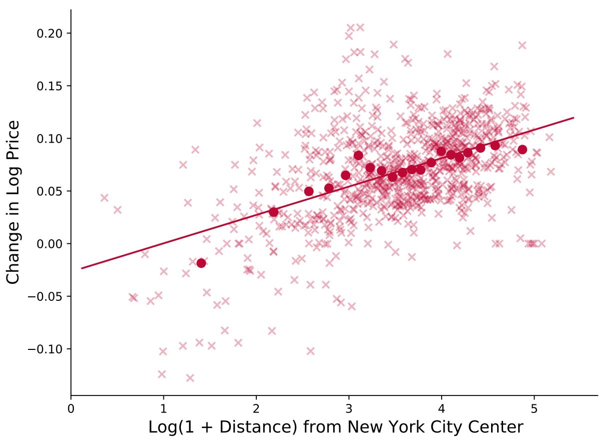
Panel A: Rent

New York

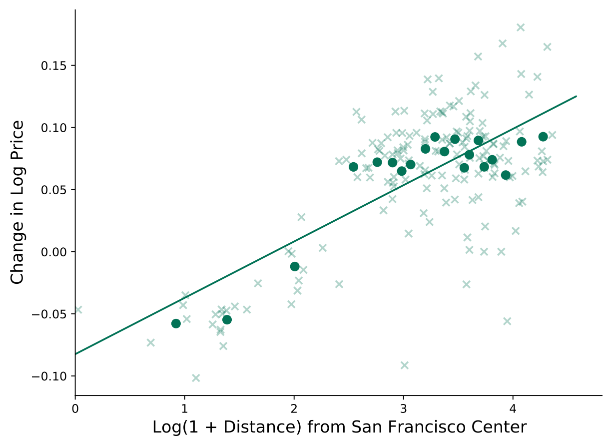


San Francisco

Panel B: Price



New York

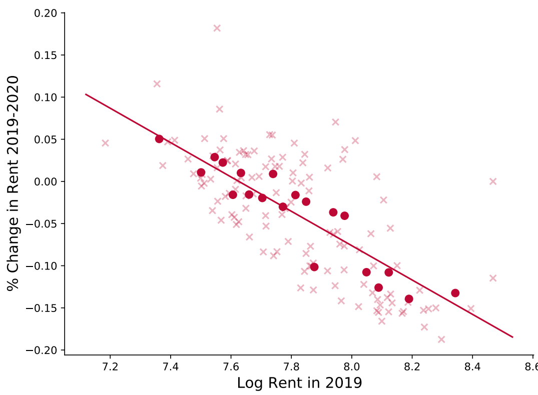


San Francisco

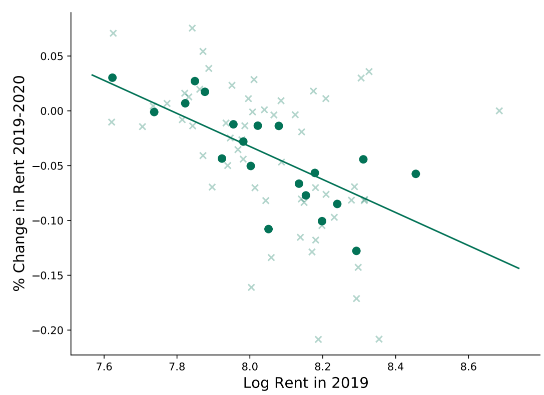
Figure A3. Change in the Bid-rent function

The change in the bid-rent functions for New York (left) and San Francisco (right). Each observation corresponds to the changes in either rents (Panel A) or prices (Panel B) between Dec 2019 and Dec 2020 within each city, plotted against the distance to the center of the city.

