Flattening the Curve: Pandemic-Induced Revaluation of Urban Real Estate

Arpit Gupta Vrinda Mittal Jonas Peeters

Stijn Van Nieuwerburgh*

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Abstract

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.

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

JEL codes: R23, R51, R12

*Gupta: Assistant Professor of Finance, Department of Finance, Stern School of Business, New York University, 44 W. 4th Street, New York, NY 10012; arpit.gupta@stern.nyu.edu; http://arpitgupta.info. Mittal: Ph.D. Candidate in Finance and Economics, Department of Finance, Columbia Business School, 3022 Broadway, Uris Hall, New York, NY 10027; vrinda.mittal@gsb.columbia.edu; https://www.vrindamittal.com/. Peeters: Ph.D. Candidate in Finance, Finance Department, Wharton School, 3733 Spruce Street, Philadelphia, PA 19104; jonasp@wharton.upenn.edu. Nieuwerburgh: Earle W. Kazis and Benjamin Schore Professor of Real Estate and Professor of Finance, Department of Finance, Columbia Business School, 3022 Broadway, Uris Hall 809, New York, NY 10027; svnieuwe@gsb.columbia.edu; NBER, CEPR, ABFER, https://www0.gsb.columbia.edu/faculty/svannieuwerburgh/. The authors would like to thank Zillow, Apartment List Rent Data, VenPath, Realtor, Infutor, Pulsenomics, and Safegraph for providing data. We thank Joshua Coven, Ki Lee, and Luofeng Zhou for excellent research assistance, and Igor Popov from Apartment List and Joshua Clark from Zillow for helpful conversations. The authors have no conflicts of interest to declare.

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 use hit historic lows in 2020 and remains low well into 2021, 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 an increasing desire from employees to do so, 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 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 over the course of the pandemic. Each observation is the slope of the bid-rent function for a particular month. The rent gradient is plotted in the left panel, and the price gradient is shown in the right panel. The bid-rent slope coefficients are estimated by pooled panel regression on a sample of all ZIP codes in the largest 30 metropolitan areas in the U.S. for which we have both rent and price data. Distance is measured as the log of one plus the distance in kilometers of the ZIP code's centroid from the city hall of the main city of the metropolitan area. The elasticity of rents to distance changes from -0.032 in December 2019 to -0.0001 in December 2020. The slope change for rents ($\Delta\delta = .032$) corresponds to suburban rents appreciating by 12.1 percentage points more than in the urban core of the metropolitan area. The rent gradient

Barrero, Bloom, and Davis (2021) estimates that the number of remote working days will increase four-fold in future years to 20%. 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.

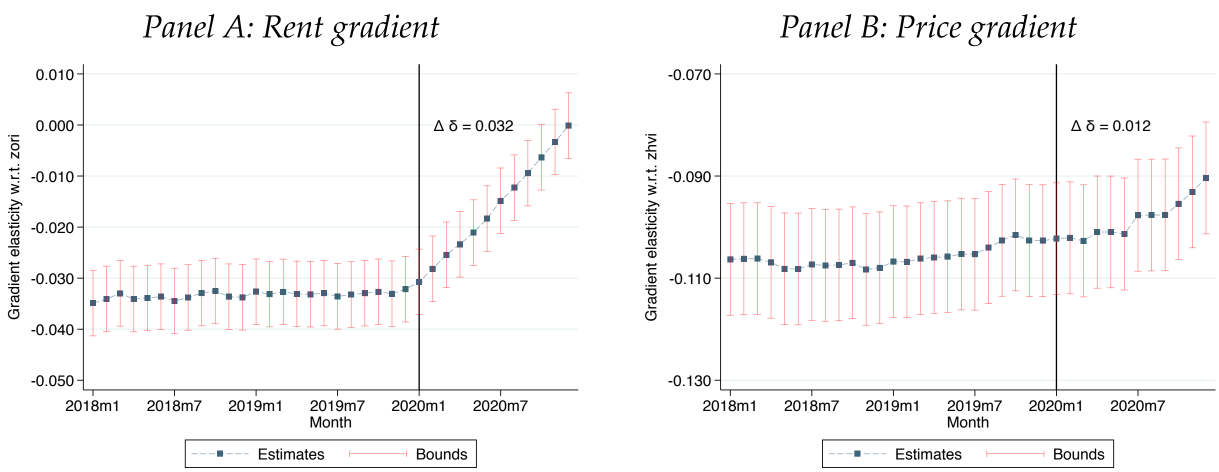


Figure 1. Rent and Price Gradients across top 30 MSAs

This plot shows bid-rent function slope coefficients estimated from the panel regression in equation (1): $\ln p_{ijt} = \delta_t \left(\text{Month}_t \times \left[\ln(1 + D(\mathbf{z}^z_{ij}, \mathbf{z}^m_j))\right]\right) + \beta X_{ij} + \alpha_t \text{Month}_t + \alpha_j \text{MSA}_j + e_{ijt}$. The dependent variable is log rent (left panel) and log price (right panel). The graph plots δ_t, the coefficients on the interaction terms of month and distance. The sample consists of all ZIP code-month observations in the largest 30 metropolitan areas for which both price and rent data from Zillow are available. The time series is from January 2018 until December 2020. Distance is measured in kilometers between the centroid of the ZIP code and the city hall of the main city of the metropolitan area. The two panels report the change in gradient from Dec 2019 to Dec 2020 as $\Delta\delta$. The controls X_{ij} are median household income, median age of the head of household, proportion of Black households, and proportion of individuals who make over $150k, all drawn from the 2019 American Community Survey. The specification also includes month and MSA fixed effects. We draw a vertical line to define the post-pandemic period, starting in January 2020.

level estimate in December 2020 indicates that the entire urban rent premium has been eliminated. The evolution of the price gradient is qualitatively similar but quantitatively weaker. The elasticity of house prices to distance changes from -0.103 pre-pandemic to -0.090 in December 2020. The change in slope for price ($\Delta\delta = .012$) means that house prices 50kms from the city center grew by 6.5 percentage points more than house prices close to the city center.

We also find large changes in housing quantities reflecting greater suburban demand. 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 short period 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 while suburban ZIP codes gained people. We show that places that experienced the strongest migration also saw 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 find similar migration patterns based on within-user changes and in address changes using data from Infutor.

To get at the underlying mechanism, we study the cross-sectional variation in the change in the slope of the bid-rent function across MSAs. We find that the changes are larger in MSAs that have (i) a higher presence of jobs that can be done from home, (ii) more stringent pandemic lock-down measures (which result in the loss of urban amenities such as theaters and restaurants), and (iii) lower housing supply elasticity stemming from higher physical or regulatory barriers to development. The strongest association is with the presence of remote workers, which suggests 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 test for the role of changing amenities by controlling for the stringency of pandemic lock-down measures across MSAs, and find that the working-from-home measure remains a strong determinant of the cross-MSA variation in the rent and price gradients.

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 a ZIP-code level analysis. A specification with MSA-fixed effects allows us to control for all MSA-specific characteristics, like common amenities. We also account for amenities measured at the ZIP-level. We find that ZIP codes with higher exposure to work-from-home (WFH) see lower house price and rent growth even after accounting for ZIP-level variation in amenities and other ZIP-level socio-economic 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. Furthermore, we find that WFH associates more strongly with rent changes than with price changes. Since prices are forward-looking, this result is consistent with housing markets anticipating a partial reversal of remote work. Still, the effect on prices suggests that many households expect permanent or at least highly persistent changes in WFH practices.

We develop 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 of 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, imply that the price-rent ratio became more steeply downward sloping in distance from the center. What the relative increase in the urban price-dividend ratio signifies for future expected rent growth depends on the model's assumptions about the long run.

If housing markets expect a gradual but full 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. Under the assumption that urban-minus-suburban risk premia did not change during the pandemic, the cumulative urban-suburban rent change is 8.1 percentage points for the average MSA. If, instead, urban risk premia rose by 1 percentage point relative to the suburbs during the pandemic, then the expected differential cumulative rent change becomes 15.6 percentage points.

We expect a different outcome, however, in the case where the pandemic has led to permanent changes to housing markets. In this scenario, the change in price-rent ratios implies that urban rents will grow by 0.6 percentage points faster than suburban rents going forward, assuming that risk premia did not change. If urban risk premia instead changed permanently by 1 percentage point, we estimate urban rents will expand by 1.6 percentage points faster than suburban rents permanently.

A key quantitative question is where we are in between these 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 of respondents 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 preferred estimate of the expected future rent growth in urban relative to suburban areas. According to this mixture model, urban rent growth is expected to exceed suburban rent growth by 3.5 percentage points in 2021 in the average MSA. The rent growth differential then gradually decreases to about 0.80 percentage points. In other words, the model points to a long-lasting urban revival as WFH recedes.

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 (2021) 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 making inference on the persistence of the work-from-home shock from the relative changes in prices and rents.

Research in real estate finance 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 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. Campbell, Davis, Gallin, and Martin (2009) were the first to apply the present value model of Campbell and Shiller (1989) 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.

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 estimation, as well as on migration. Section 4 studies cross-sectional variation in the price and rent gradients to assess the underlying mechanisms. Section 5 uses a present-value model to extract market expectations about the future expected rent changes from the relative changes in price and rent gradients. The last section concludes. Appendix A provides additional results. Appendix B contains additional details on data construction and representativeness, and Appendix C contains additional information on price and rent decomposition.

2 Data

We focus on the largest 30 MSAs by population, presented in Table A.I in Appendix A. Our core data focuses on measuring rent and price gradients, for which we use Zillow data at the ZIP level.[3] For prices, we focus on the Zillow House Value Index (ZHVI), which adjusts for house characteristics using machine learning techniques for a sample of all residential properties; and for rents we use the Zillow Observed Rental Index (ZORI), which is a constant-quality rent index capturing asking rents. Housing units include both single-family and multi-family units for both the price and the rent data series. Appendix B describes this data, and in particular the construction and coverage of the ZORI data, in more detail. This section also directly compares Zillow rental data with rental data from Department of Housing and Urban Development (HUD), the American Community Survey (ACS), the Apartment List Rent Data, and data used in the Consumer Price Index (CPI) to establish broad similarity of rental data across different data providers. To ensure ease of comparison in price and rent gradient estimates, our main results are for a common sample of ZIP-month observations for which both the ZHVI and ZORI data are available. We explore robustness to a sample which uses all ZIP-month observations.

To measure changes in housing inventory, we also use monthly data from the listing agent Realtor 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 connect housing changes with migration using two datasets to capture high-frequency population moves. We measure changes in physical presence 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

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

actively using an application) to determine user residence and migration over the period February 1 to July 13, 2020. We also draw on migration information from Infutor, which covers address changes from a sample of close to 150 million properties.

We connect changes in house prices and rents with covariates at both MSA and ZIP levels. A crucial measure for the paper is the measurement of remote work. We use the Dingel and Neiman (2020) measure of the fraction of local jobs which can potentially be performed remotely. We use this variable both at the MSA level and at the ZIP-code level.[4] We also measure the stringency of local lockdowns during the pandemic using the MSA-level measure of Hale, Atav, Hallas, Kira, Phillips, Petherick, and Pott (2020). Also at the MSA-level, we measure constraints on local housing development by combining three measures commonly used in the literature. The Wharton regulatory index (Gyourko, Hartley, and Krimmel, 2021) captures man-made constraints on urban construction.[5] We also measure physical constraints on housing using using the Lutz and Sand (2019) measure of land unavailability and the Saiz (2010) measure. We estimate the first principal component of these three measures, which we label the supply inelasticity index.

We connect price and rent changes with other ZIP code level variables from the 2019 ACS. We measure the median household income, the median age of the head of household, the proportion of Black residents, and the proportion of residents who make over $150k. We also define, at the ZIP level, a measure of number of bars and restaurants from Safegraph to proxy for local amenities, defined as the count of full-service restaurants, limited-service restaurants, snack and non-alcoholic beverage bars, and drinking places (alcoholic beverages).

[4]We calculate the ZIP-level WFH metric using the occupational make-up of the ZIP code and each occupation's specific WFH rating.

[5]We use the 2016 values for all MSAs, except for Las Vegas where we use the Gyourko, Saiz, and Summers (2008) survey due to the unavailability of 2016 estimate.

3 Results

We begin by showing descriptive evidence of price and rent changes across ZIP codes to highlight increased suburban rents and prices. We first show evidence for New York City and San Francisco—two of the real estate markets most affected by the pandemic. We then move to main estimates pooling across the largest 30 metropolitan areas, and discuss a number of other MSAs in Appendix A.

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 over the period December 2019–December 2020. We observe strong rent decreases in the urban core (Manhattan, centered around Grand Central Terminal) and rent increases in the suburbs, with particularly high shifts 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- and post-pandemic patterns. We observe flatter relationships 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 plot 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 rents in ZIP codes in the urban

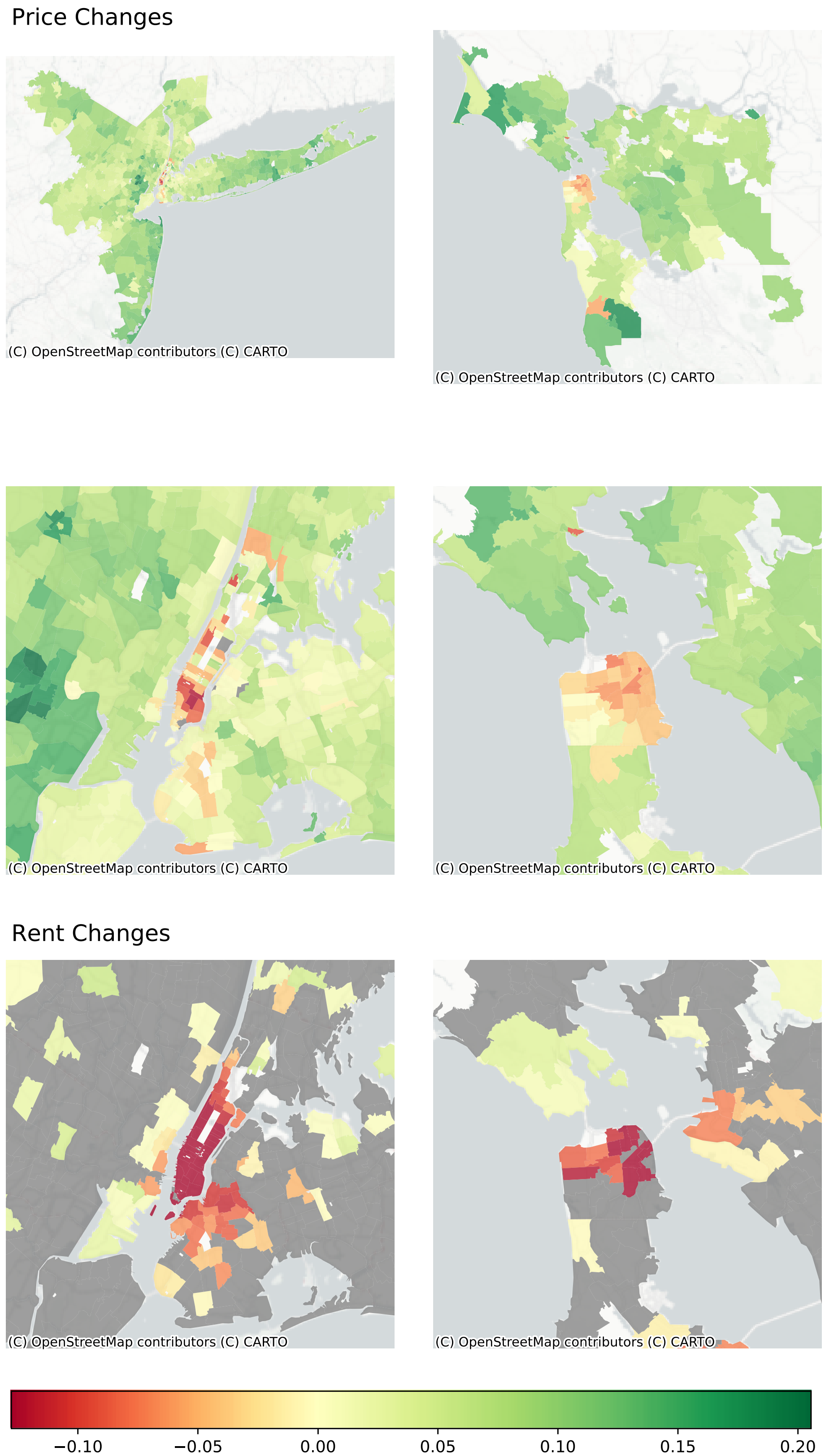


Figure 2. Price and Rent Growth, NYC and SF

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 December 2019–December 2020. The bottom two rows zoom in on the city center. Darker green colors indicate larger increases, while darker red colors indicate larger decreases.

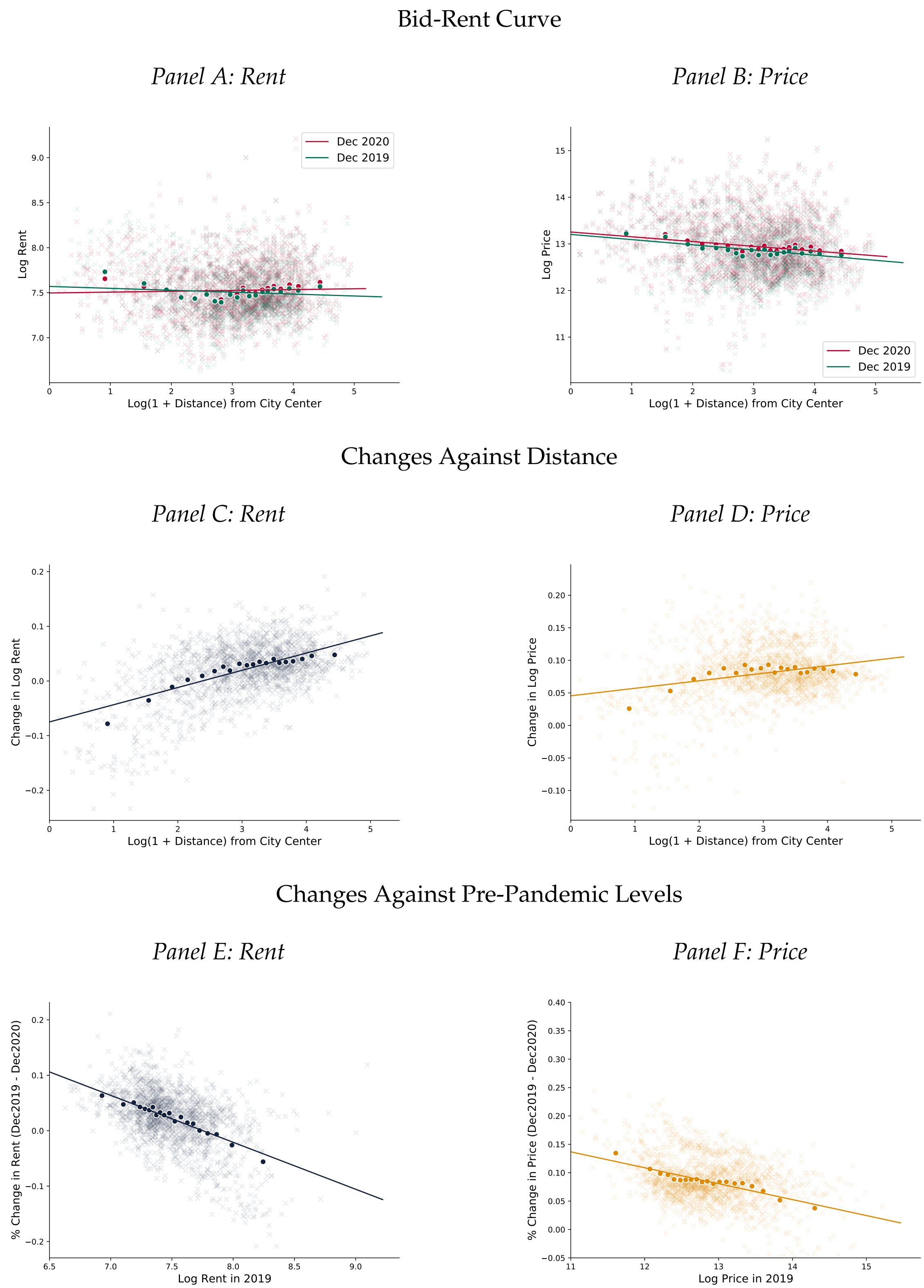


Figure 3. Pandemic Induced Changes in Prices and Rents

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. These figures are generated using those ZIP codes that have both rent and price data available.

core, and strongly rising rents in suburban ZIP codes. For house prices, urban ZIP codes feature smaller price increases than suburban ZIP codes.