Panel A: Rent

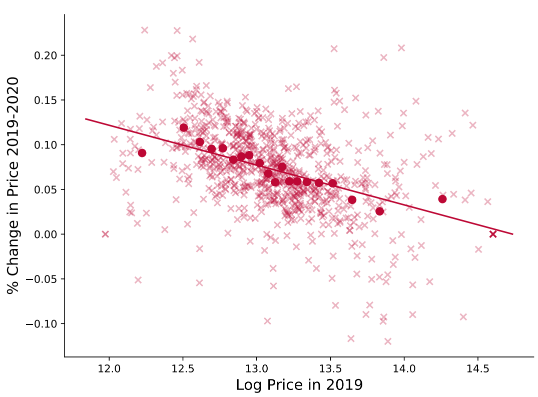


New York

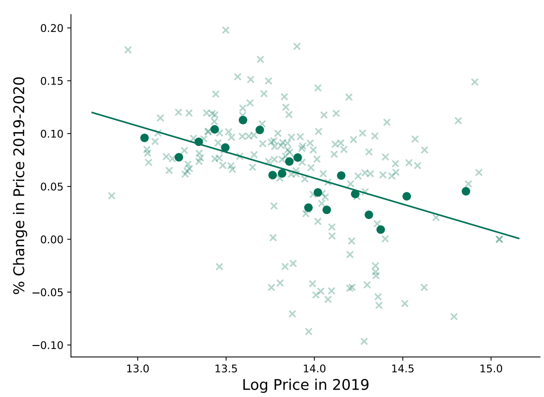


San Francisco

Panel B: Price



New York

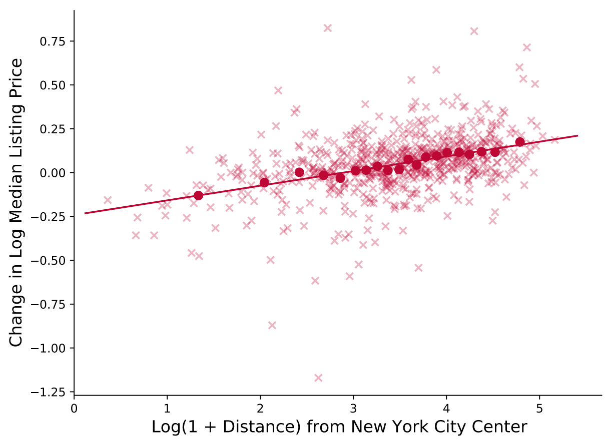


San Francisco

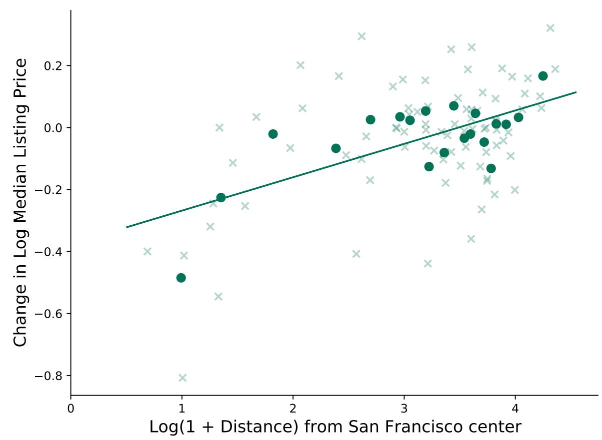
Figure A4. Changes in Rents and Prices Against Pre-Pandemic Levels

The changes in rents (Panel A) and prices (Panel B) against pre-pandemic levels of rents and prices for New York (left) and San Francisco (right). Each observation corresponds to the changes in either rents (Panel A) or prices (Panel B) between Dec 2019 and Dec 2020 within each city, plotted against the Dec 2019 log level of rents or prices.

Panel A: Median listing price

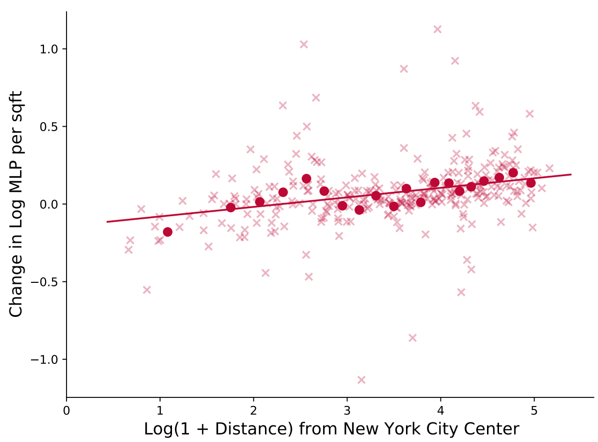


New York



San Francisco

Panel B: Median listing price per sq. ft.



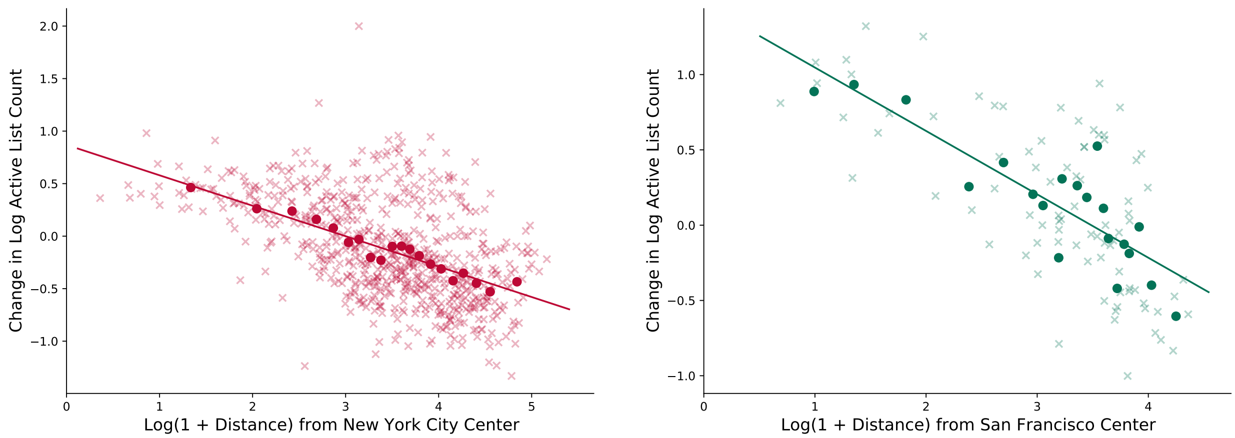
New York

San Francisco

Figure A5. Changes in Listing Prices

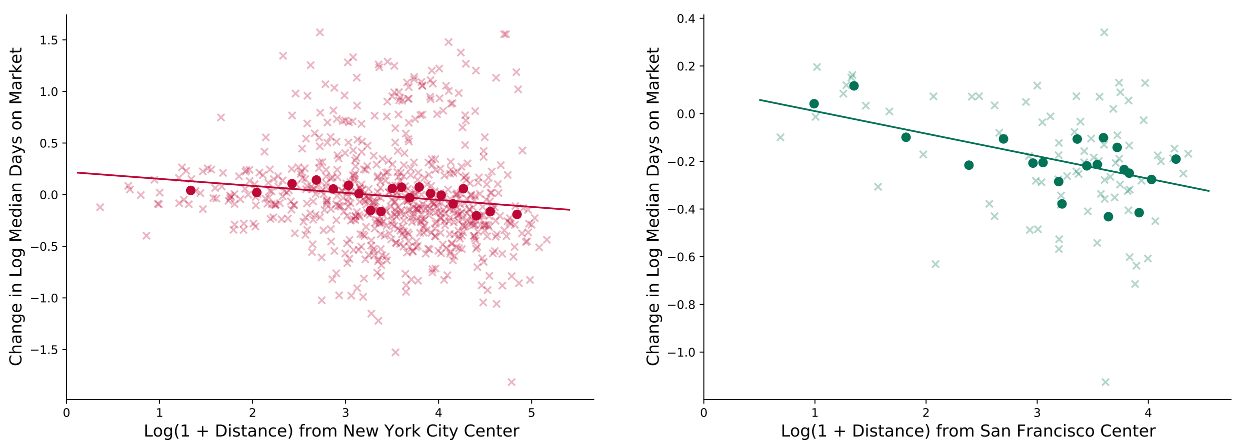
The relationship between changes in listing prices, measured as either the median listing price (Panel A) or the median listing price per sq. ft. (Panel B) with respect to distance. Each observation is at the ZIP code level, and measures the change in the listing price variable from 2019–Dec 2020, plotted against distance from the center of city for the New York MSA (left) as well as San Francisco (right).

Panel A: Active listings



New York San Francisco

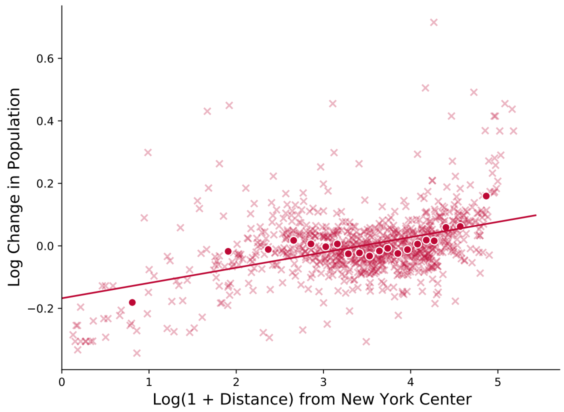
Panel B: Median Days on Market



New York San Francisco

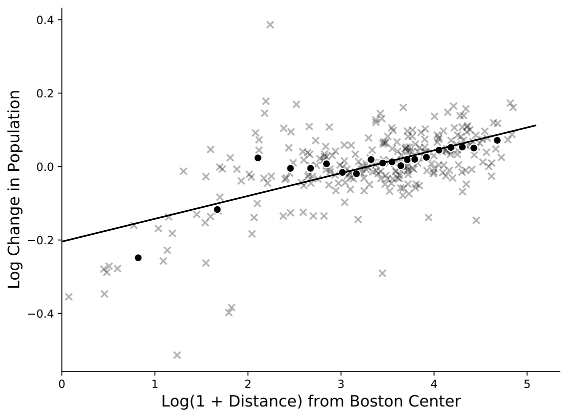
Figure A6. Changes in Market Inventory

Changes in two measures of market inventory, active listings (Panel A) and median days on market (Panel B) against distance from the center of the city for New York (left) and San Francisco (right). Each observation is a ZIP Code and represents the change in the market inventory measure from Dec 2019 to Dec 2020.