When plotted against the pre-pandemic levels, the changes in rents and prices indicated strong reversals of value in the most expensive ZIP Codes (Panels E & 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–A3 highlight the relationship between rents, prices, rent changes, price changes, and distance for New York and San Francisco.

3.3 Estimating the Bid-Rent Function

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

$$\ln p_{ijt} = \delta_t \left(\text{Month}_t \times \left[\ln(1 + D(\mathbf{z}^z_{ij}, \mathbf{z}^m_j)) \right] \right) + \beta X_{ij} + \alpha_t \text{Month}_t + \alpha_j \text{MSA}_j + e_{ijt}. \quad (1)$$

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 $i \in j$.[6] We control for time fixed effects (α_i), MSA fixed effects (α_j), and ZIP-code level control variables (X_{ij}). The ZIP-code controls are: log of annual median household income, median age of the head of household, proportion of Black households, and proportion of households who earn over \$150k. The controls are all measured pre-pandemic, based on the latest available data from the ACS in 2019, and do not vary over time during our estimation window. Our main estimation sample restricts to ZIP code-month observations for which we have both price and rent data to ensure comparability of price and rent gradients.[7]

[6] 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 Terminal as the center.

[7] We use all ZIP codes within the MSA boundary with price and rent data for our analysis. We find similar results when enforcing distance limits within MSAs which restrict to 1) the smallest maximum

The key coefficient of interest is δ_t which measures the elasticity of prices or rents to distance between the ZIP code and the center of the MSA in any given month t. We refer to it as the price or rent gradient. Historically, δ_t is negative, as prices and rents decrease as we move away from the city center. An important statistic of interest is $\Delta\delta \equiv \delta_{Dec2020} - \delta_{Dec2019}$, shown in Figure 1, which is the change in gradient over the period from December 2019–December 2020. We observe rising gradients over this time period, which means that properties away from the city center have become more valuable over the course of 2020, *flattening the bid-rent curve*. As emphasized, the increase in the rent gradient of 0.032 is more pronounced than the increase in the price gradient of 0.012.

We find flattening bid-rent curves across samples. Figure 4 explores estimates of the price gradient based on different samples of ZIP codes, weighting schemes, and property sub-types. Panels B, C, and D use all ZIP codes for which there is price data but not necessarily rent data. In Panel B, there is no weighting, in Panel C we exclude ZIP codes with populations below 5,000, and in Panel C we estimate the panel regression weighting ZIPs by their population. We find increases in the average price gradient in each panel. The changes in gradient across samples are smaller than the baseline estimate since the baseline sample is tilted towards ZIP codes with higher population. Indeed, excluding ZIP codes with small populations or population-weighting ZIP codes results in larger gradient changes.[8] Across property types in Panels E–H, we find particularly large increases in gradients among condos/co-ops and small apartments and smaller increases for single-family housing. Overall, this evidence suggests that changes in prices were stronger in areas that had higher population (density) and more multi-family housing. Households in single-family homes would naturally be better equipped to work from home and find shelter from the pandemic.

In Section 4 we analyze the cross-sectional variation in rent and price gradient changes

distance from the center based on top 6 MSAs; 2) the smallest maximum distance from the center based on top 30 MSAs; 3) the 25th percentile of the maximum distance from the center based on top 30 MSAs; and 4) the 75th percentile of the maximum distance from the center based on top 30 MSAs.

[8]Figure A4 finds similar results reproducing Figure 3 by including all ZIP codes with price data.

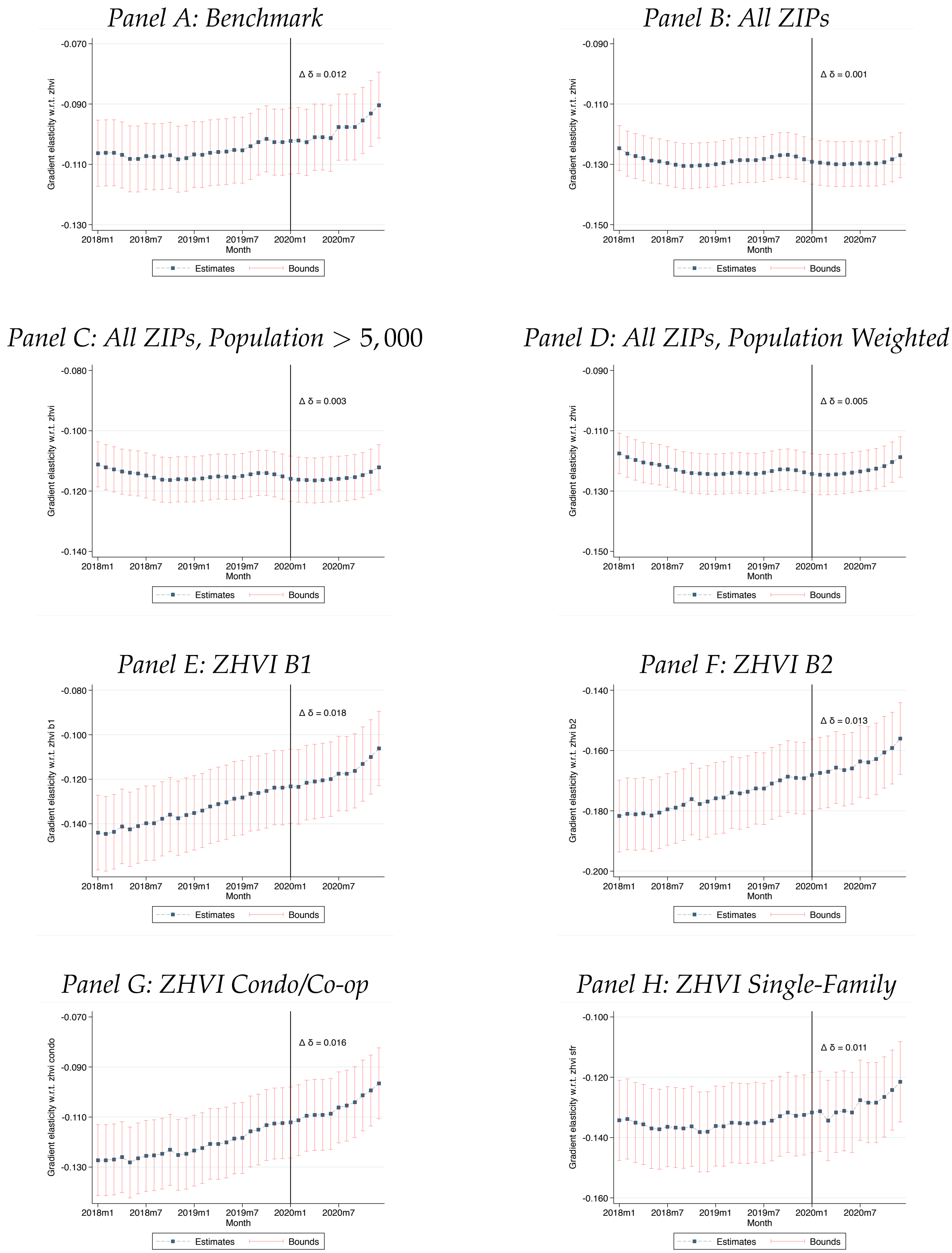


Figure 4. Robustness in Bid-Rent Curve Estimation Across Price Series

This plot shows bid-rent function slope coefficient estimates δ_t from a panel regression at the ZIP code level for the top 30 MSAs over the period January 2018–December 2020 following equation (1). The panels also report $\Delta\delta$: the change in gradient from Dec 2019 – Dec 2020. Panel A is the benchmark specification, which repeats the house price gradient plotted in Panel B of Figure 1. Panel B estimates the same price gradient from a sample of all ZIP Codes with house price data. Panel C includes all ZIPs, but restricts to those for which the Census ACS population from 2019 was at least 5,000. Panel D uses all ZIPs, but population-weights the gradient estimation. Panels E–H focus on different Zillow housing submarkets indices: one bedroom, two bedroom, condo/co-op units, and single family homes for the benchmark sample.

across MSAs. For that exercise, we estimate the following regression MSA-by-MSA for the top 30 MSAs:

$$\ln p_{ijt} = \delta_{jt}\left(\text{Month}_{jt} \times \left[\ln(1 + D(\mathbf{z}^z_{ij}, \mathbf{z}^m_j))\right]\right) + \beta_j X_{ij} + \alpha_{jt}\text{Month}_{jt} + e_{ijt}. \qquad (2)$$

The main object of interest is the gradient change for each MSA j: $\Delta\delta_j \equiv \delta_{j,Dec2020} - \delta_{j,Dec2019}$ for $j = 1, 2, \ldots, 30$. It captures the changing valuation of urban versus suburban prices and rents across urban areas. Figure 5 shows the change in price and rent gradient across U.S. metros.

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 6 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 suburban prices relative to urban prices using an alternate measure of prices.[9]

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. Panel C of Figure 6 shows 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. Buyers depleted large fractions of the available housing inventory in the suburbs during the pandemic, even after taking into account that a strong sellers' market

[9] Appendix Figure A5 shows a very similar relationship for a larger sample of all ZIPs for which we have house price data. Figure A6 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). It confirms the full-sample patterns.

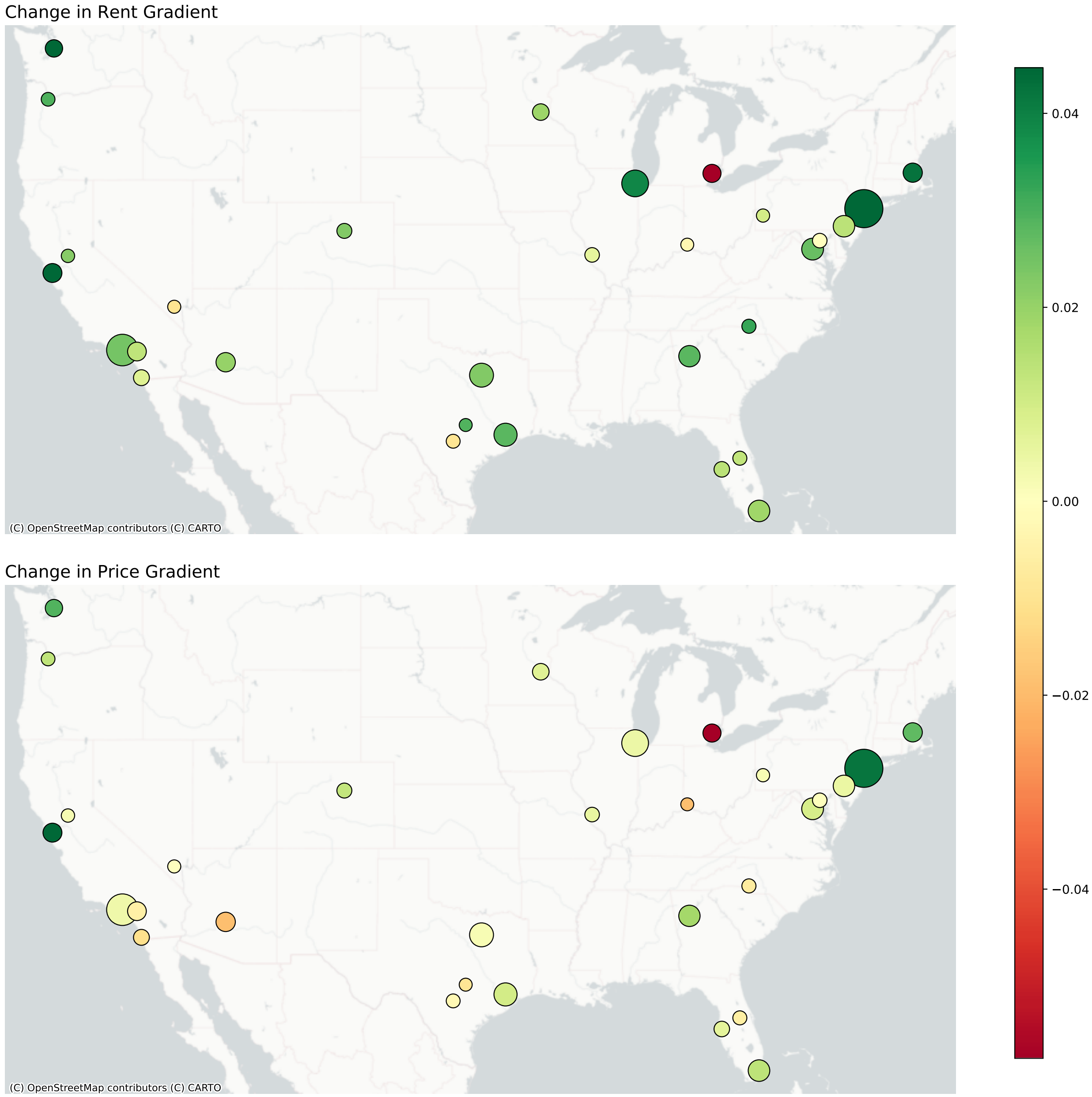


Figure 5. MSA level Changes in Price and Rent Gradients

This map plots the change in price and rent gradients across the U.S. over the period December 2019–December 2020. For each MSA, we estimate the price and rent gradient as in equation 2, and plot the resulting change ($\Delta\delta_j$) 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.

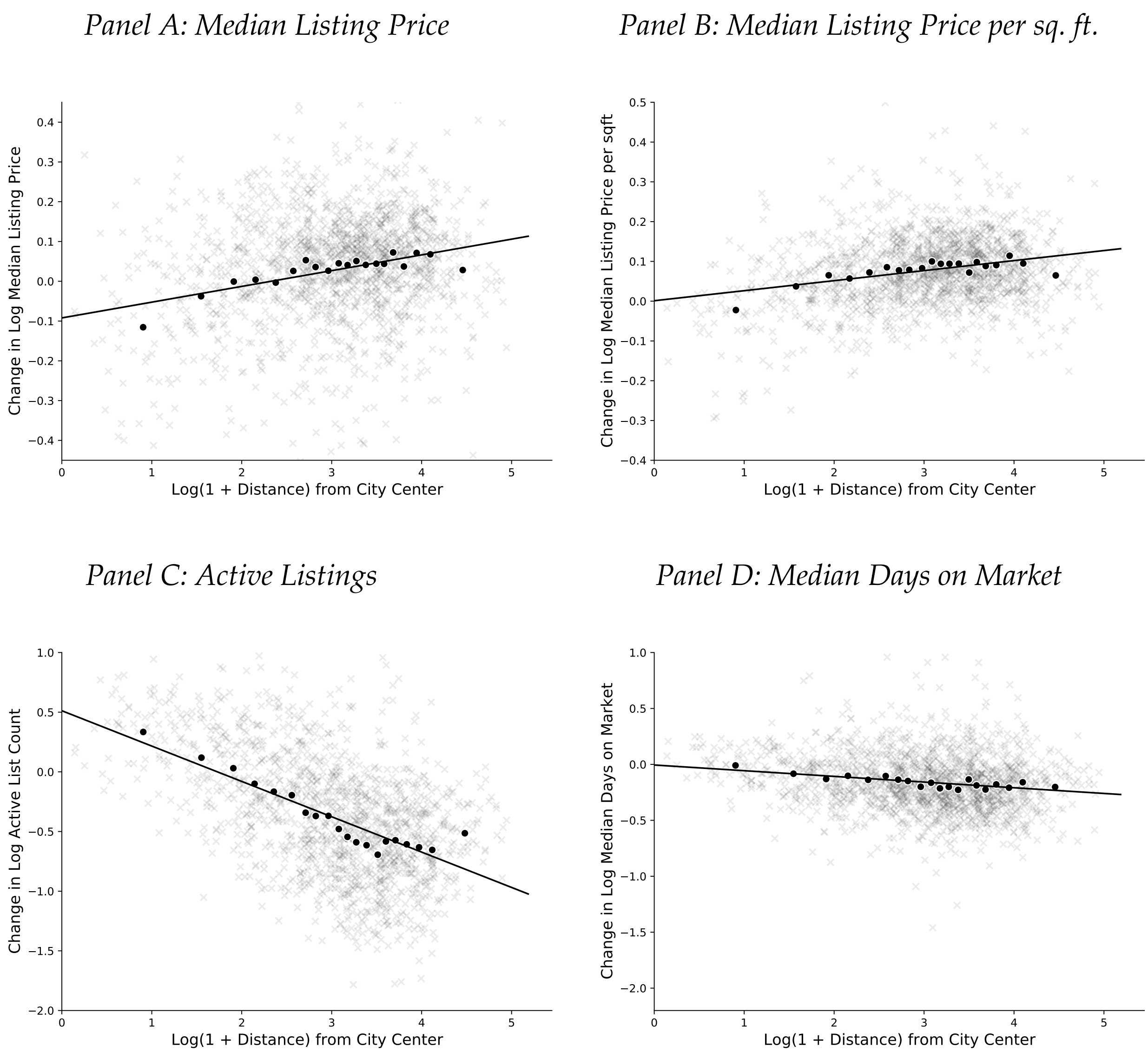


Figure 6. Changes in Listing Prices and Market Inventory

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 December 2019 to December 2020. These figures are generated using those ZIP codes that have both rent and price data available.

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. Panel D of Figure 6 shows that DOM rose in the urban core and fell in the suburbs. Housing liquidity improved dramatically in the suburbs and deteriorated meaningfully in the center.[10]

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 7). 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.[11]

Panel A: Price change against active listing changes

Panel B: Price and median days on market changes

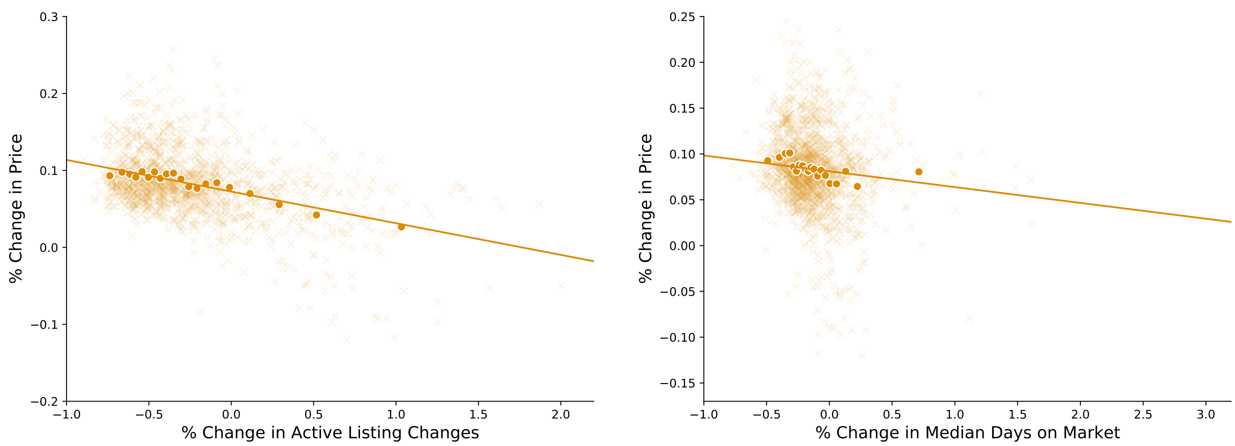


Figure 7. Price change against Changes in Inventory

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. These figures are generated using those ZIP codes that have both rent and price data available.

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 valuation changes to the migration pattern of individuals over this time period, and the role of remote work in facilitating these moves.

[10] Figure A6, Panel C, shows similar results for New York and San Francisco.

[11] The same relationship holds for a larger sample of all ZIPs for which we have house price data; see Figure A7.

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.[12] We observe a large migration elasticity with respect to distance to the city center. The population of ZIP codes near the center of the city falls between February and March of 2020, and populations rise in the suburbs (Figure 8, Panel A).