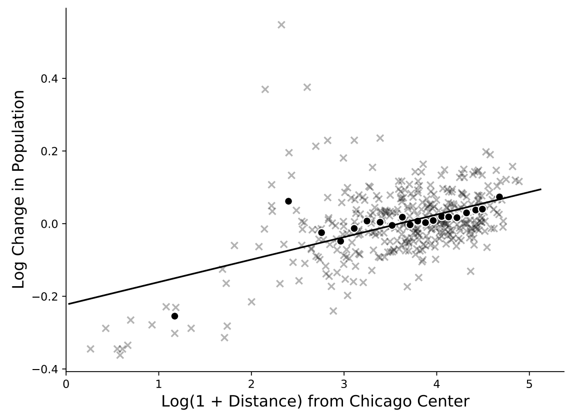


New York

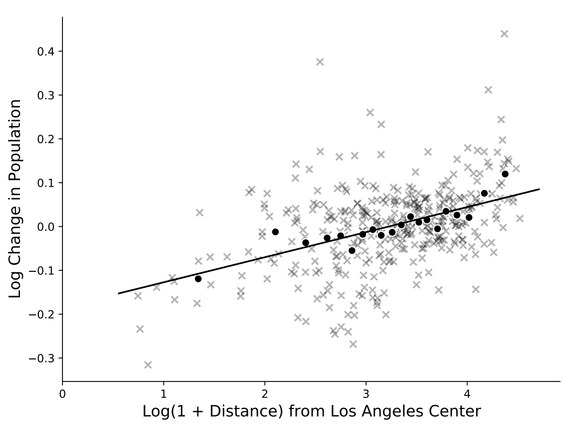
San Francisco



Boston



Chicago

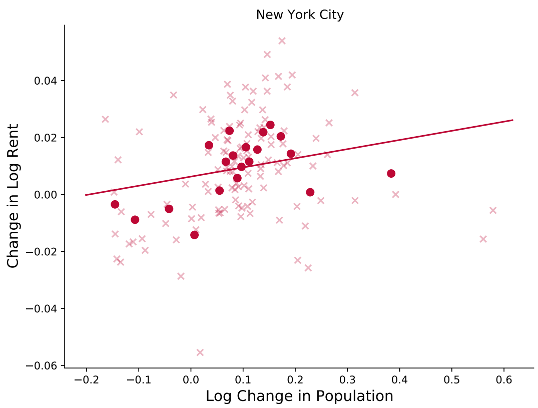


Los Angeles

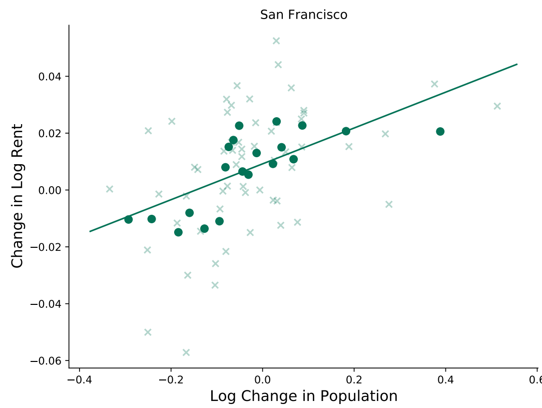
Figure A7. Changes in Population

Shows the change in population from February to March as measured in VenPath against log(1 + distance) to the city center for New York, San Francisco, Boston, Chicago and Los Angeles.

Panel A: Rent

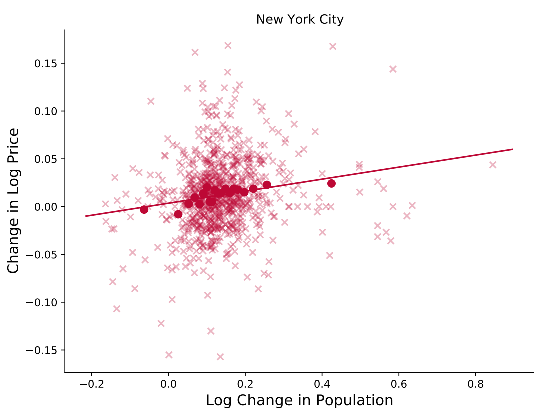


New York

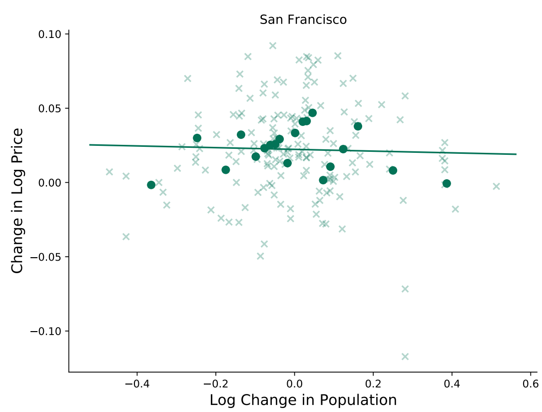


San Francisco

Panel B: Price



New York



San Francisco

Figure A8. Changes in Rents and Prices Against Migration

Shows change in population plotted against change in rents (Panel A) and changes in prices (Panel B) for New York City (left) and San Francisco (right).

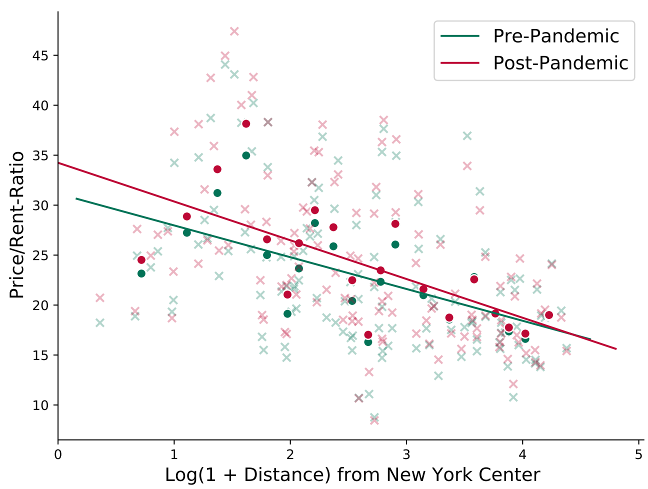


Figure A9. Price-Rent Ratio against Distance for New York

The relationship between the price-to-rent ratio before the pandemic (2019 Q4, in green) and during the pandemic (2020 Q4, in red) across distance, measured as log of 1 + distance to Grand Central in kilometers.