We connect these population changes to remote work in Panel B of Figure 8, 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.

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 meaningful correlation with price changes, suggesting that the housing markets may be affected for the long-run.[13]

Figure A10 reports the relationship between population changes and distance, and between rent and price changes on the one hand and population changes on the other hand for New York and San Francisco, finding a considerable exodus to the suburbs for these two superstar cities.

We find similar migration patterns when we contrast the home Census tract of individuals (based on nighttime activity) in February with their changed location in March of 2020. This measure only captures migration rates of individuals which we are able to consistently track in both months. This within-user analysis is more demanding, but guards

[12]We require three or more pings nighttime pings in a given census tract to designate a user as a possible resident, and require at least five associations of individuals with nighttime pings in the same location in the same month to assign a residence. Our definition of nighttime is from 5pm–8am, but results are robust to the alternative nighttime definitions of 10pm–8am and 4am–8am. Appendix Figure A8 finds similar results for the population change across location gradients for the different definitions of nighttime residence.

[13]The results are robust to looking at the full sample of ZIP codes for where there are house price data; see Figure A9.

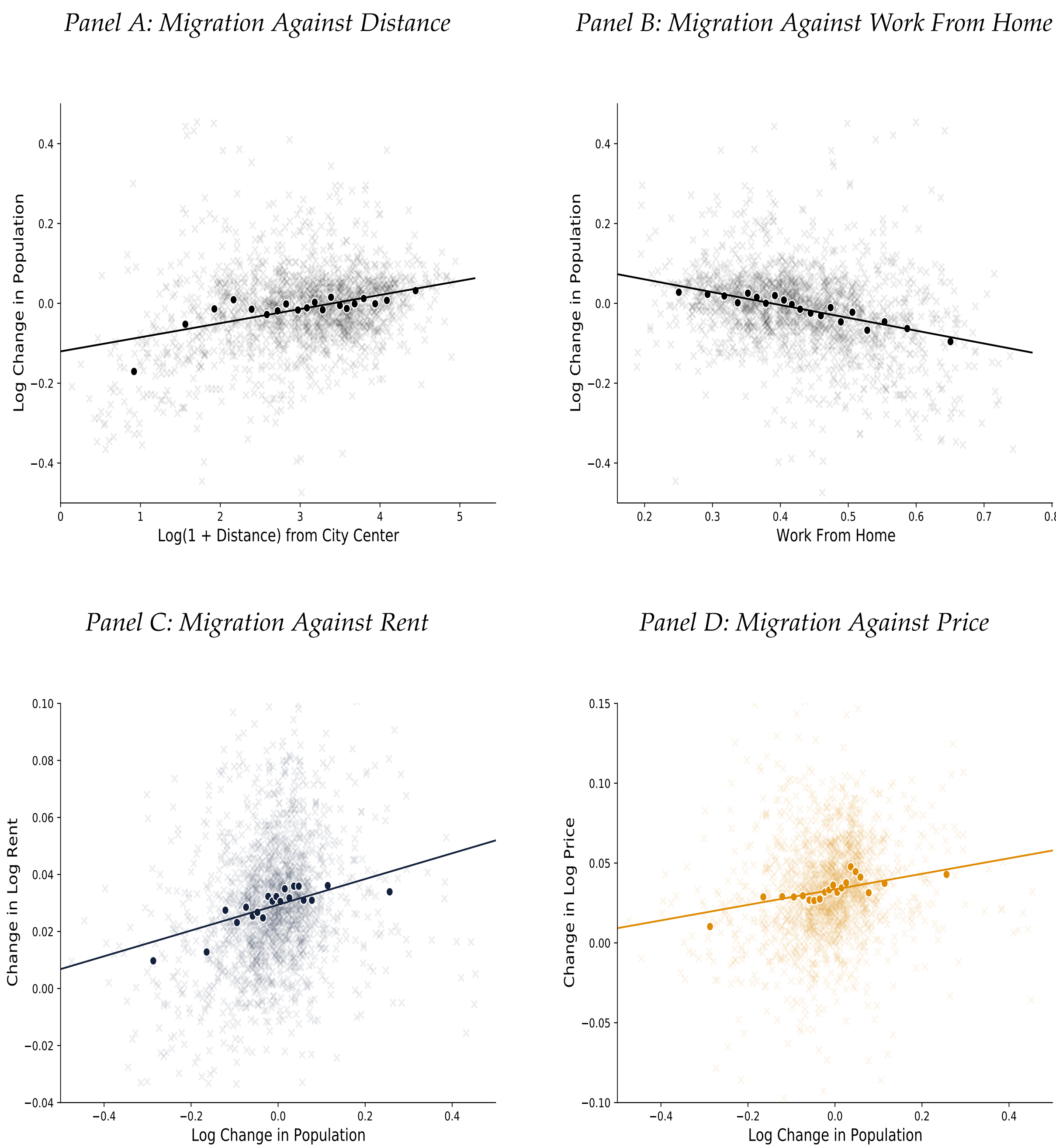
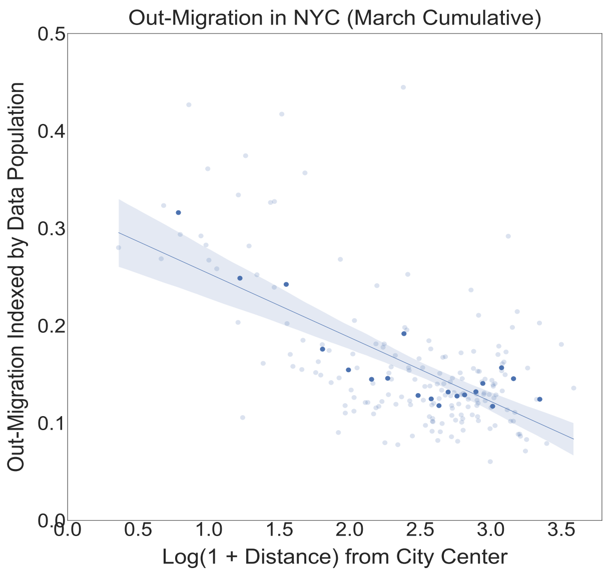


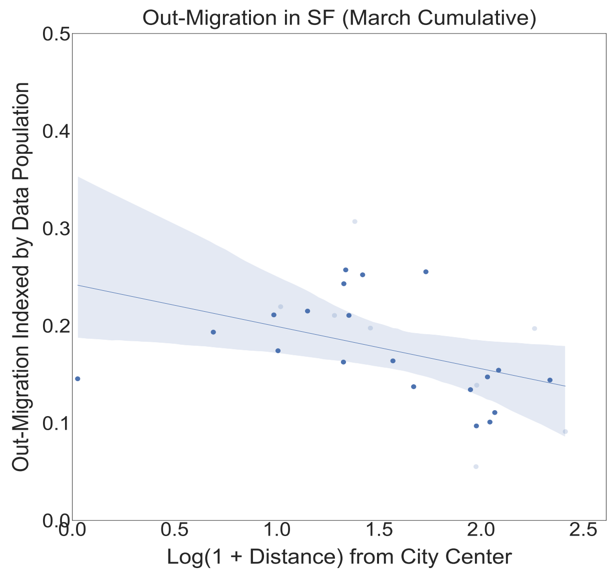
Figure 8. Associations of Intracity Migration

This Figure 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) WFH metric for the top 30 MSAs (Panel B). We then connect changes in population plotted against changes in rents at the ZIP level (Panel D) and changes in prices (Panel D) for the top 30 MSAs. These figures are generated using those ZIP codes that have both rent and price data available.

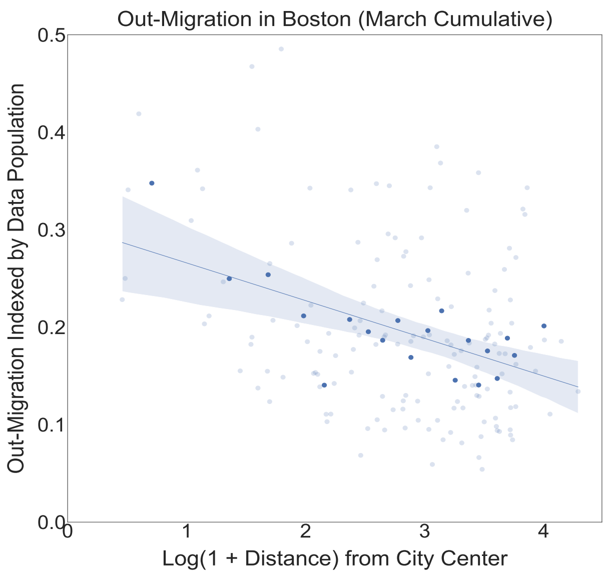
Panel A: New York



Panel B: San Francisco



Panel C: Boston



Panel D: Top MSAs

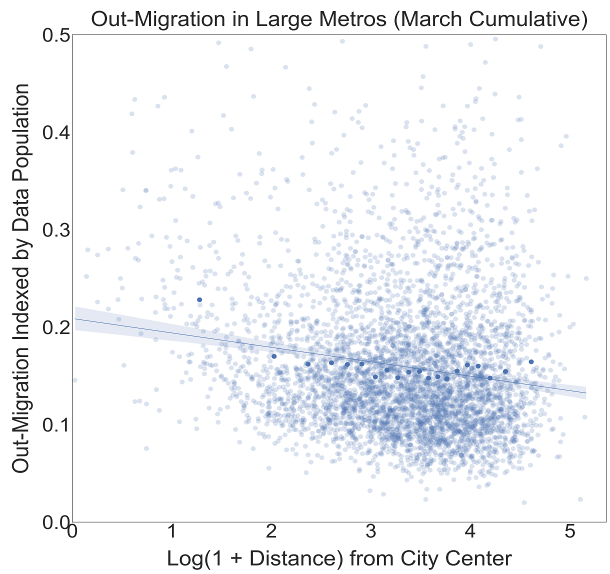


Figure 9. Out-Migration Rates Using VenPath Data

This Figure plots the out-migration rate at the ZIP level from VenPath across three MSAs: New York, San Francisco, Boston, as well as broad sample of all MSAs considered in Table III. To measure out-migration, we examine individual's home Census tracts in February based on their preponderant nighttime ping activity. We then examine their home tract at the end of March, and estimate out-migrants as those individuals who have changed their home tract. Individuals who drop out of the data are not considered.

against the possibility that the population counts in the previous graph reflect data coverage changes rather than migration. Figure 9 reports the within-user out-migration rates. We observe high out-migration rates of individuals close to the city center. Appendix Figure A11 shows that these relationships persist for net migration, so that outflows from urban areas are not fully offset by greater inflows from elsewhere.

We consider a second data source, Infutor, to measure migration patterns during the pandemic. The Infutor data measure changes of address, covers about 150 million residences and has been used in prior literature (Diamond, McQuade, and Qian, 2019) to study migration. For our purposes, we consider changes of address between March 1, 2020 and the end of October 2020. This serves not only as a robustness check on our cell phone ping results, but may also speak to the lasting nature of the relocation. Changes of address may capture mostly persistent relocation (changing homes is costly to reverse), while the cell phone ping data may capture both transitory and persistent moves.

Figure 10 highlights an urban gradient using out-migration rates drawn from the Infutor data. We show similar migration gradients with respect to distance from the city center for the New York, San Francisco, and Boston metropolitan areas, as well as for a five-city sample which also adds Los Angeles and Chicago. Out-migration rates are high near the urban core and low in the suburbs. These results complement our mobile phone location data in suggesting that changes in physical location also result in changes in residence as measured by changes in address.

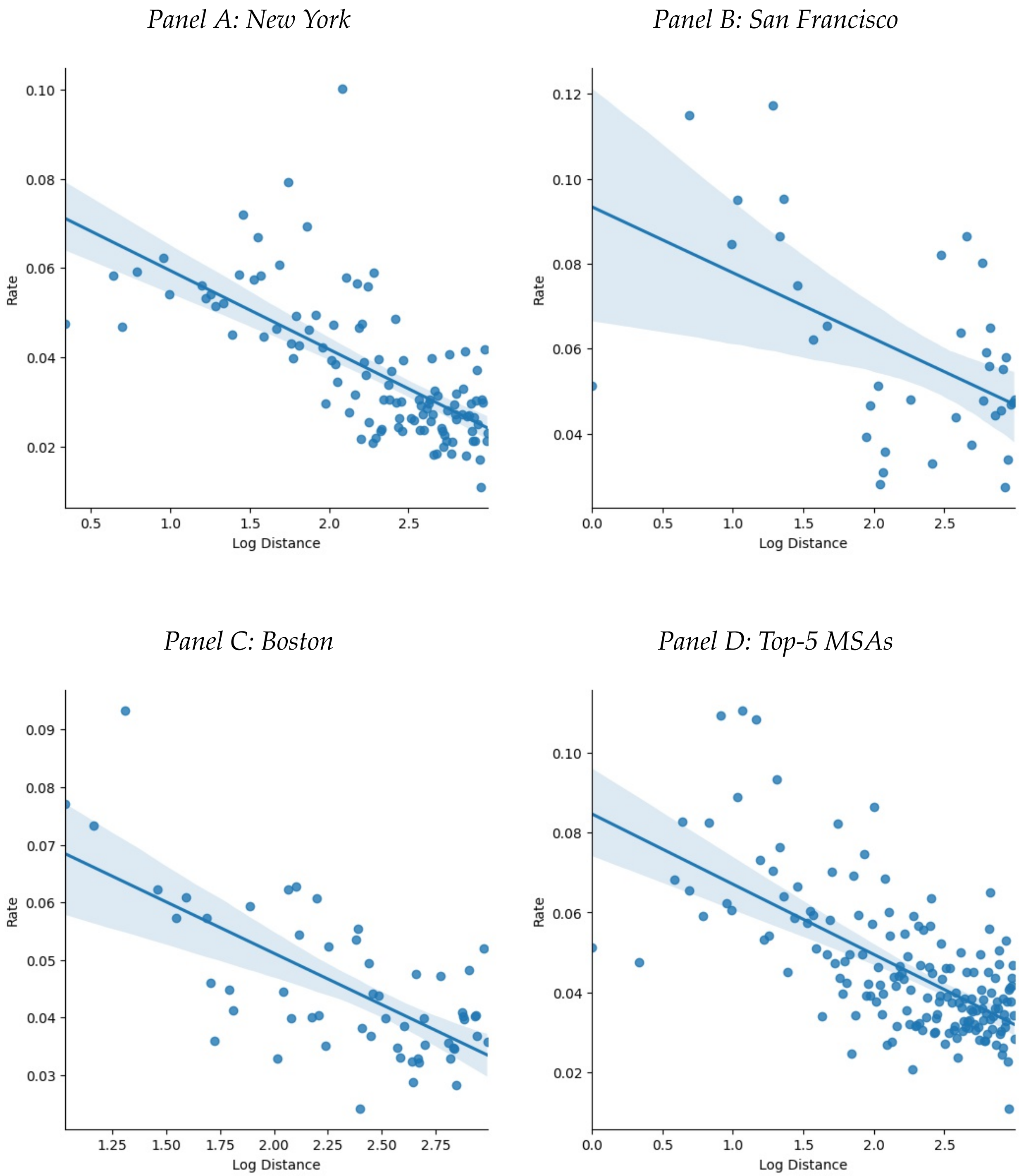


Figure 10. Out-Migration Rates Using Infutor Data

This Figure plots the out-migration rate from Infutor across three MSAs: New York, San Francisco, Boston, as well as sample of five MSAs which also includes Los Angeles and Chicago. Residents are included if Infutor reports an active date for that individual after January 1, 2019—this restriction is used to remove inactive or deceased individuals. Migration is measured by estimating whether any individuals have an address change to another location over the period from March 1, 2020–October 31 2020. Dots correspond to ZIP codes with at least 5,000 in measured population.

This section has shown large migration away from the center of cities that began at the onset of the pandemic. This relocation was boosted by several factors. Initially, there was considerable concern that densely populated metropolitan areas presented additional risk for disease transmission. Additionally, the ensuing lockdowns lowered the value of local amenities such as restaurants and bars. Through both government-enforced closures as well as voluntary cutbacks in behavior, the value of these urban consumption goods was drastically lowered, further diminishing the value of urban life. Work-from-home (WFH) policies also enabled many workers to work remotely rather than commute to work. These WFH policies were born out of necessity because offices were not allowed to reopen.

As the pandemic wore on, and cities gradually reopened, the continued ability to work from home became a major source of uncertainty for individuals. Some employers have since 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 indicated by the Infutor analysis, as workers anticipate less frequent commutes. The remainder of the paper studies the persistence in these trends, first using a cross-sectional analysis in Section 4 and then a time-series analysis in Section 5.

4 Mechanisms

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.

4.1 MSA-Level Analysis

We first explore the potential drivers of increased suburban valuation for rents and prices by exploiting variation across MSAs. We focus on three key variables: the fraction of the population 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),[14] and a measure of housing inelasticity (the first principal component of the Saiz (2010) supply elasticity measure, the Gyourko, Hartley, and Krimmel (2021) land use regulatory index, and the Lutz and Sand (2019) measure of land availability).

We regress the change in the rent gradient for each of the top 30 MSAs against several MSA-level characteristics in Panel A of Table I. Panel B of Table I presents the results for the change in the price gradient as the dependent variable.[15] Column (1) shows that variation in remote work (Dingel and Neiman, 2020) across MSAs alone explains 27.8% of variation in rent gradient changes and 21.0% of variation in price gradient changes, and is a strong economic predictor of changes in these gradients. A 10% point increase in the fraction of jobs in an MSA which can be done remotely changes the rent gradient by 3.02% points and the price gradient by 2.15% points. These are substantial increases which reflect large revaluations of suburban vs. urban real estate in areas with more remote work.

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

[15] Table A.I reports the rent and price gradient changes for each MSA which are the dependent variables of these cross-MSA regressions.

Table I. Determinants of Cross-MSA Variation in Rent and Price Gradient Changes

Panel A: MSA-Level Rent Changes

	(1)	(2)	(3)	(4)	(5)
Work from Home	0.302***			0.239**	0.302***
	(0.0919)			(0.0950)	(0.0891)
Stringency Measure		0.192**		0.122	
		(0.0697)		(0.0759)	
Supply Inelasticity Index			0.0215	0.00483	
			(0.0156)	(0.0148)	
Orthogonalized Stringency Index					0.132*
					(0.0690)
Orthogonalized Supply Inelasticity					0.00483
					(0.0148)
Constant	-0.0997**	-0.0689**	0.00828	-0.133***	-0.0997***
	(0.0364)	(0.0322)	(0.00897)	(0.0406)	(0.0353)
Observations	30	30	30	30	30
R^2	0.278	0.213	0.063	0.370	0.370

Panel B: MSA-Level Price Changes

	(1)	(2)	(3)	(4)	(5)
Work from Home	0.215**			0.174**	0.215***
	(0.0789)			(0.0817)	(0.0767)
Stringency Measure		0.128**		0.0492	
		(0.0597)		(0.0653)	
Supply Inelasticity Index			0.0248*	0.0162	
			(0.0124)	(0.0128)	
Orthogonalized Stringency Index					0.0838
					(0.0593)
Orthogonalized Supply Inelasticity					0.0162
					(0.0128)
Constant	-0.0806**	-0.0545*	-0.00854	-0.0954**	-0.0806**
	(0.0312)	(0.0276)	(0.00711)	(0.0349)	(0.0303)
Observations	30	30	30	30	30
R^2	0.210	0.140	0.125	0.306	0.306

In both panels, we first estimate a gradient specification separately for each MSA following our equation 2. We then calculate $\delta_{j,\Delta} = \delta_{j,Dec2020} - \delta_{j,Dec2019}$ from this specification, corresponding to the change in gradient, for each MSA, over the period December 2019–December 2020. The change in rent gradient is key dependent variable in Panel A and the change in the price gradient is the dependent variable in Panel B. We regress this gradient change against three independent variables at the MSA-level: the (Dingel and Neiman, 2020) WFH measure, a lockdown stringency measure from Hale, Atav, Hallas, Kira, Phillips, Petherick, and Pott (2020), and a housing supply inelasticity index (the first principal component of the Saiz (2010) supply elasticity measure, the Gyourko, Hartley, and Krimmel (2021) land use regulatory index, and the Lutz and Sand (2019) measure of land availability). Column (5) orthogonalizes stringency to the WFH variable and land inelasticity to both WFH and stringency measures. Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$.