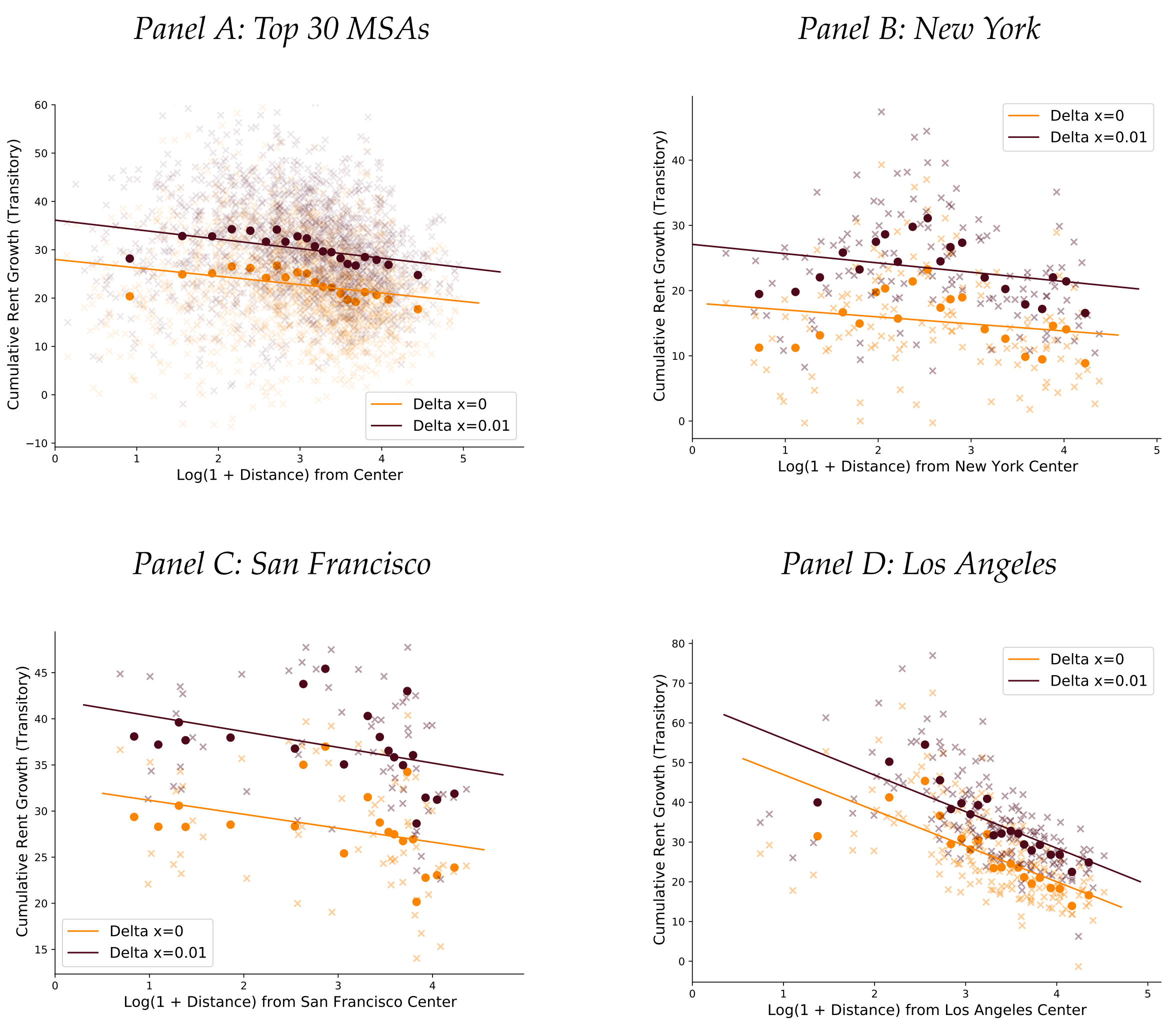


Figure A10. Cumulative Rent Growth under Transitory Case for Top 30 MSAs, New York, San Francisco, Los Angeles

The cumulative rent growth over all future years under the transitory case is predicted under two assumptions of the model: (1) $\Delta x = 0$, and (2) $\Delta x = 0.01$ at the ZIP level. These are plotted against log of 1 + distance from the MSA center. The cumulative rent changes are calculated using Equation (15), but at the ZIP level.