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—which are forward-looking—capture expectations of real estate markets over longer horizons, this evidence supports the urban revival results we will find in Section 5.6. An expected future reduction in work from home practices relative to the high 2020 WFH levels would result in higher urban rents. At the same time, the substantial impact on price gradients suggests that some of the effect is expected to be long-lived.

While this specification shows the importance of remote work in accounting for the cross-section of urban real estate repricing, WFH may affect housing markets through two important channels. One channel is that workers who could theoretically work remotely saw this possibility realized over the course of the pandemic. Survey data suggest that many employers and employees expect remote work to continue in the future, at least on a hybrid basis.[16] The ability to work from home allowed households to re-optimize their housing choices, move away from the urban centers without increasing their commuting times.

At the same time, the class of workers who can work remotely, which consists of mostly higher-skilled workers, 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 could also lower urban gradients—even if these workers still anticipate regular commuting in the future.

We are able to measure one possible component of amenity revaluation in column (2), which measures policy lockdown measures. These correspond to government-imposed restrictions in private activity, which directly affected the ability of residents to take advantage of local amenities. This variable is normalized to be the same range (0–1) as

[16]Survey evidence in Barrero, Bloom, and Davis (2021) indicates a persistence in remote working policies.

the WFH measure to enable comparability. We find that MSAs which feature more strict COVID restrictions see more revaluation towards suburban properties. The effects are substantial for rents, with a coefficient of 0.19 and a R^2 of 21.3%. They are smaller for prices with a coefficient of 0.128 and a R^2 of 14%. Yet, for both rent and price gradients, the impact of lockdowns is smaller than for the WFH variable.

We also investigate the role of housing supply inelasticity in column (3), again normalized to be the same range (0–1) as the WFH measure. Cities where urban premia reflect supply constraints also see urban revaluation in house prices (but not in rents), suggesting that affordability constraints in superstar cities may drive interest in suburban lifestyles. The magnitude of the effect is again smaller than for WFH.

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 37.2% of the cross-MSA variation in rent gradient changes and 30.6% of the variation in price 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 and the supply inelasticity become much smaller and insignificant determinants for both rent and price gradients.

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. However, the coefficients on the orthogonalized stringency and supply inelasticity measures do not change much in magnitude, suggesting that there is not much correlation between these variables in the first place.

In Appendix Figure A12, we decompose the 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 prevalence 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 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 of real estate supplied, rather than higher prices.

Table A.II shows robustness of the results on the cross-MSA determinants of price gradient changes for gradients estimated from different samples of ZIP codes and different types of owner-occupied housing.

Our preliminary conclusion from the MSA-level analysis is that the WFH effect reflects the importance of commuting costs relative to urban amenities. We refine this analysis next with ZIP-level analysis.

4.2 ZIP-Level Analysis

Next, we revisit the commuting-versus-amenities question at the finer level of granularity of the ZIP code. This analysis uses a ZIP-level WFH measure as well as a measure of ZIP-level amenities, namely the number of bars and restaurants. We also include MSA fixed effects which captures amenities common to the metropolitan area.

In Table II, Panel A, we regress rent changes from Dec 2019–Dec 2020 against a variety of ZIP-level covariates. Panel B repeats the estimation for price changes. We find that the fraction of remote workers at the ZIP-code level remains strongly predictive of real estate changes even after controlling for MSA-fixed effects and ZIP-level amenities, alongside other socio-economic covariates.[17]

For rents, a 10% point increase in the fraction of remote work in a ZIP code is associated with a 1.3–2.5% 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.

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 0.5–1.9% 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. Because MSA fixed effects and the ZIP-level measure of restaurants and bars 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 where they live. 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, we find that the nature of urban revaluation is for remote workers to leave expensive urban areas for less expensive suburban locations within their MSAs now that they need to commute to the office less frequently.

[17]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; the work from home measure remains significant.

Table II. Intra-city Rent and Price Changes

Panel A: ZIP-Level Rent Changes

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Distance)	0.0298***		0.0241***	0.0253***	0.0149***	0.0173***
	(6.15)		(5.30)	(6.37)	(4.14)	(5.44)
Work from Home		-0.246***	-0.251***	-0.195***	-0.125***	-0.147***
		(-8.73)	(-8.15)	(-12.16)	(-3.78)	(-6.47)
Median Household Income ('000)					0.000622***	0.000508***
					(5.66)	(8.03)
Median Age					0.00105***	0.00103***
					(3.20)	(4.22)
Percent of Black Households					0.00993	0.0201*
					(0.47)	(1.80)
Share of High Income Households					-0.560***	-0.341***
					(-6.77)	(-6.45)
Log(Restaurants & Bars)					-0.0106***	-0.00657***
					(-3.86)	(-4.04)
Constant	-0.0700***	0.126***	0.0554***	0.0281**	0.0298	0.00465
	(-4.82)	(10.32)	(3.72)	(2.45)	(1.22)	(0.36)
MSA fixed effects	✓	✓		✓		✓
Observations	1697	1697	1697	1697	1697	1697
R squared	0.580	0.536	0.484	0.676	0.557	0.709

Panel B: ZIP-Level Price Changes

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Distance)	0.0118***		0.00629	0.00780**	0.00298	0.00669**
	(3.05)		(1.66)	(2.39)	(0.96)	(2.40)
Work from Home		-0.189***	-0.179***	-0.173***	-0.0483	-0.108***
		(-9.84)	(-5.15)	(-10.33)	(-1.19)	(-3.79)
Median Household Income ('000)					0.000215**	0.000115
					(2.35)	(1.42)
Median Age					-0.0000566	0.000284
					(-0.13)	(1.23)
Percent of Black Households					-0.00653	0.0283***
					(-0.35)	(2.91)
Share of High Income Households					-0.358***	-0.139**
					(-5.11)	(-2.37)
Log(Restaurants & Bars)					-0.00902***	-0.00327**
					(-3.13)	(-2.15)
Constant	0.0447***	0.162***	0.138***	0.131***	0.147***	0.108***
	(3.86)	(19.50)	(8.16)	(11.45)	(4.82)	(6.75)
MSA fixed effects	✓	✓		✓		✓
Observations	1697	1697	1697	1697	1697	1697
R squared	0.500	0.600	0.231	0.621	0.292	0.640

Panel A of this Table shows a regression of changes in ZIP-level log rents from Dec 2019 to Dec 2020 against a variety of ZIP level covariates. Panel B shows a regression in which the change in log rents is the key dependent variable. Independent variables include: the (Dingel and Neiman, 2020) WFH measure constructed at a ZIP-level, a variety of controls from the 2019 ACS (median household income in thousands, median age of household head, percentage of Black households, and share of high income households), and the log of the number of restaurants and bars from Safegraph. The presence of MSA-fixed effects is indicated in the table bottom. The sample is restricted to ZIP codes for which we can measure both rent and price changes. Standard errors in parenthesis are clustered at the MSA level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

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. The effect of WFH in our preferred specification in column (6) is -0.147 for rents in panel A and -0.108 for prices in panel B. This suggests that some component of WFH associated urban flight is temporary, reflecting particularly flexible remote working policies during this period which may not last. However, the effect of WFH on prices is also substantial at the ZIP level, pointing to the role of persistently changed (expectations) about future remote work policies and commuting patterns.

Table A.III shows robustness of the results on the cross-ZIP determinants of price changes for different samples of ZIP codes and different types of owner-occupied housing.

5 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.

5.1 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 11 illustrates this pattern for the New York MSA.

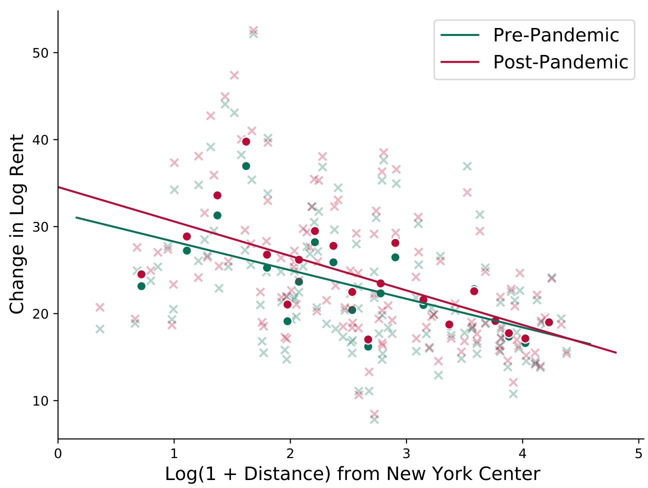


Figure 11. Price-Rent Ratio against Distance for New York
The Figure shows the relationship between the price-to-rent ratio in New York City before the pandemic (Jan 2014 to Dec 2019, in green) and during the pandemic (2020 Q4, in red) across distance to the center of the city, measured as log of 1 + distance to Grand Central in kilometers.

We also compute the price-rent ratio in the fourth quarter of 2020, averaging the price-rent ratios of October, November, and December 2020.[18] The "Post-Pandemic" line in Figure 11 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

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

pandemic. Put differently, it became relatively cheaper to rent than to own in the core.

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 12 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*

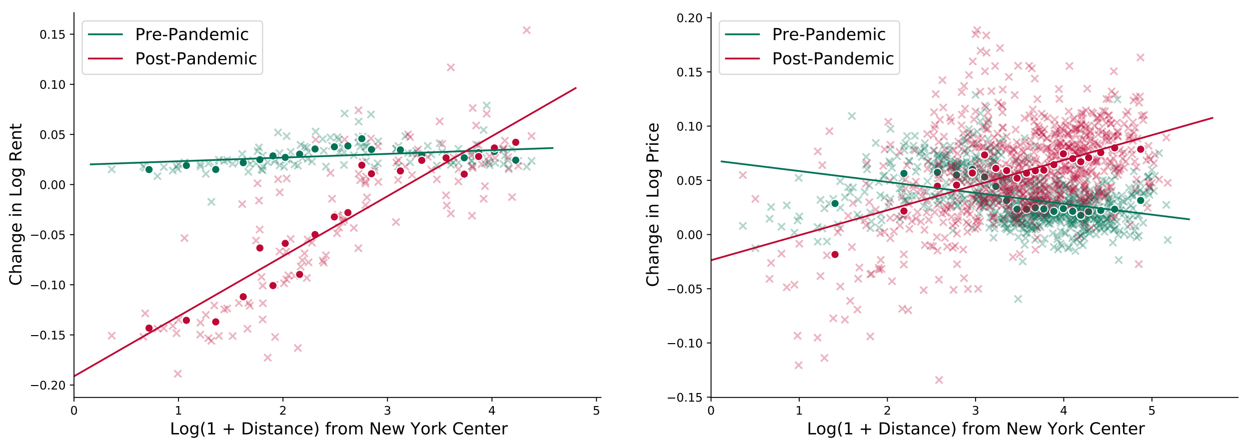


Figure 12. Changes in Rent and Price Growth Rates

This Figure shows 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 (Oct 2020–Dec 2020) across distance from the center of New York, measured as the log of (1 + distance to Grand Central Terminal in kilometers).

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

5.2 Present-Value Model

We consider a present-value model in the vein of Campbell and Shiller (1989) to interpret the observed changes in the price-dividend ratio. Appendix C contains additional details.

Starting with a basic definition of housing returns, we 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:

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

By iterating forward, log-linearizing the definition of cum-dividend returns, and imposing a transversality condition, we obtain the present-value relationship equating the price-dividend ratio to the difference between the cumulative discounted expected rent growth rates, $g_t = E_t[\Delta d_{t+1}]$, and the cumulative discounted expected housing returns $x_t = E_t[r_{t+1}]$:

$$pd_t = \frac{k}{1-\rho} + \sum_{s=1}^{+\infty} \rho^{s-1} g_{t+s} - \sum_{s=1}^{+\infty} \rho^{s-1} x_{t+s}. \tag{3}$$

This relationship holds for every ZIP code i in every MSA j. 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 (3).

To make further progress on the relationship between current prices and future projections, we need to take a stance on whether the pandemic has transitory or permanent effects. We first discuss the details of our estimation under either condition, and then combine both cases based on survey evidence on the persistence of the covid shock.

5.3 Case 1: Pandemic is Transitory

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 their pre-pandemic averages $\left(\overline{x}^{ij}, \overline{g}^{ij}, \overline{pd}^{ij}\right)$. Under this assumption, 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 (4) below 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:

$$\begin{aligned} \Delta pd^j &= \left[A^{uj}\left(g_t^{uj} - \overline{g}^{uj}\right) - A^{sj}\left(g_t^{sj} - \overline{g}^{sj}\right)\right] - \left[B^{uj}\left(x_t^{uj} - \overline{x}^{uj}\right) - B^{sj}\left(x_t^{sj} - \overline{x}^{sj}\right)\right]. \\ \Delta pd^j &\equiv \left(pd_t^{uj} - \overline{pd}^{uj}\right) - \left(pd_t^{sj} - \overline{pd}^{sj}\right) \end{aligned} \tag{4}$$

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 follow an AR(1) with the same persistence across geographies: $\rho_x^{ij} = \rho_x$ and $\rho_g^{ij} = \rho_g$. We also assume that $\rho^{ij} = \rho^j$.[19]

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:

$$g_t^{uj} - g_t^{sj} = \overline{g}^{uj} - \overline{g}^{sj} + (1 - \rho^j\rho_g)\Delta pd^j + \frac{1 - \rho^j\rho_g}{1 - \rho^j\rho_x}\Delta x^j \tag{5}$$

where

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

Equation (5) gives the expected rent growth differential over the next twelve months,

[19]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 (10).

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

$$\frac{g_t^{uj} - g_t^{sj}}{1 - \rho^j \rho_g} = \frac{\overline{g}^{uj} - \overline{g}^{sj}}{1 - \rho^j \rho_g} + \Delta pd^j + \frac{\Delta x^j}{1 - \rho^j \rho_x}. \tag{6}$$

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 alternative assumption we make is that the pandemic narrowed this gap. Specifically, the annual urban risk premium increases by one percentage point relative to the suburban risk premium:

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

Under this assumption the urban-minus-suburban risk premium increase is transitory: it increases by 1% point and that increase gradually reverts back to zero at rate

ρ_x. Naturally, the model can handle any other change besides 1% point or a change that varies by MSA.

5.4 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 again use the present-value relationship 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:

$$\widehat{g}^{uj} - \widehat{g}^{sj} = \left(\widehat{pd}^{uj} - \widehat{pd}^{sj}\right) - \left(\log\left(1 + e^{\widehat{pd}^{uj}}\right) - \log\left(1 + e^{\widehat{pd}^{sj}}\right)\right) + \widehat{x}^{uj} - \widehat{x}^{sj}. \tag{7}$$

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.

5.5 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:

$$\widetilde{g}_t^{uj} - \widetilde{g}_t^{sj} = p\big(g_t^{uj} - g_t^{sj}\big) + (1-p)\big(\widehat{g}_t^{uj} - \widehat{g}_t^{sj}\big). \tag{8}$$

The first term comes from equation (5), while the second term uses equation (7).

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:

$$\widetilde{pd}_t^{uj} - \widetilde{pd}_t^{sj} = p\big(pd_t^{uj} - pd_t^{sj}\big) + (1-p)\big(\widehat{pd}_t^{uj} - \widehat{pd}_t^{sj}\big). \tag{9}$$

The first term is calculated from the transitory model, 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.

5.6 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 III). In these specifications, we are interested in both rent and price information for not just the urban core, but also suburban areas.

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 (13) in the appendix to compute the expected annual returns in columns (5) and (6). These expected returns are also multiplied by 100. Expected returns are between 5% and 14% per year. 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 last quarter of 2020.

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. For the average MSA, the increase is 6.99%. What this implies depends on the model in question.

5.6.1 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 in 2020, 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 (6) under assumptions 2 and 3, respectively.

To implement equation (6), 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-rent ratio.[20] We compute ρ^j from equation (10), 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 (Assumption 2), urban rent growth is expected to exceed suburban rent growth by 8.13% points in the average MSA over the next several years cumulatively (column 10). However, if the urban risk premium temporarily rises by 1% point relative to the suburban risk premium (Assumption 3), then urban rent growth will exceed suburban rent growth by 15.6% cumulatively (column 11).

There are large differences across MSAs. Los Angeles is expected to see much larger cumulative urban-suburban rent growth between 20.12% (column 10) and 28.69% (column 11). This is because the change in the urban-minus-suburban price-rent ratio is much larger (13.41%). 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 lower price-rent ratios, lower rent growth, and higher risk premia in the urban core than in the suburbs before the pandemic. If the gap between the urban and suburban risk premium rises by a further 1% point during the pandemic (column 11), urban rent growth must exceed suburban growth by 8.81% to restore the old price-rent ratios.

Figure A13 shows the expected rent growth for each ZIP code, which is a declining

[20] 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.

function of distance from the city center. The transitory model predicts higher urban rent growth in 2021 and beyond.

5.6.2 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 (7) 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, the average MSA's price-rent ratio in December 2020 implies permanently higher annual rent growth of 0.61% in urban than in suburban ZIP codes. If the urban-suburban risk premium rises permanently by 1% point, urban rent growth is expected to exceed suburban growth by 1.61% 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.[21] In sum, the permanent model also expects the rent in urban ZIP codes to grow more strongly than in the suburbs in the future.

[21] 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.

Table III. Backing Out Expected Rents

		(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	24.73	17.23	2.55	3.01	6.51	8.65	26.88	17.74	5.42	3.80	11.87	-0.31	0.69
2	Los Angeles-Long Beach-Anaheim, CA	29.71	24.13	6.06	4.18	9.37	8.25	35.38	25.12	13.41	20.12	28.69	2.25	3.25
3	Chicago-Naperville-Elgin, IL-IN-WI	17.39	11.24	2.86	2.80	8.45	11.33	18.73	11.88	1.80	2.00	9.04	0.00	1.00
4	Dallas-Fort Worth-Arlington, TX	15.40	12.57	4.30	4.02	10.59	11.67	17.82	13.75	5.62	6.55	13.31	0.48	1.48
5	Houston-The Woodlands-Sugar Land, TX	19.92	14.44	1.06	1.59	5.96	8.29	21.52	14.87	4.87	3.13	9.90	-0.36	0.64
6	Washington-Arlington-Alexandria, DC-VA-MD-WV	23.62	17.85	3.14	2.08	7.28	7.53	26.63	18.89	6.31	9.96	17.83	1.22	2.22
7	Miami-Fort Lauderdale-Pompano Beach, FL	15.83	11.67	2.94	4.14	9.06	12.36	17.70	12.70	2.64	-1.26	5.40	-1.22	-0.22
8	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	10.21	15.00	3.35	2.44	12.69	8.90	12.86	15.83	17.70	20.66	27.42	2.43	3.43
9	Atlanta-Sandy Springs-Alpharetta, GA	15.97	13.84	6.35	4.58	12.42	11.55	18.57	14.55	10.10	15.91	22.74	2.27	3.27
10	Phoenix-Mesa-Chandler, AZ	14.57	15.84	7.36	6.38	14.00	12.50	16.42	16.16	9.99	13.29	20.60	1.59	2.59
11	Boston-Cambridge-Newton, MA-NH	20.63	17.18	4.00	4.88	8.73	10.54	23.72	18.64	5.78	2.74	10.62	-0.71	0.29
12	San Francisco-Oakland-Berkeley, CA	34.13	25.65	4.01	4.90	6.89	8.73	39.64	28.20	5.47	2.25	11.02	-0.84	0.16
15	Seattle-Tacoma-Bellevue, WA	31.78	16.08	5.66	6.63	8.76	12.67	37.69	18.70	1.96	-1.47	6.74	-1.32	-0.32
17	San Diego-Chula Vista-Carlsbad, CA	21.47	21.86	5.88	4.90	10.43	9.37	23.61	23.33	3.00	6.44	14.65	1.11	2.11
18	Tampa-St. Petersburg-Clearwater, FL	11.75	9.35	5.00	5.26	13.16	15.43	14.73	11.18	4.64	3.79	10.24	-0.27	0.73
19	Denver-Aurora-Lakewood, CO	21.31	18.55	5.77	5.02	10.36	10.27	24.03	19.67	6.18	8.78	16.52	0.97	1.97
20	St. Louis, MO-IL	13.84	12.86	3.20	2.69	10.17	10.18	14.84	13.94	-1.12	0.50	6.80	0.40	1.40
21	Baltimore-Columbia-Towson, MD	8.68	14.93	1.48	1.57	12.38	8.05	9.39	15.74	2.53	2.25	8.81	0.37	1.37
22	Charlotte-Concord-Gastonia, NC-SC	15.00	13.39	6.08	4.07	12.53	11.28	18.28	13.98	15.42	22.04	28.95	2.84	3.84
23	Orlando-Kissimmee-Sanford, FL	12.40	11.82	5.67	4.22	13.42	12.34	14.63	13.00	7.04	11.75	18.47	1.88	2.88
24	San Antonio-New Braunfels, TX	11.28	13.94	4.21	2.46	12.70	9.39	12.87	15.13	5.03	10.67	17.24	2.23	3.23
26	Sacramento-Roseville-Folsom, CA	18.07	22.18	7.08	7.99	12.47	12.40	19.38	19.97	17.48	14.32	22.16	-0.08	0.92
29	Austin-Round Rock-Georgetown, TX	21.10	14.44	4.30	3.10	8.93	9.79	25.61	16.27	7.43	11.51	18.98	1.27	2.27
	MSA Population Weighted Average									6.99	8.13	15.60	0.61	1.61

5.6.3 Headline Result: Combining Transitory and Permanent Cases

The Pulsenomics survey held in February of 2021 finds that 64% of 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.[22]

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 (8).

Figure 13 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 main, combination case ($p = 0.64$). 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 2.39% points in the left panel and 4.59% 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 0.61% in the left and 1.61% in the right panel. For our preferred combination case, the trajectory of expected rent growth naturally lies in be-

[22]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).

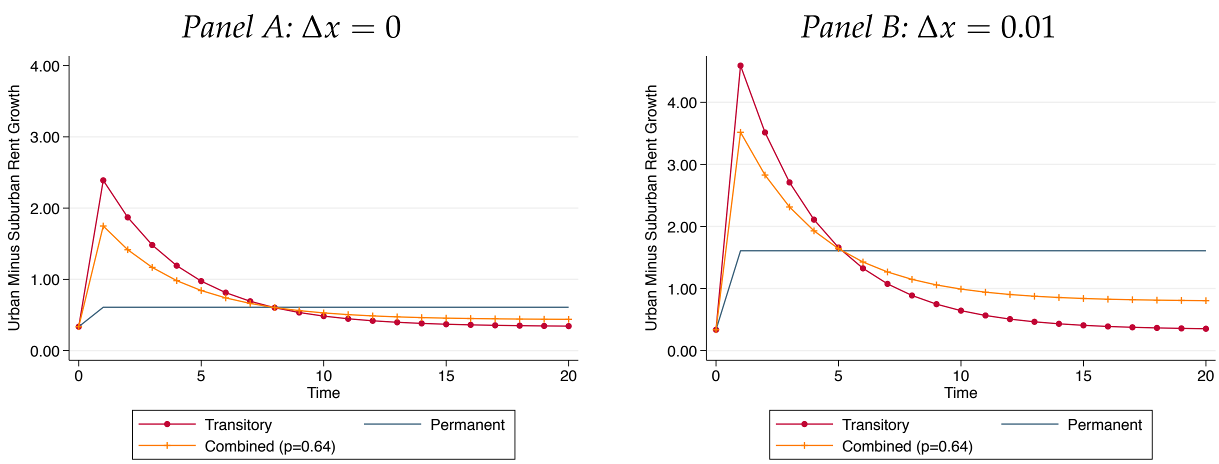


Figure 13. Evolution of Rent Growth when Pandemic is Transitory and Permanent along with a Combination of Two Regimes

This Figure shows 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 III: (1) $\Delta x = 0$, and (2) $\Delta x = 0.01$.

tween the two extreme cases. Under our preferred assumption on expected returns in the right-hand side panel, the model predicts rent growth in 2021 for urban ZIP codes that exceeds that in suburban ZIP codes by 3.52% points. In the long-run, urban rent growth exceeds suburban growth by 0.80% points.

Appendix Figure A17 reports the combination model's prediction for individual MSAs. There is substantial variation in predicted urban rent growth revival, with large values for Los Angeles, Sacramento, Charlotte, Philadelphia, and Phoenix.

Appendix Figure A18 discusses the various models' implications for the evolution of price-rent ratios in urban versus suburban ZIP codes. After rising during the pandemic, price-rent ratios reverse back down but remain above pre-pandemic levels with interesting dynamics in our preferred combination case with rising urban risk premia.

6 Conclusion

A central paradox of the internet age has been that digital tools enable greater collaboration at further distances, yet have led to ever more concentrated economic activity into a handful of dense urban areas. We document that the COVID-19 pandemic, and the migration flows it triggered, 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. 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. Combining a present-value model with professional forecasters' opinion 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.

A key benefit to workers of this changing economic geography is access the large 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. Our results point to important challenges and opportunities in the context of a radically reshaped urban landscape.

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A Additional Results

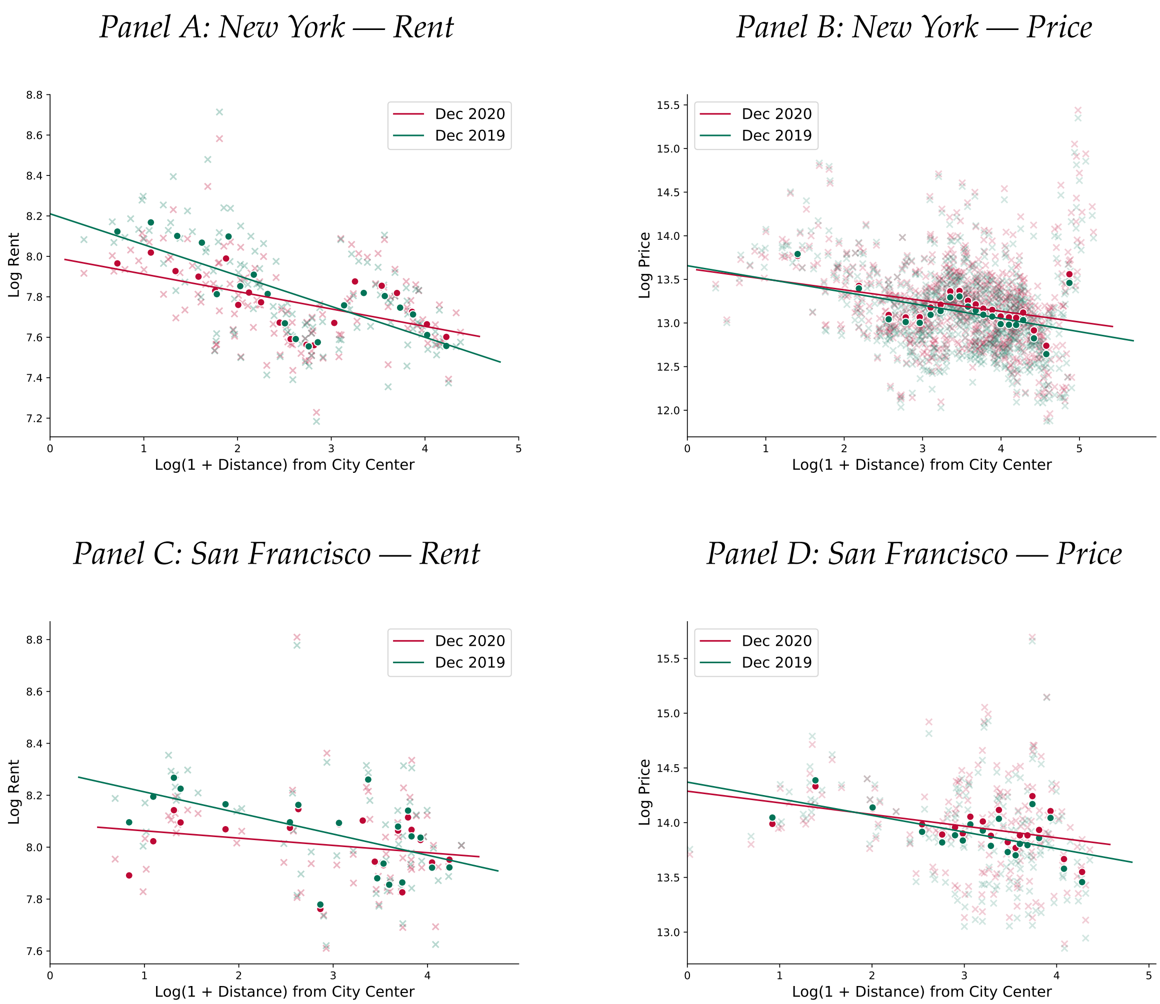
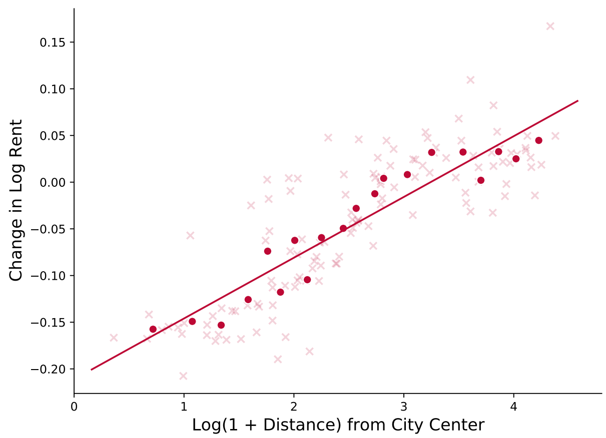


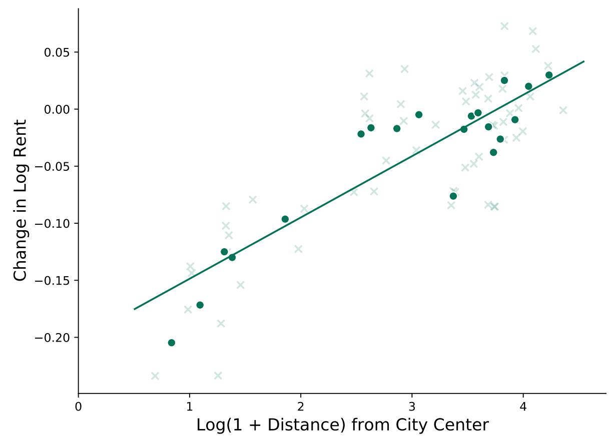
Figure A1. Bid-rent Functions for San Francisco and New York

This Figure shows 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).

Panel A: Rent

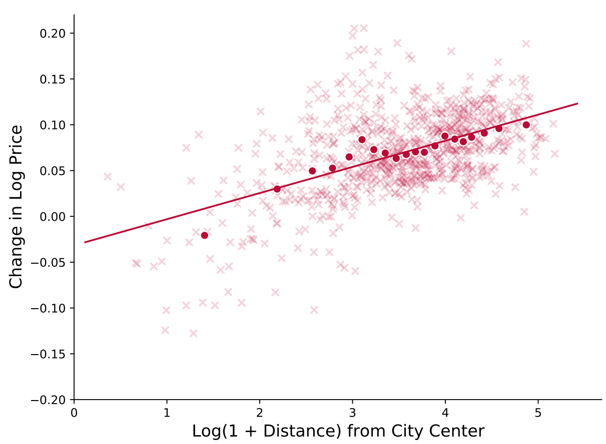


New York

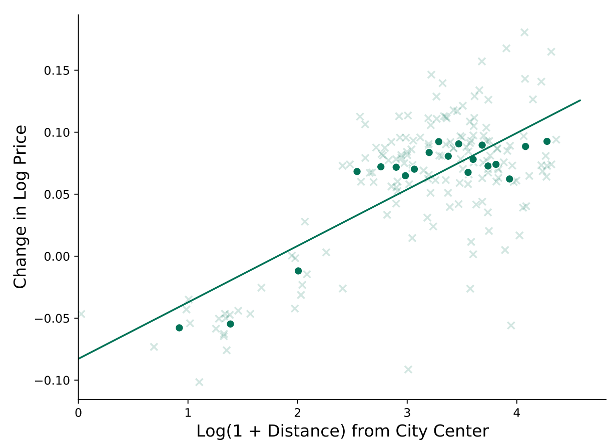


San Francisco

Panel B: Price



New York

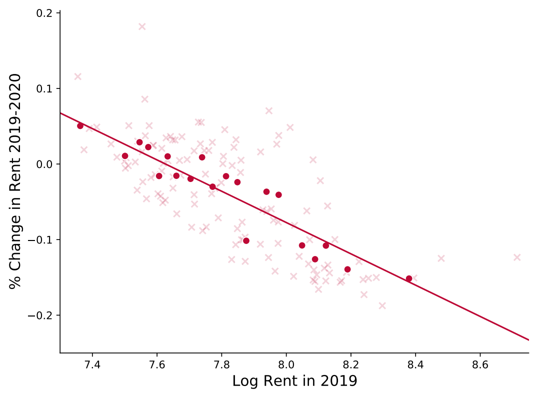


San Francisco

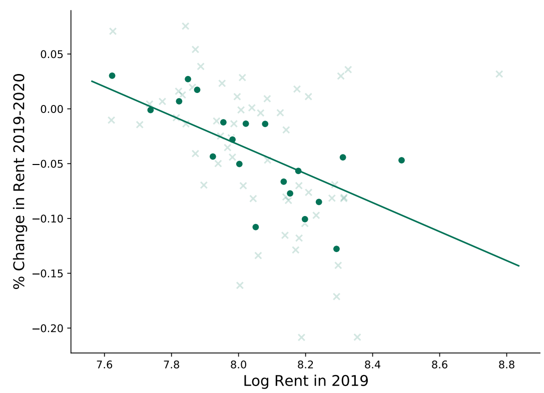
Figure A2. Change in the Bid-rent function

This Figure shows 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

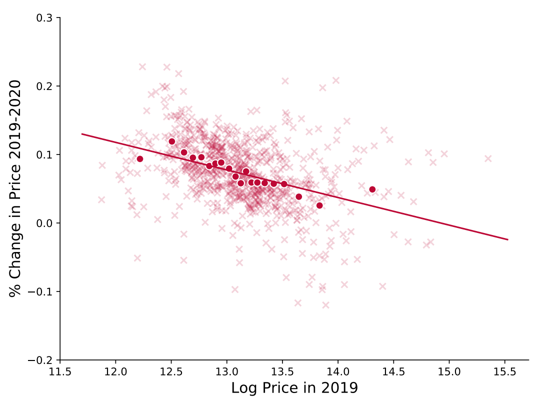


New York

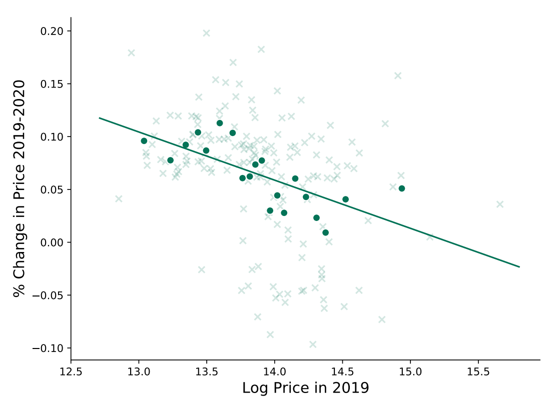


San Francisco

Panel B: Price



New York



San Francisco

Figure A3. 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.

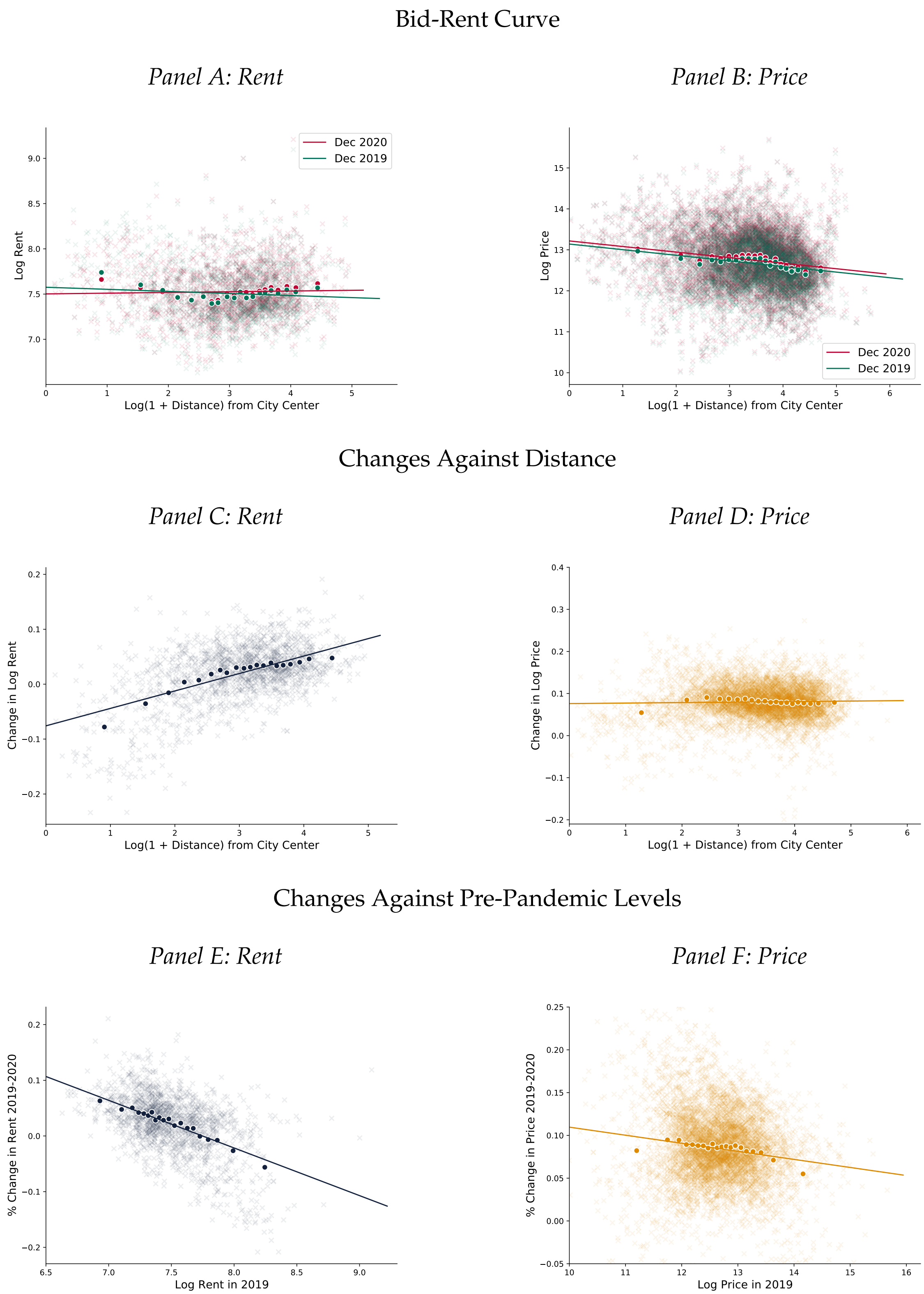
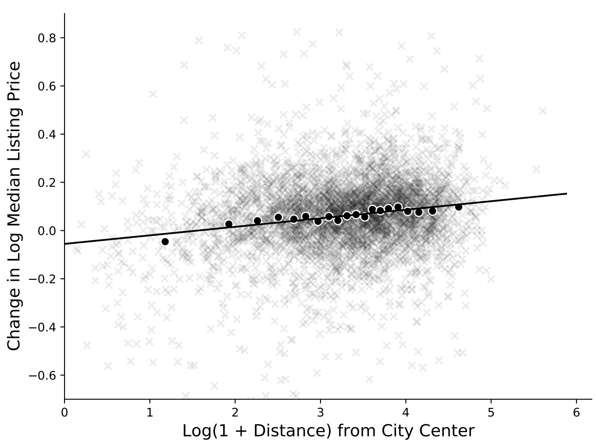


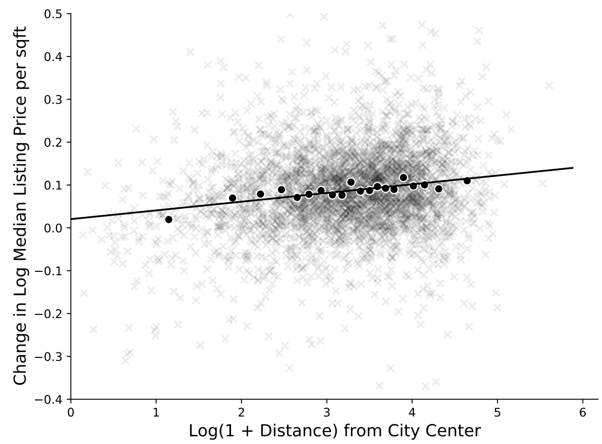
Figure A4. Pandemic Induced Changes in Prices and Rents without Sample Restrictions

The top two panels 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.