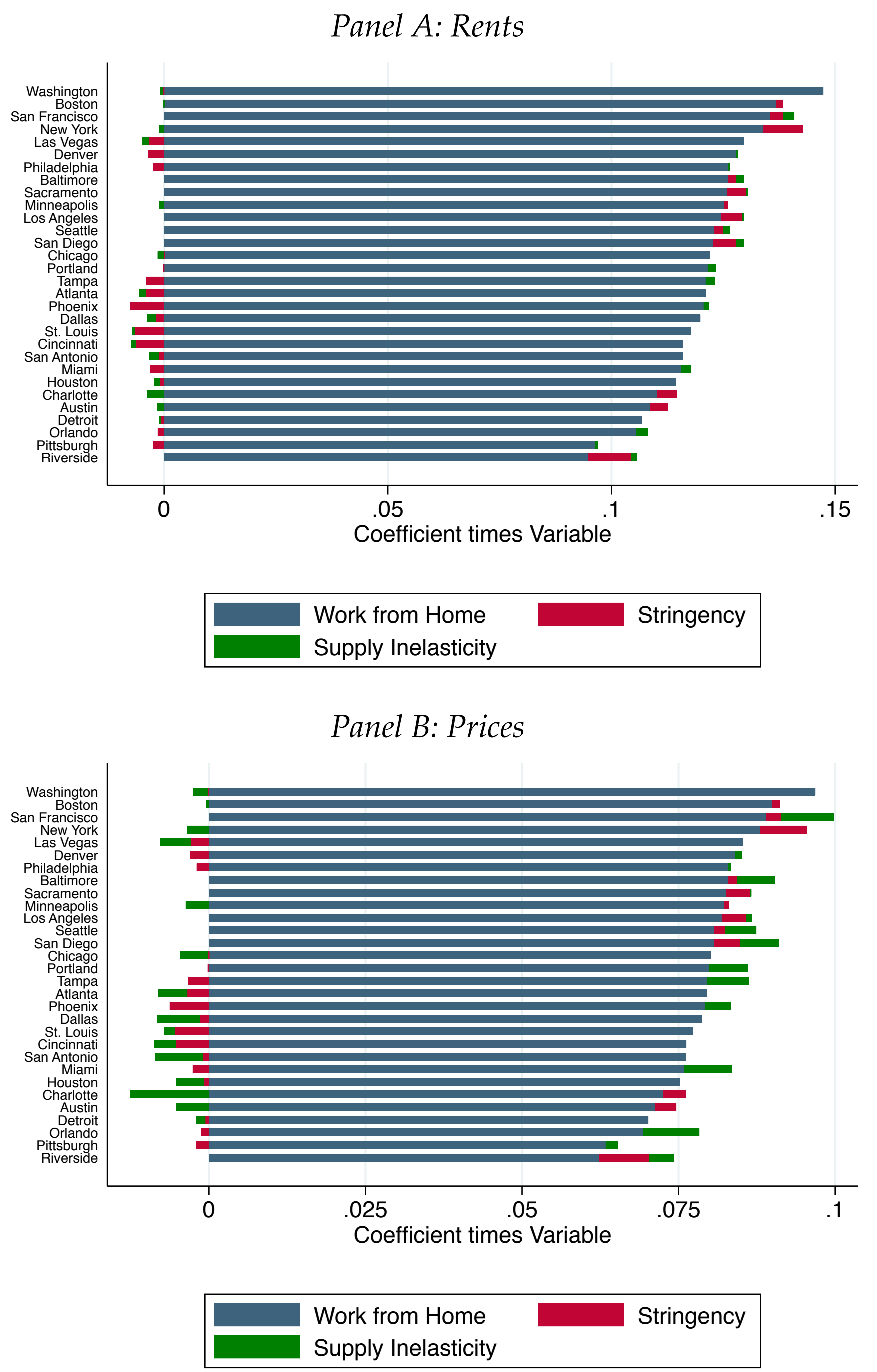


Figure A11. Decomposition of Effects by MSA

The figure plots the total effect of work from home, stringency measure (orthogonalized), and supply inelasticity measure (orthogonalized) on the rent (price) gradient in Panel A (Panel B). The total effect is calculated using $\beta_i \cdot x_{ij}$ for covariate i and MSA j, where β_i is from Table III (Table II) for rents (prices), and x_{ij} corresponds to the work from home, stringency, and supply inelasticity index.

Table A.I. Explaining the Variation in Price Gradient Changes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Price 2018	0.0209***									
	(0.00462)									
Saiz Supply Elasticity		-0.00968***								
		(0.00317)								
Land Unavailable Percent			0.0650**							
			(0.0265)							
Wharton Regulatory Index				0.0111**						
				(0.00443)						
Cumulative COVID Cases 2020 per Mn					0.00959					
					(0.0173)					
Work from Home						0.215***				
						(0.0747)				
College Share in Core							0.100***			
							(0.0312)			
Poverty Rate in Core								-0.152***		
								(0.0382)		
Log(MSA GDP)									0.0103**	
									(0.00384)	
Stringency Measure										0.107**
										(0.0464)
Constant	-0.261***	0.0199***	-0.00865	0.000362	0.00260	-0.0750**	-0.0649***	0.0381***	-0.195**	-0.0447**
	(0.0587)	(0.00573)	(0.00585)	(0.00303)	(0.00405)	(0.0277)	(0.0216)	(0.00884)	(0.0745)	(0.0213)
Observations	30	30	30	30	30	30	30	30	30	30
R^2	0.422	0.249	0.177	0.183	0.011	0.228	0.270	0.361	0.204	0.160
Adjusted R^2	0.401	0.223	0.148	0.153	-0.025	0.200	0.244	0.338	0.176	0.130

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.II. Explaining the Variation in Rent Gradient Changes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Rent 2018	0.0490***									
	(0.0132)									
Saiz Supply Elasticity		-0.00585								
		(0.00499)								
Land Unavailable Percent			0.0411							
			(0.0400)							
Wharton Regulatory Index				0.0142**						
				(0.00629)						
Cumulative COVID Cases 2020 per Mn					0.0253					
					(0.0239)					
Work from Home						0.326***				
						(0.101)				
College Share in Core							0.142***			
							(0.0434)			
Poverty Rate in Core								-0.255***		
								(0.0460)		
Log(MSA GDP)									0.0158***	
									(0.00521)	
Stringency Measure										0.145**
										(0.0651)
Constant	-0.342***	0.0298***	0.0122	0.0154***	0.0161***	-0.100**	-0.0771**	0.0773***	-0.287***	-0.0461
	(0.0973)	(0.00902)	(0.00884)	(0.00430)	(0.00558)	(0.0375)	(0.0300)	(0.0107)	(0.101)	(0.0300)
Observations	30	30	30	30	30	30	30	30	30	30
R^2	0.331	0.047	0.036	0.153	0.039	0.270	0.276	0.523	0.248	0.151
Adjusted R^2	0.307	0.013	0.002	0.123	0.004	0.244	0.250	0.506	0.221	0.121

Standard errors in parentheses

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

B Data Appendix

Table B.I shows the MSAs included in our sample. Table B.II shows the variables used at the ZIP code level.