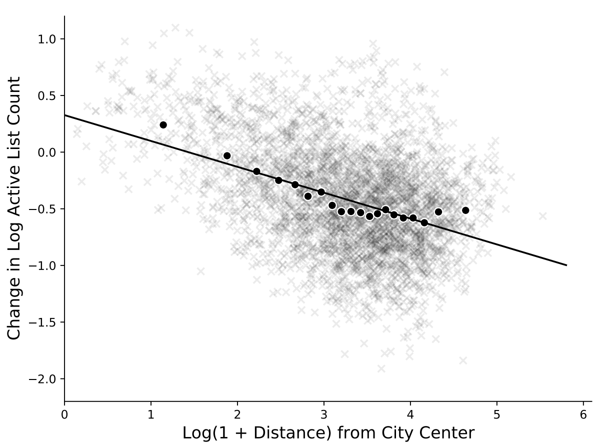
Panel A: Median Listing Price



Panel B: Median Listing Price per sq. ft.



Panel C: Active Listings



Panel D: Median Days on Market

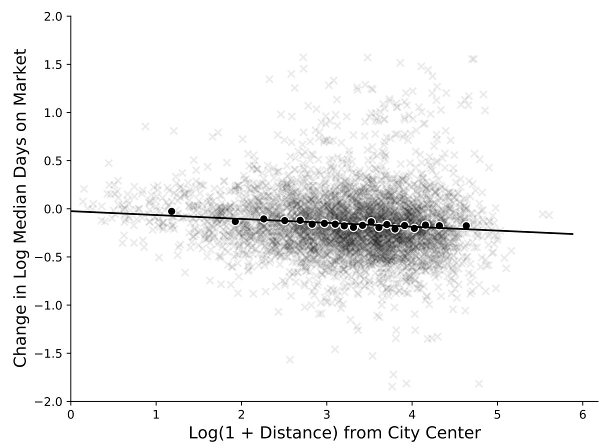
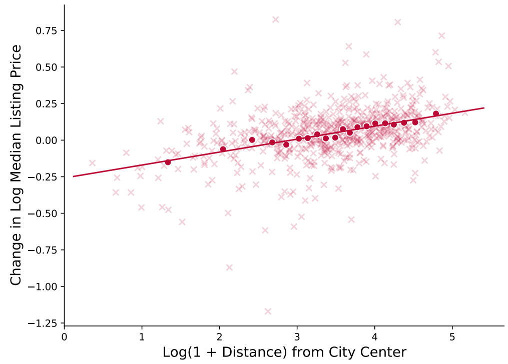


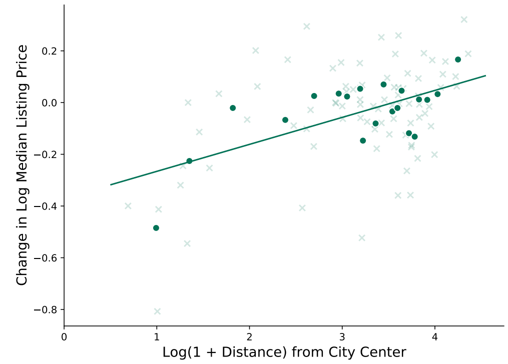
Figure A5. Changes in Listing Prices and Market Inventory without Sample Restrictions

This Figure shows 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 at the ZIP level. The next two panels show the 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 represents the change in the market inventory or listing price measure from Dec 2019 to Dec 2020. Listing counts greater than or equal to 20 per zip-month are considered, and observations with 12 month changes of median listing price per sq. ft. greater than 1000% are omitted.

Panel A: Median listing price

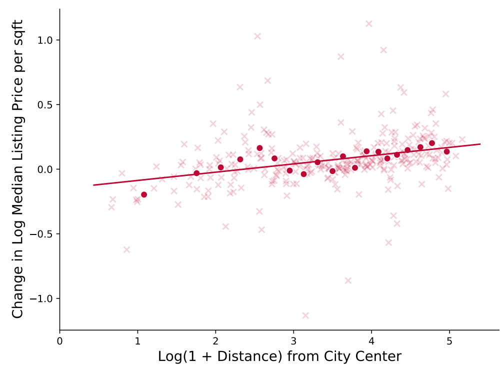


New York

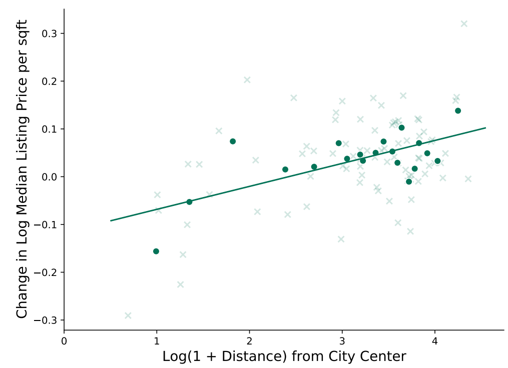


San Francisco

Panel B: Median listing price per sq. ft.

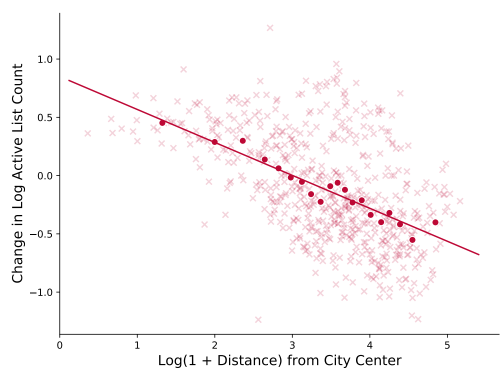


New York

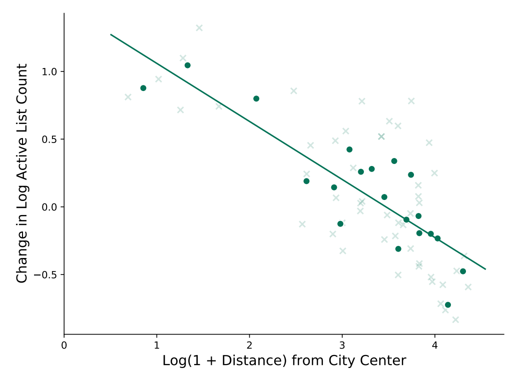


San Francisco

Panel C: Active listings



New York



San Francisco

Figure A6. Changes in Listing Prices and Market Inventory

The Figure show 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). Observations with 12 month changes of median listing price per sq. ft. greater than 1000% are omitted. Panel C represents the change in market inventory, measured by the active listing count on Realtor 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. Listing counts greater than or equal to 20 per zip-month are considered.

Panel A: Price change against active listing changes

Panel B: Price and median days on market changes

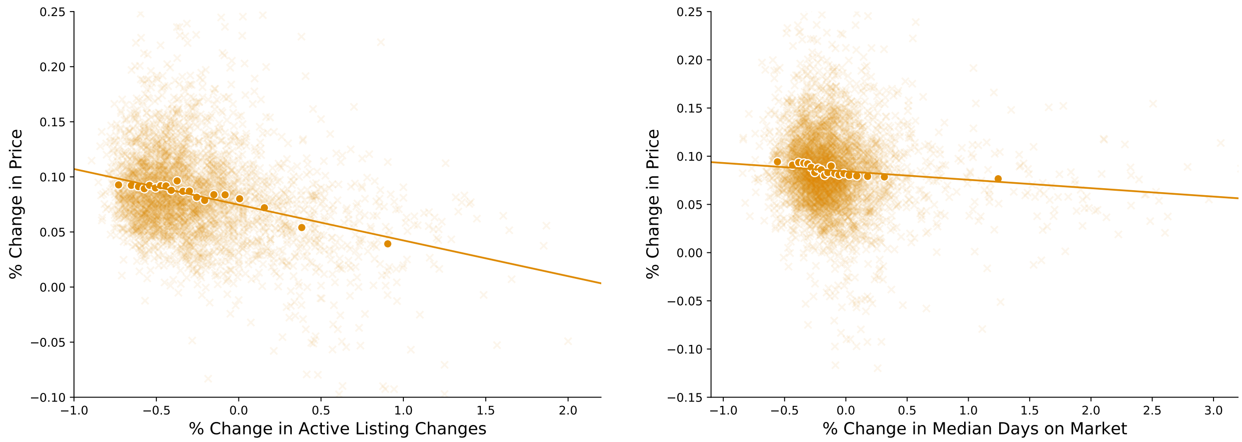


Figure A7. Price change against Changes in Inventory without Sample Restrictions

Changes in prices against changes in two measures of inventories for the top 30 MSAs. 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. Listing counts greater than or equal to 20 per zip-month are considered.

(a) Baseline (5pm–8am)

(b) 10pm–8am

(c) 4am–8am

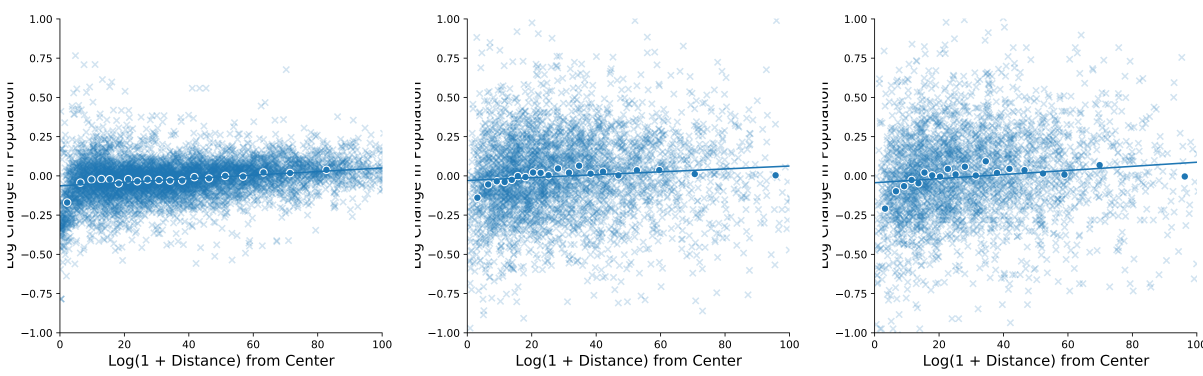


Figure A8. Population Change by Distance From Center: Nighttime Definition

This Figure plots the population change gradient from VenPath across different definitions of population measurement. All measures requires three or more pings nighttime pings in a given census tract to designate a user as a possible resident and require at least five associations of individuals with nighttime pings in the same location in the same month to assign a residence. All measures also measure population change from March 2020 – April 2020. Our baseline estimate measures nightime as 5pm–8am (Panel A), but results are robust to the alternative nighttime definitions of 10pm–8am (Panel B) and 4am–8am (Panel C).

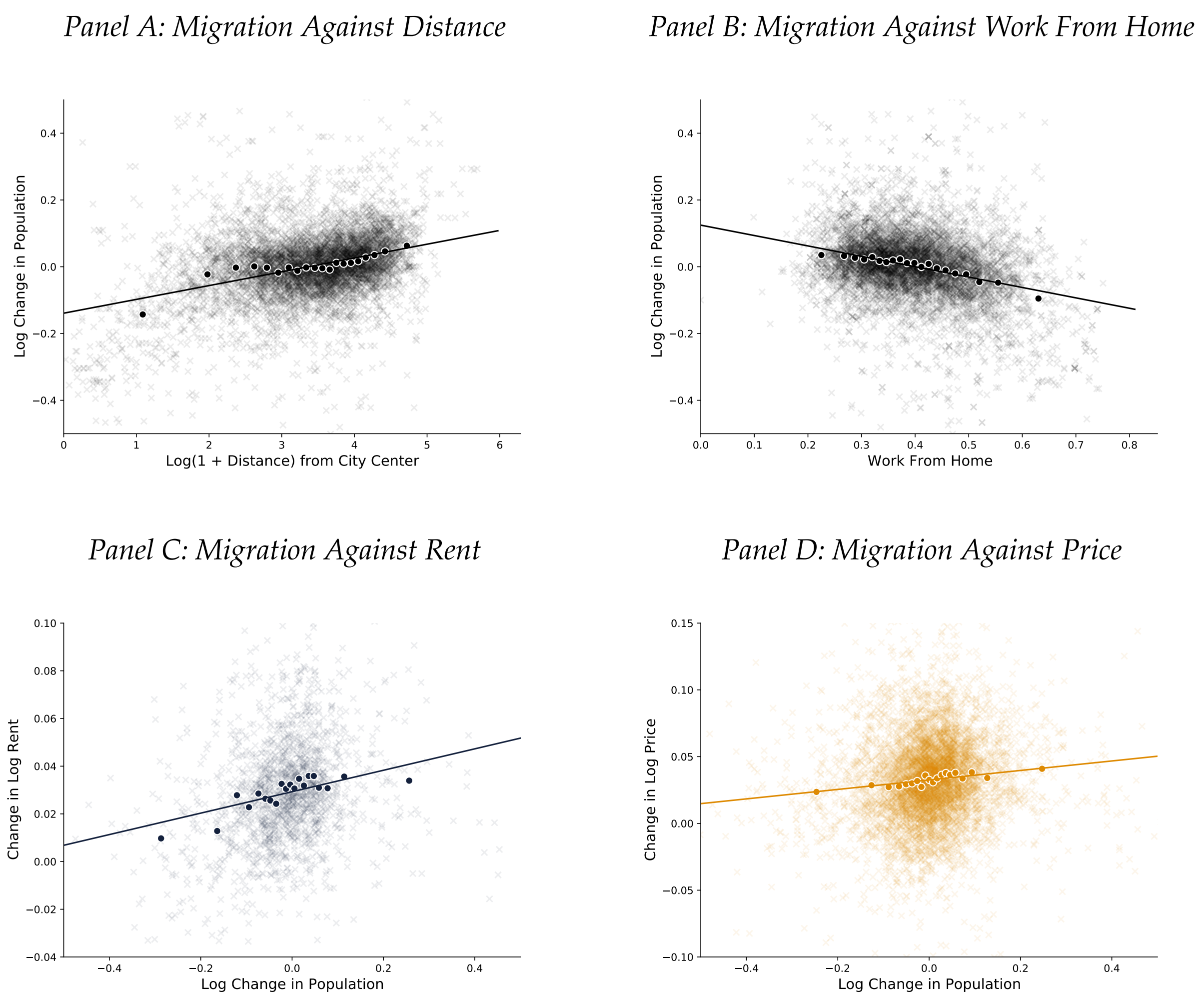


Figure A9. Associations of Intracity Migration without Sample Restrictions

This graph shows the change in population from February to March as measured in VenPath against log(1 + distance) to the city center (Panel A) and the Dingel and Neiman (2020) Work From Home metric at the ZIP level for the top 30 MSAs (Panel B). We also show the change in population plotted against changes in rents at the ZIP level (Panel D) and changes in prices (Panel D).

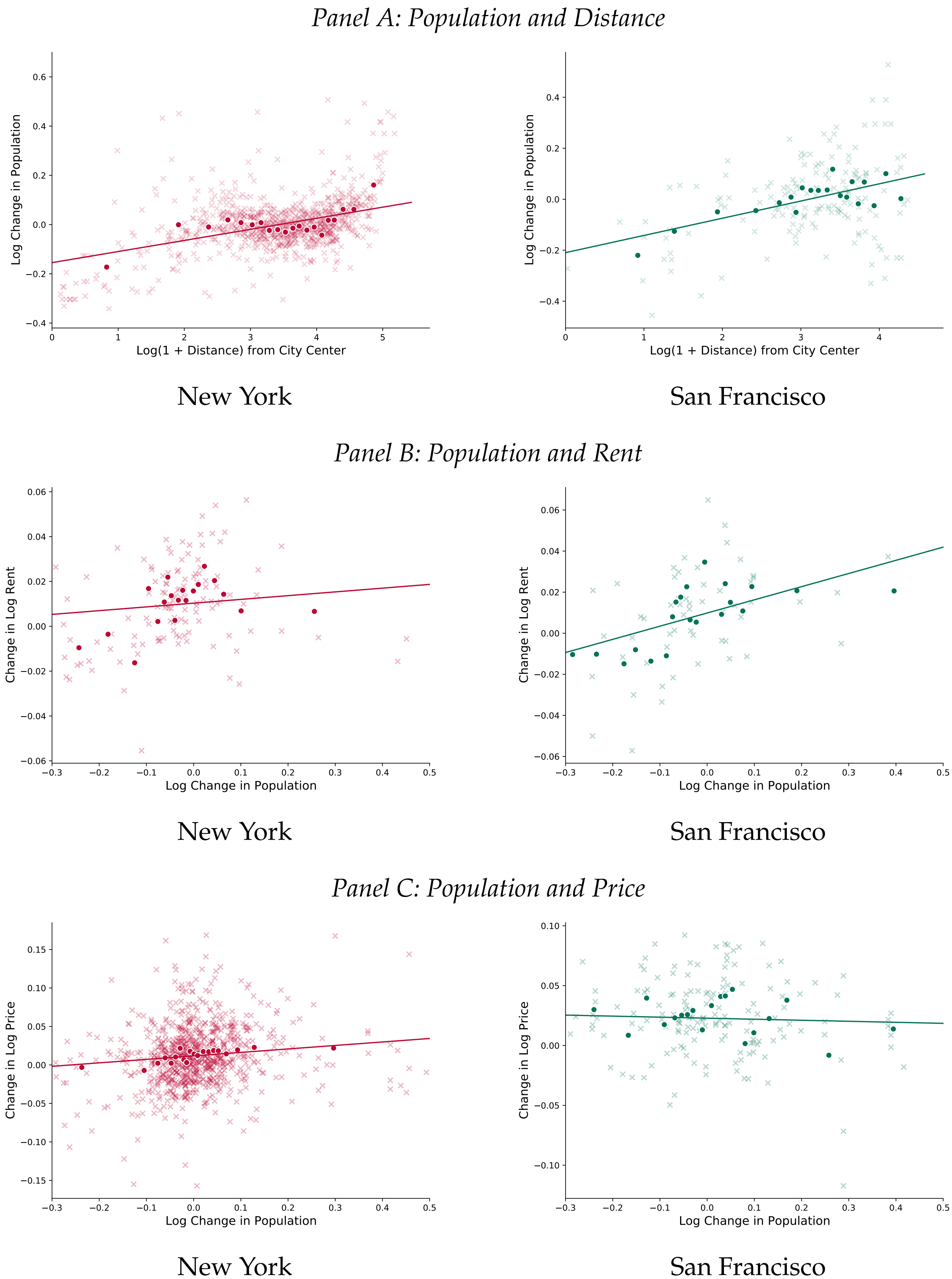
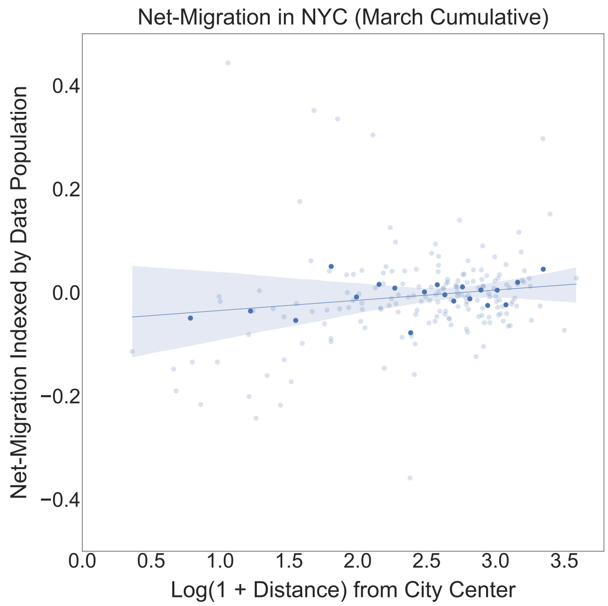


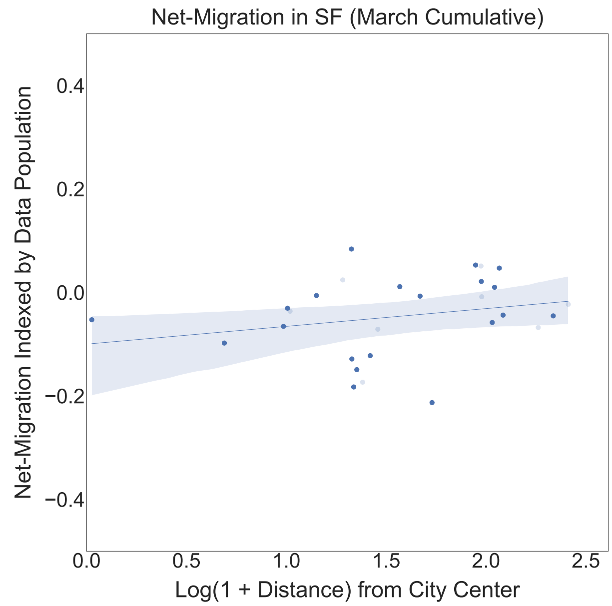
Figure A10. Migration Against Distance, Rents, and Prices

This Figure shows change in population measured in VenPath over the period March 2020 – April 2020 plotted against distance (Panel A), change in rents (Panel B) and changes in prices (Panel C) for New York City (left) and San Francisco (right).