Table B.I. Top-30 MSAs

#	MSA	Population (Millions)	Pre-pandemic Price Gradient	Pre-pandemic Rent Gradient	Change in Price Gradient	Change in Rent Gradient
1	New York-Newark-Jersey City, NY-NJ-PA	19.22	-0.241	-0.133	0.032	0.056
2	Los Angeles-Long Beach-Anaheim, CA	13.21	-0.227	-0.056	0.005	0.024
3	Chicago-Naperville-Elgin, IL-IN-WI	9.46	-0.170	-0.052	0.006	0.040
4	Dallas-Fort Worth-Arlington, TX	7.57	-0.092	0.006	0.001	0.024
5	Houston-The Woodlands-Sugar Land, TX	7.07	-0.089	-0.051	-0.011	0.026
6	Washington-Arlington-Alexandria, DC-VA-MD-WV	6.28	-0.162	-0.064	0.011	0.033
7	Miami-Fort Lauderdale-Pompano Beach, FL	6.17	-0.131	-0.006	0.010	0.019
8	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	6.10	-0.011	-0.042	0.001	0.005
9	Atlanta-Sandy Springs-Alpharetta, GA	6.02	-0.212	-0.040	0.005	0.031
10	Phoenix-Mesa-Chandler, AZ	4.95	-0.063	0.103	-0.016	0.037
11	Boston-Cambridge-Newton, MA-NH	4.87	-0.239	-0.132	0.017	0.036
12	San Francisco-Oakland-Berkeley, CA	4.73	-0.159	-0.081	0.042	0.052
13	Riverside-San Bernardino-Ontario, CA	4.65	-0.166	-0.019	-0.001	0.017
14	Detroit-Warren-Dearborn, MI	4.32	0.033	0.295	-0.015	-0.049
15	Seattle-Tacoma-Bellevue, WA	3.98	-0.151	-0.031	0.029	0.055
16	Minneapolis-St Paul-Bloomington, MN-WI	3.64	-0.116	-0.025	0.005	0.034
17	San Diego-Chula Vista-Carlsbad, CA	3.34	-0.071	0.043	-0.008	0.010
18	Tampa-St Petersburg-Clearwater, FL	3.19	-0.079	-0.029	0.007	0.014
19	Denver-Aurora-Lakewood, CO	2.97	-0.092	0.060	0.010	0.024
20	St Louis, MO-IL	2.80	0.004	0.043	0.010	0.014
21	Baltimore-Columbia-Towson, MD	2.80	0.069	0.025	0.008	0.010
22	Charlotte-Concord-Gastonia, NC-SC	2.64	-0.223	-0.003	0.002	0.031
23	Orlando-Kissimmee-Sanford, FL	2.61	-0.044	0.023	-0.002	0.017
24	San Antonio-New Braunfels, TX	2.55	-0.040	0.130	-0.012	0.001
25	Portland-Vancouver-Hillsboro, OR-WA	2.49	-0.101	0.168	0.018	0.016
26	Sacramento-Roseville-Folsom, CA	2.36	-0.083	0.032	0.010	0.029
27	Pittsburgh, PA	2.32	0.028	-0.350	-0.032	0.041
28	Las Vegas-Henderson-Paradise, NV	2.27	0.015	0.074	0.008	0.006
29	Austin-Round Rock-Georgetown, TX	2.23	-0.329	-0.124	-0.015	0.032
30	Cincinnati, OH-KY-IN	2.22	0.009	0.204	-0.036	-0.017

Table B.II. List of variables used at the ZIP code level

Variable Name	Source	Description
Zillow Home Value Index (ZHVI)	Zillow	All Homes (SFR, Condo/Co-op) Time Series, Smoothed, Seasonally Adjusted ($)
Zillow Observed Rent Index (ZORI)	Zillow	All Homes Plus Multifamily Time Series, Smoothed, Seasonally Adjusted ($)
Median List Price	Realtor	The median listing price within the specified geography during the specified month ($)
Median List Price Per Sqft	Realtor	The median listing price per square foot within the specified geography during the specified month ($)
Active Listing Count	Realtor	The active listing count tracks the number of for sale properties on the market, excluding pending listings where a pending status is available. This is a snapshot measure of how many active listings can be expected on any given day of the specified month.
Median Days on Market	Realtor	The median number of days property listings spend on the market between the initial listing of a property and either its closing date or the date it is taken off the market.
Median Household Income	Census Bureau	Median income of a household (2017).
Proportion of Rich Households	Census Bureau	Proportion of households with yearly income higher than 150 thousand dollars (2016).
Proportion of Black Residents	Census Bureau	Proportion of Black residents (2016).
Restaurants and Bars	Safegraph	Count of full-service restaurants, limited-service restaurants, snack and non-alcoholic beverage bars, and drinking places (alcoholic beverages).