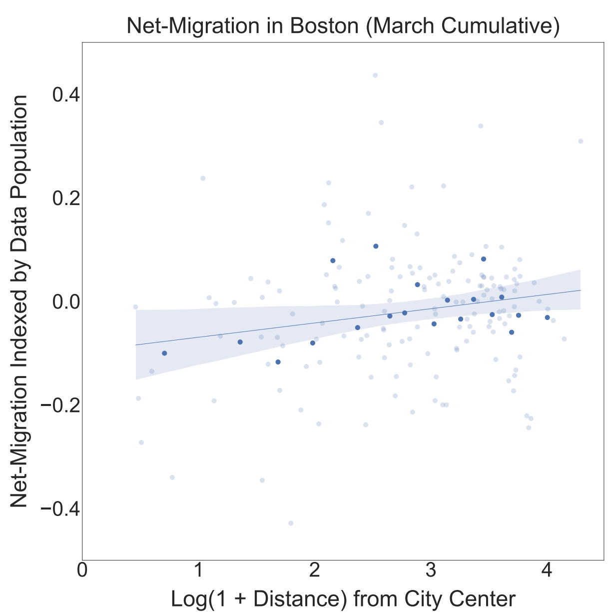
Panel A: New York



Panel B: San Francisco



Panel C: Boston



Panel D: Top MSAs

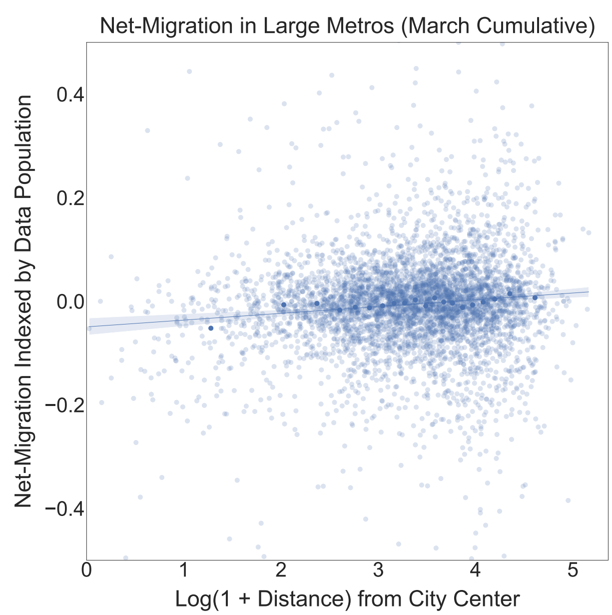


Figure A11. Net Migration Rates Using VenPath Data

This Figure plots the net migration rate from VenPath across three MSAs: New York, San Francisco, Boston, as well as broad sample of all MSAs considered in Table III. To measure net migration, we examine individual's home tracts in February based on their preponderant nighttime ping activity. We then examine their home tract at the end of March, and estimate net migrants as the change in people who have out-migrated, compared with the number of have migrated into the ZIP code. Individuals who drop out of the data are not considered.

Panel A: Rents

Panel B: Prices

Figure A12. Determinants of Rent and Price Gradient Changes 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 column (5) of Panel A of Table I for rents, and Panel B of this Table for prices. x_{ij} corresponds to the covariates from this Table measuring work from home, stringency, and the supply inelasticity index.

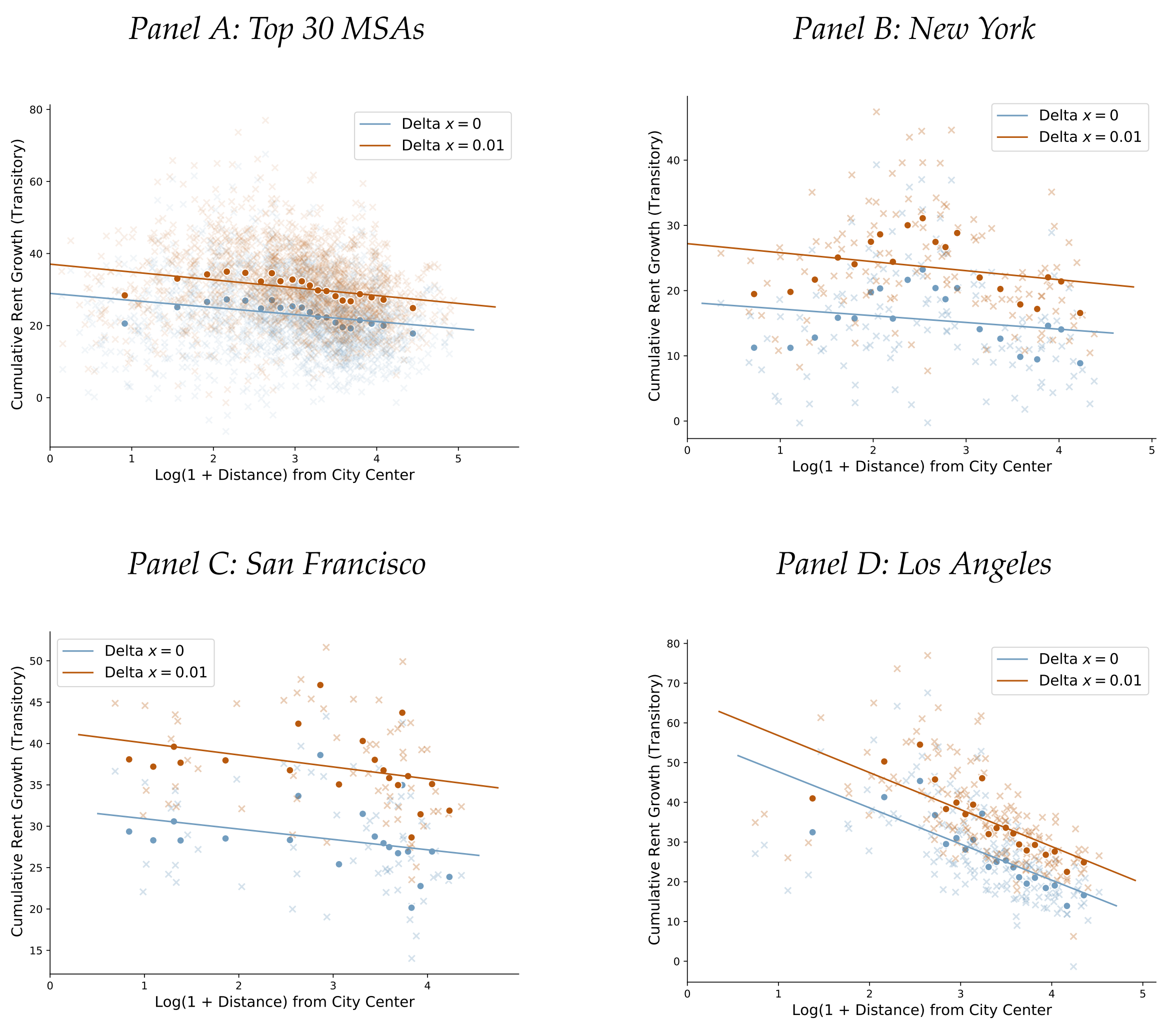


Figure A13. Cumulative Rent Growth under Transitory Case for Top 30 MSAs, New York, San Francisco, Los Angeles

This Figure shows 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 (6), but at the ZIP level.

Table A.I. Top-30 MSAs

#	MSA	Population (Millions)	Pre-pandemic Rent Gradient	Change in Rent Gradient	Pre-pandemic Price Gradient	Change in Price Gradient	Pre-pandemic Price Gradient*	Change in Price Gradient*
1	New York-Newark-Jersey City, NY-NJ-PA	19.22	-0.095	0.069	-0.240	0.042	-0.220	0.029
2	Los Angeles-Long Beach-Anaheim, CA	13.21	-0.066	0.025	-0.215	0.003	-0.165	-0.002
3	Chicago-Naperville-Elgin, IL-IN-WI	9.46	-0.081	0.039	-0.311	0.004	-0.287	0.003
4	Dallas-Fort Worth-Arlington, TX	7.57	-0.021	0.023	-0.032	0.002	-0.074	-0.001
5	Houston-The Woodlands-Sugar Land, TX	7.07	-0.118	0.028	-0.035	0.010	-0.044	-0.013
6	Washington-Arlington-Alexandria, DC-VA-MD-WV	6.28	-0.101	0.026	-0.207	0.009	-0.179	0.005
7	Miami-Fort Lauderdale-Pompano Beach, FL	6.17	-0.032	0.019	-0.128	0.014	-0.171	0.011
8	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	6.10	-0.031	0.014	-0.079	0.005	0.015	-0.010
9	Atlanta-Sandy Springs-Alpharetta, GA	6.02	-0.047	0.028	-0.078	0.018	-0.216	-0.004
10	Phoenix-Mesa-Chandler, AZ	4.95	0.077	0.020	-0.070	-0.019	-0.109	-0.024
11	Boston-Cambridge-Newton, MA-NH	4.87	-0.149	0.043	-0.166	0.027	-0.237	0.019
12	San Francisco-Oakland-Berkeley, CA	4.73	-0.098	0.054	-0.230	0.045	-0.203	0.045
13	Riverside-San Bernardino-Ontario, CA	4.65	-0.025	0.014	-0.185	-0.005	-0.223	-0.000
14	Detroit-Warren-Dearborn, MI	4.32	0.194	-0.059	0.356	-0.057	0.037	-0.018
15	Seattle-Tacoma-Bellevue, WA	3.98	-0.099	0.052	-0.194	0.029	-0.183	0.026
16	Minneapolis-St Paul-Bloomington, MN-WI	3.64	0.012	0.019	-0.035	0.007	-0.099	-0.004
17	San Diego-Chula Vista-Carlsbad, CA	3.34	0.047	0.007	-0.021	-0.011	-0.081	-0.014
18	Tampa-St Petersburg-Clearwater, FL	3.19	-0.073	0.014	-0.037	0.006	-0.045	0.006
19	Denver-Aurora-Lakewood, CO	2.97	-0.064	0.023	-0.007	0.013	-0.053	-0.003
20	St Louis, MO-IL	2.80	0.108	0.006	-0.094	0.005	-0.060	-0.011
21	Baltimore-Columbia-Towson, MD	2.80	0.037	-0.000	0.066	0.000	0.164	-0.001
22	Charlotte-Concord-Gastonia, NC-SC	2.64	-0.125	0.032	-0.160	-0.007	-0.307	-0.000
23	Orlando-Kissimmee-Sanford, FL	2.61	0.034	0.013	-0.011	-0.006	-0.047	-0.002
24	San Antonio-New Braunfels, TX	2.55	0.034	-0.010	0.024	-0.003	0.030	-0.011
25	Portland-Vancouver-Hillsboro, OR-WA	2.49	0.040	0.030	-0.060	0.014	-0.107	0.005
26	Sacramento-Roseville-Folsom, CA	2.36	0.054	0.022	0.066	0.002	-0.012	-0.005
27	Pittsburgh, PA	2.32	-0.416	0.010	0.434	0.002	-0.129	-0.033
28	Las Vegas-Henderson-Paradise, NV	2.27	-0.005	-0.010	-0.019	0.000	-0.083	0.009
29	Austin-Round Rock-Georgetown, TX	2.23	-0.115	0.029	-0.129	-0.009	-0.227	-0.024
30	Cincinnati, OH-KY-IN	2.22	-0.021	-0.003	0.056	-0.019	-0.004	-0.031

*: Gradients and changes in gradient calculated without restricting the sample to ZIP codes where both rent and price metrics are available.

Table A.II. Explaining the Cross-MSA Variation in Price Gradient Changes

	(1) Benchmark	(2) All ZIPs	(3) Pop>5000	(4) Pop Weight	(5) Bed1	(6) Bed2	(7) Condo	(8) SFR
Work from Home	0.215***	0.128*	0.158**	0.166**	0.227***	0.171**	0.0816	0.227**
	(0.0767)	(0.0704)	(0.0661)	(0.0679)	(0.0774)	(0.0649)	(0.0862)	(0.0862)
Orthogonalized Stringency Index	0.0838	0.110*	0.104*	0.128**	-0.0116	0.0234	-0.0367	0.0925
	(0.0593)	(0.0545)	(0.0511)	(0.0525)	(0.0599)	(0.0502)	(0.0652)	(0.0652)
Orthogonalized Supply Inelasticity	0.0162	0.0176	0.0177	0.0139	-0.00883	0.000996	0.0128	0.0155
	(0.0128)	(0.0117)	(0.0110)	(0.0113)	(0.0129)	(0.0108)	(0.0140)	(0.0140)
Constant	-0.0806**	-0.0521*	-0.0628**	-0.0675**	-0.0770**	-0.0610**	-0.0194	-0.0876**
	(0.0303)	(0.0279)	(0.0262)	(0.0268)	(0.0306)	(0.0257)	(0.0340)	(0.0339)
Observations	30	30	30	30	30	30	29	29
R^2	0.306	0.270	0.324	0.341	0.259	0.217	0.076	0.285
Adjusted R^2	0.226	0.185	0.246	0.265	0.174	0.126	-0.035	0.199

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

Table A.III. Explaining the Cross-ZIP Variation in Price Changes

	(1) Benchmark	(2) All ZIPs	(3) Pop>5000	(4) Pop Weight	(5) Bed1	(6) Bed2	(7) Condo	(8) SFR
Log(Distance)	0.00669**	0.00329	0.00295	0.00489	0.0118***	0.00785***	0.00896***	0.00614**
	(2.40)	(0.72)	(0.66)	(1.02)	(4.21)	(3.17)	(3.32)	(2.19)
Work from Home	-0.108***	-0.0758***	-0.0846***	-0.1000***	-0.0774***	-0.0986***	-0.0745***	-0.0886***
	(-3.79)	(-3.58)	(-3.83)	(-4.57)	(-4.05)	(-5.44)	(-3.92)	(-4.38)
Median Household Income ('000)	0.000115	0.000196***	0.000225***	0.000226***	0.0000425	0.0000755	0.000179	0.0000468
	(1.42)	(4.59)	(5.69)	(4.04)	(0.44)	(0.88)	(1.66)	(0.63)
Median Age	0.000284	0.0000903	0.000171	0.00000219	0.000109	0.000215	0.000166	0.000436*
	(1.23)	(0.86)	(1.10)	(0.01)	(0.39)	(0.80)	(0.61)	(1.96)
Percent of Black Households	0.0283***	0.0369***	0.0333***	0.0365***	0.0160	0.0327***	0.0151	0.0316***
	(2.91)	(6.60)	(6.43)	(6.49)	(1.62)	(3.23)	(1.52)	(3.55)
Share of High Income Households	-0.139**	-0.166***	-0.209***	-0.173***	-0.0756	-0.104	-0.191***	-0.129**
	(-2.37)	(-3.81)	(-4.65)	(-3.46)	(-1.25)	(-1.60)	(-2.99)	(-2.68)
Log(Restaurants & Bars)	-0.00327**	0.00171***	-0.000430	-0.00107	-0.00190	-0.00210	-0.00223	-0.00181*
	(-2.15)	(2.89)	(-0.56)	(-0.92)	(-1.04)	(-1.27)	(-1.12)	(-1.71)
Constant	0.108***	0.0829***	0.0954***	0.100***	0.0747***	0.0948***	0.0747***	0.0957***
	(6.75)	(5.11)	(6.40)	(7.80)	(3.37)	(6.58)	(4.03)	(6.73)
MSA fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1697	5943	4943	5943	1578	1694	1653	1697
R squared	0.640	0.323	0.414	0.483	0.371	0.561	0.434	0.655
Adj. R squared	0.632	0.319	0.410	0.480	0.356	0.551	0.421	0.647

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Data Appendix

B.1 ZORI Underlying Data and Construction

In this section, we describe the construction of the Zillow ZORI rental index which we use in this paper. The ZORI (and also ZHVI) indices are constructing using data from all platforms that are owned by the company Zillow, which includes Trulia, Hotpads, Naked Apartments, and StreetEasy, in addition to Zillow.com. Zillow also uses the Multiple Listing Services (MLS) data. It buys data from multi-family rental data aggregators, as well as from large multi-family landlords. As such, it has excellent coverage of both urban apartment complexes and suburban mom-and-pop single-family rentals who list directly on Zillow.

The ZORI index is a repeat-rent index. As a result, it only compares changes in rents *within* units over time. Just like repeat-sales indices, repeat-rent indices have the virtue that they control for well for housing unit characteristics including hard-to-measure aspects of quality. Just like repeat-sales indices, they have the downside that they result in fewer observations than hedonic indices since, by definition, it is harder to see two listings of the same rental unit than just one listing. This is the main reason why ZORI is not available for all ZIP codes.

To address representativeness, Zillow computes the fraction of housing units by decade of construction and by type, where type takes on three values (single-unit detached and attached, 2–4 units, and 5+ units), from the government's American Community Survey (ACS), and reweights its (repeat) rental listings accordingly. The ACS data is taken from the latest five-year ACS. Because of this reweighting, ZORI is not affected by changes in the composition of listings over time. Concretely, the rental weight w_i for a particular unit i based on the decade of construction d and structure type u is:

$$w_i = \frac{S_i^{ACS}(d,u)}{S_i^{Zillow}(d,u)},$$

where $S_i^{ACS}(d,u)$ reflects the share of ACS units built in decade d, with structure type u and $S_i^{Zillow}(d,u)$ is the share of Zillow listings with that same combination of unit characteristics.

As a consequence of (i) the massive amount of data it is based on, (ii) the re-weighting to capture the distribution of the rental housing stock, and (iii) the within-rental change inherent to the repeat-rent approach, the ZORI index should adequately capture the representative rental trends we are interested in investigating.

B.2 Comparisons Across Different Rental Data Sets

Next, we investigate the representativeness of the Zillow rental data against other data sets. In Figure A14a, we correlate the ZORI series with the HUD Fair Market Rent Index at the ZIP-code level. The Fair Market Rent index is the rent on a representative rental unit, which the government collects for the purposes of determining rental assistance amounts in the Section 8 Housing Voucher program. We combine FMR data for 1-, 2-, 3-, and 4-bedroom units, by aggregating them based on the frequency of each type of unit at the Census tract level. Both HUD FMR and ZORI data are for 2020. We find a high correlation of 79.8% at the ZIP code level.

Figure A14b shows that the log difference between ZORI and HUD-FMR rents does not vary systematically by distance to the city center. The R^2 of a regression of the log difference in rents on $log(1+dist)$ is only 0.0059. This evidence suggests that rent levels in ZORI are broadly representative of rental markets in the U.S., and that potential data coverage issues are not biased in the dimension of distance from the city center.

Second, we also compare ZORI against Census ACS estimates in Figure A14c. The ACS data are for the five-year ACS that ends in 2019; the ZORI data is for December 2019. Again, we find high comparability across these two data sets, with correlations in rent levels across zip codes of 80.6%. Figure A14d shows little systematic difference in relative rents as a function of distance from the urban core of the MSA. The R^2 of this relationship is 0.0137.

Third, we compare against another private-sector rental data provider, Apartment List.[23] Both Apartment List and ZORI data in this comparison are for December 2020. Figure A14e also shows high comparability of ZORI and Apartment List rent data, with a correlation of 83.6% between rent levels in the cross-section of ZIPs. Figure A14f shows minimal sensitivity of relative rents to distance from the city center. The R^2 of this relationship is 0.0525.

A final data set we explore to substantiate the representatives of ZORI data is the Bureau of Labor Statistic's Consumer Price Index for all Urban Consumers: Rent of Primary Residence (hereafter, referred to as the "CPI Rental Index"). The CPI Rental Index is available for 20 MSAs, all of which are part of the top-30 MSAs in our sample. For two MSAs, the CPI Rental Index series in discontinued after 2017, so we end up having data for 18 out of the top 30 MSAs. Figure A15 plots the difference in log CPI Rental Index between December 2014 and December 2020 against the same difference for ZORI (which starts in 2014). We see a strong positive correlation showing that the ZORI and the CPI Rental Index line up well in the cross-section of MSAs.

The overall conclusion of this analysis is that the Zillow ZORI index appears to line up with multiple alternative rental data sources, providing confidence that we are identifying representative patterns for the overall rental market in our analysis.

[23] Publicly accessible Apartment List data, with information on the methodology, can be found at https://www.apartmentlist.com/research/category/data-rent-estimates.

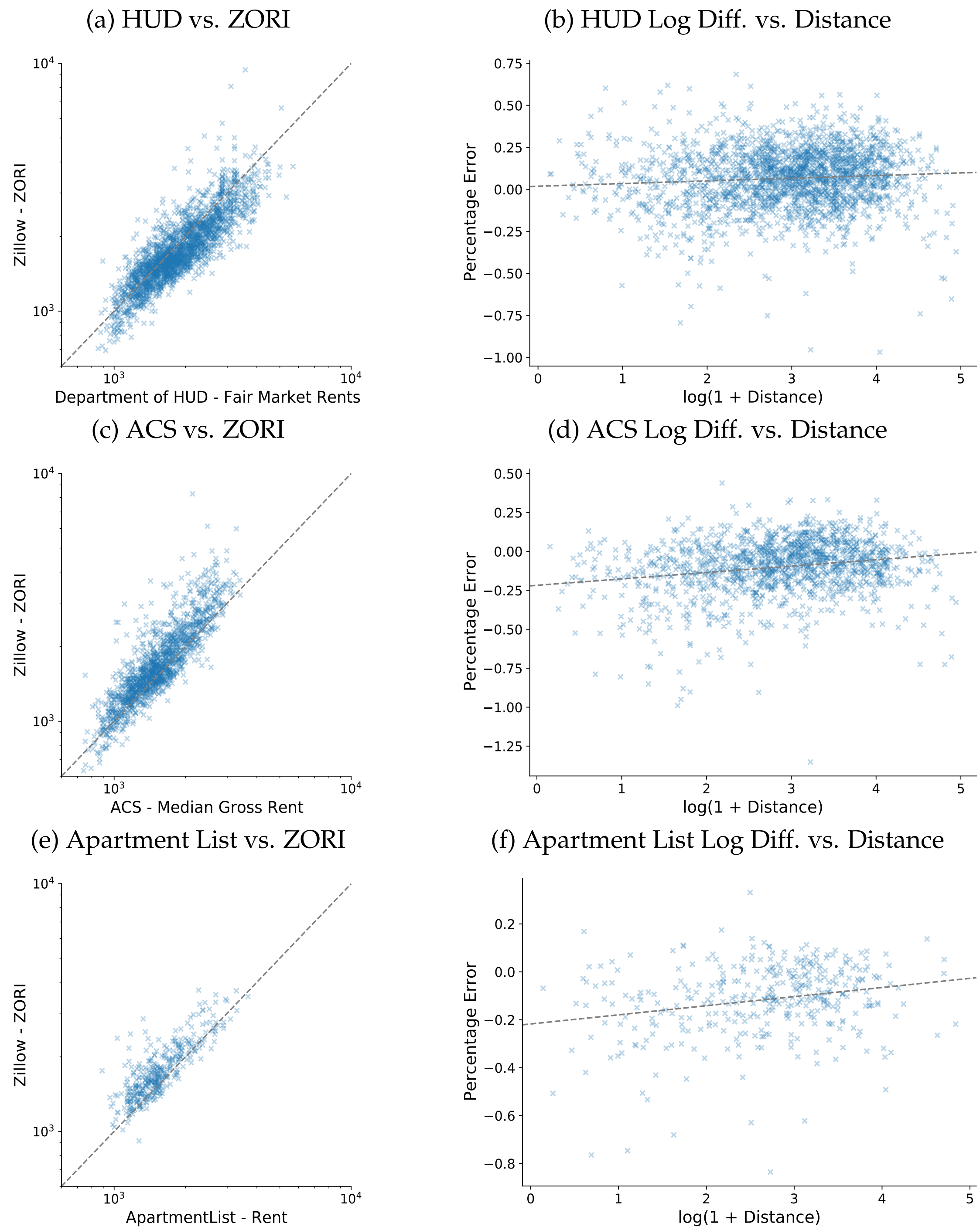


Figure A14. Comparing Rental Series Across Data Sets

This Figure plots Zillow data against other rental data series in levels and against distance to the city center. The top row uses rental data from the Department of Housing and Urban Development's Fair Market Rents. Each observation is a ZIP code. The left panel compares rent levels for HUD FRM (x-axis) and ZORI (y-axis). The right panel plots log differences between ZORI and HUD FMR rent levels against $log(1 + dist)$, where distance is measured from the centroid of the metropolitan area. The centroid of the MSA is City Hall, except for New York where it is Grand Central Terminal. The second row uses rental data from the 2019 five-year American Community Survey and ZORI data for January 2019. The third row uses rental data from the Apartment List and ZORI for December 2020.

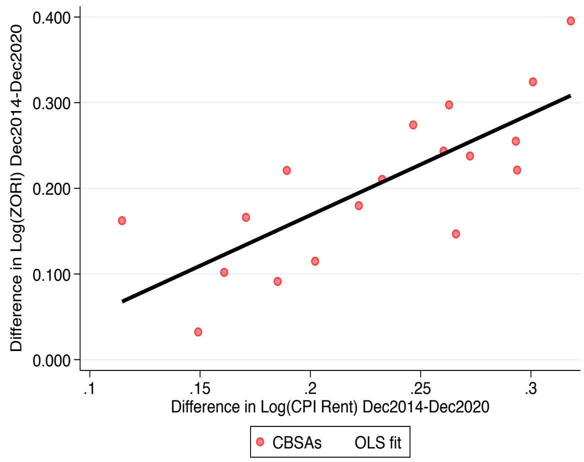


Figure A15. Correlation Between CPI Rent of Primary Residence and ZORI at MSA level

This Figure plots the relationship between the ZORI index at the ZIP level and the Bureau of Labor Statistic's Consumer Price Index for all Urban Consumers: Rent of Primary Residence. We plot this index for 18 MSAs, excluding MSAs that do not have CPI data throughout our entire series. We plot the difference between the log CPI Rental Index between December 2014 and December 2020 against the same difference for ZORI over the same time period.

B.3 ZORI Coverage Across ZIPs

While Zillow ZHVI data is broadly available across U.S. ZIP codes, ZORI data is available in fewer ZIP codes. We investigate the representativeness of ZORI data across geographies, especially comparing areas by distance to the city center.

First, Figure A16a shows that there is a strongly negative relationship between the share of renters in a ZIP code (from the ACS data) and distance from the city center. This means that rental index data coverage will naturally be declining as we get farther from the city center. Indeed, Figure A16b shows that the frequency of reporting a ZORI index is declining as a function of distance from the city center.

Table B.I analyzes the role of rental data availability and distance formally. It presents estimates of logit models where the dependent variable is the availability (1 or 0) of a ZORI index for a particular ZIP code. Column 1 of this table shows that ZORI rental data is indeed somewhat more likely to be absent for ZIP codes more distant from the city center. However, column 2 of this table highlights the point that ZIP codes are missing

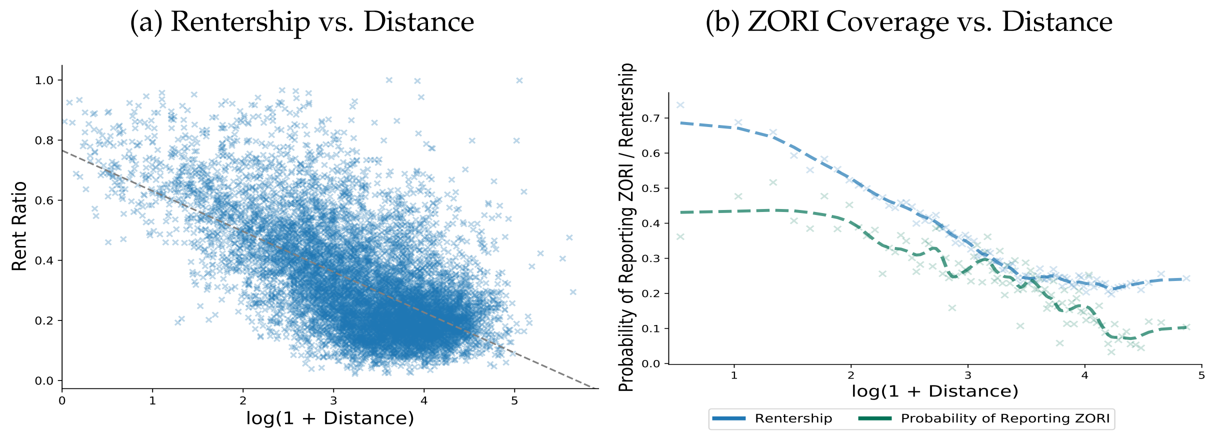


Figure A16. Relationship between Distance and Rentership

Panel A of this Figure shows the strong relationship between the fraction of individuals who rent, drawn from ACS data, against distance to the center of the city. Figure B shows, plotted together, the renter fraction against the probability that the ZIP code has ZORI data available.

rental data frequently because they simply lack renters (as measured by the ACS rentership rate). In fact, column (3) shows that including just the rentership rate drastically reduces the coefficient on distance from -0.675 in column 1 to -0.319 in column 3. This suggests that ZORI is substantially missing due to a lack of sufficient rental buildings. Including a larger set of demographic and income controls in column 5 further drives the coefficient on distance down to 1/6 of its initial estimate.

C Present Value Model Analysis

C.1 Model Details

We briefly review the the present-value model of Campbell and Shiller (1989), a standard tool in asset pricing.

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:

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

Table B.I. ZORI Availability, Distance, and Rentership

	(1) ZORI Reported	(2) ZORI Reported	(3) ZORI Reported	(4) ZORI Reported	(5) ZORI Reported
ZORI Reported					
Log Distance	-0.675***		-0.319***		-0.119***
	(0.0293)		(0.0354)		(0.0450)
Rentership		3.334***	2.554***	3.639***	3.420***
		(0.124)	(0.150)	(0.214)	(0.230)
Median Income (1000)				0.0390***	0.0394***
				(0.00536)	(0.00538)
Share income > \$ 150k				3.700***	3.260**
				(1.430)	(1.446)
Median Age				-0.000106	0.00258
				(0.00649)	(0.00659)
Share Black				0.712***	0.657***
				(0.169)	(0.170)
Population (1000)				0.0716***	0.0719***
				(0.00198)	(0.00199)
Density (1000/km^2)				-0.0609***	-0.0644***
				(0.00979)	(0.00988)
Constant	0.881***	-2.456***	-1.155***	-6.244***	-5.874***
	(0.0943)	(0.0539)	(0.152)	(0.363)	(0.390)
Observations	9657	9650	9650	9537	9537

Standard errors in parentheses

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

This Table estimates a logit model of the presence of the ZORI index in a ZIP code (1/0) using ZIP-code level characteristics. Column (1) shows a role for distance to city center to explain the availability of ZORI; column (2) includes only the rental rate drawn from ACS (Rentership). Column (3) includes both distance and rental rate measures, while columns (4) and (5) include other covariates drawn from ACS. Standard errors in parenthesis $*p < 0.10, **p < 0.05, ***p < 0.01$.

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,

$$\rho = \frac{\exp(\overline{pd})}{1 + \exp(\overline{pd})}, \qquad k = \log(1 + \exp(\overline{pd})) - \rho\overline{pd}. \tag{10}$$

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):

$$pd_t = \frac{k}{1-\rho} + E_t\left[\sum_{j=1}^{+\infty} \rho^{j-1} \Delta d_{t+j}\right] - E_t\left[\sum_{j=1}^{+\infty} \rho^{j-1} r_{t+j}\right]. \tag{11}$$

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:

$$\overline{pd} = \frac{k}{1-\rho} + \frac{\bar{g}}{1-\rho} - \frac{\overline{x}}{1-\rho}, \tag{12}$$

where $\bar{g} = E[\Delta d_t]$ and $\overline{x} = E[r_t]$ are the unconditional expected rent growth and expected return, respectively. Equation (12) can be rewritten to deliver the well-known Gordon Growth model (in logs) by plugging in for k:

$$\log\left(1 + \exp \overline{pd}\right) - \overline{pd} = \overline{x} - \bar{g}. \tag{13}$$

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

Subtracting equation (12) from (11), we obtain:

$$pd_t - \overline{pd} = E_t\left[\sum_{j=1}^{+\infty} \rho^{j-1}\left(\Delta d_{t+j} - \bar{g}\right)\right] - E_t\left[\sum_{j=1}^{+\infty} \rho^{j-1}\left(r_{t+j} - \overline{x}\right)\right]. \tag{14}$$

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:

$$g_t = (1-\rho_g)\overline{g} + \rho_g g_{t-1} + \varepsilon_t^g. \tag{15}$$

Under this assumption, the rent growth term in equation (14) can be written as a function of the current period's expected rent growth in excess of the long-run mean:

$$E_t\left[\sum_{j=1}^{+\infty}\rho^{j-1}\left(\Delta d_{t+j}-\overline{g}\right)\right] = \frac{1}{1-\rho\rho_g}(g_t-\overline{g}). \tag{16}$$

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):

$$x_t = (1-\rho_x)\overline{x} + \rho_x x_{t-1} + \varepsilon_t^x \tag{17}$$

Under this assumption, the return term in equation (14) can be written as a function of the current period's expected return in excess of the long-run mean:

$$E_t\left[\sum_{j=1}^{+\infty}\rho^{j-1}\left(r_{t+j}-\overline{x}\right)\right] = \frac{1}{1-\rho\rho_x}(x_t-\overline{x}). \tag{18}$$

Implied Dividend Growth Expectations With equations (16) and (18) in hand, we can restate equation (14)

$$pd_t - \overline{pd} = A(g_t - \overline{g}) - B(x_t - \overline{x}). \tag{19}$$

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

From equation (19), we can back out the current-period expectations about future rent growth:

$$g_t = \overline{g} + (1-\rho\rho_g)\left(pd_t - \overline{pd}\right) + \frac{1-\rho\rho_g}{1-\rho\rho_x}\left(x_t - \overline{x}\right). \tag{20}$$

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 (12) given $\overline{pd}$ and $\overline{x}$.

C.2 Additional Results

Expected Rent Growth For Individual MSAs Figure A17 reports the combination model's prediction for expected urban-minus-suburban rent growth, relative to the pre-pandemic level, for individual MSAs. 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.

Implications for Dynamics of Price-Rent Ratios Finally, we show the evolution of the (population-weighted average) urban-minus-suburban price-rent ratio (Figure A18). 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

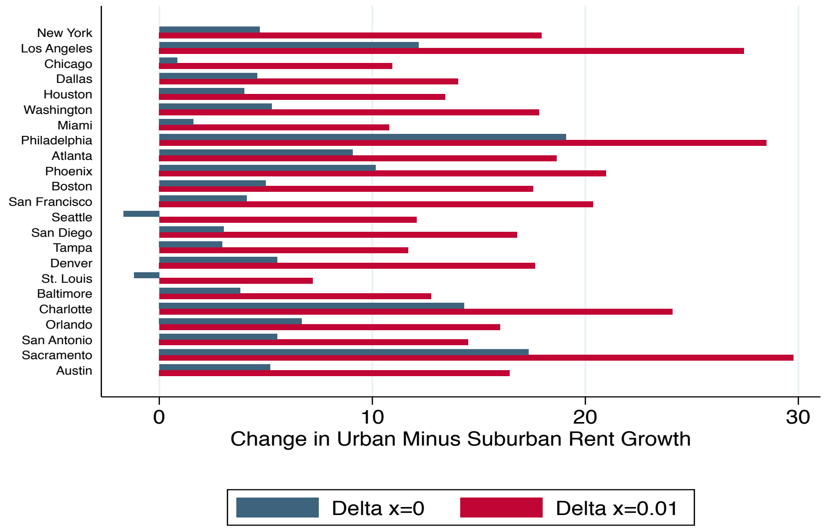
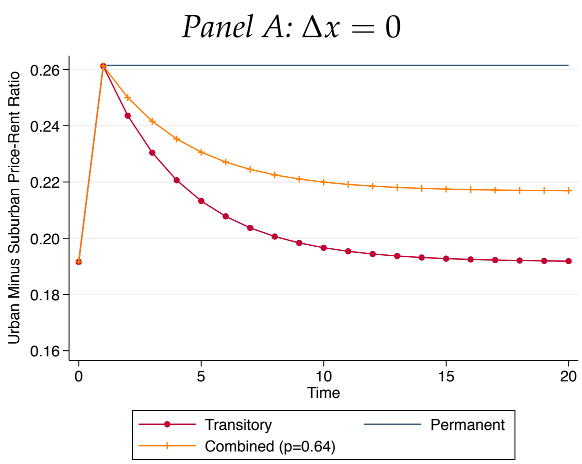


Figure A17. Change in Urban Minus Suburban Rent Growth Relative to Pre-Pandemic for Combination of Transitory and Permanent Regime

This Figure shows the change in urban minus suburban rent growth 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 III: (1) $\Delta x = 0$, and (2) $\Delta x = 0.01$.

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 undershooting after year four. In the permanent 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 1% point above the pre-pandemic levels in the long-run. Owning in the city center becomes permanently more expensive than renting.



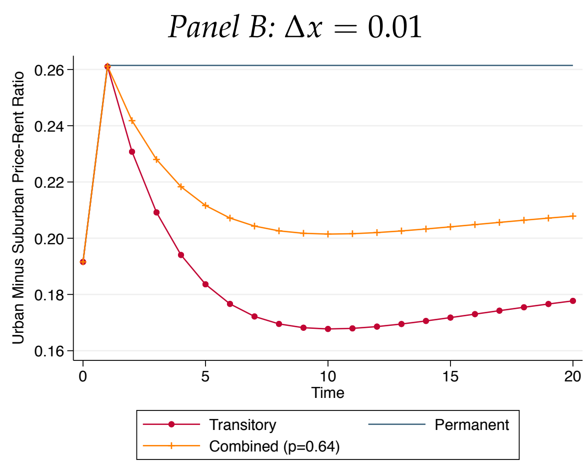


Figure A18. Evolution of Price-Rent Ratio when Pandemic is Transitory and Permanent along with a Combination of Two Regimes

This Figure shows 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 III: (1) $\Delta x = 0$, and (2) $\Delta x = 0.01$.