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JUE Insight: Are City Centers Losing Their Appeal? Commercial Real Estate, Urban Spatial Structure, and COVID-19

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Abstract

This paper estimates the value firms place on access to city centers and how this has changed with COVID-19. Pre-COVID, across 89 U.S. urban areas, commercial rent on newly executed long-term leases declines 2.3 percent per mile from the city center and increases 8.4 percent with a doubling of zipcode employment density. These relationships are stronger for large, dense "transit cities" that rely heavily on subway and light rail. Post-COVID, the commercial rent gradient falls by roughly 15% in transit cities, and the premium for proximity to transit stops also falls. We do not see a corresponding decline in the commercial rent gradient in more car-oriented cities, but for all cities the rent premium associated with employment density declines sharply following the COVID-19 shock.

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I. Introduction

Cities are valuable because they allow agents to interact in beneficial ways. These include agglomeration economies, peer effects, preference externalities, and a range of other spatial interactions. COVID-19 has changed the cost-benefit calculus for urban interactions. Disease transmission increases with physical proximity, with crowded indoor spaces presenting particularly large risks. Elevators, subways, and crowded office settings have newly understood costs. At the same time, lockdowns have caused many to realize that working from home can be productive. For all these reasons, COVID-19 may reduce the value that firms place on cities. Since city centers are the most urban of urban locations, dense central locations may see the largest effects.

The possibility that COVID-19 would negatively impact cities has been the subject of considerable media speculation. The issue is sometimes phrased as a portentous question, such as: "Is New York City Over?" This calls into question the willingness or even ability of firms to continue to pay a large premium to benefit from urban interactions. Debate over this issue is vigorous, with as many urban boosters as those who see a future dimming of city lights. See, for instance, Altucher (2020), the rebuttal by Jerry Seinfeld (2020), or the more cautious discussion in Kim (2020).

This paper considers whether city centers are losing their appeal by estimating spatial patterns of commercial rent before and after COVID-19. Commercial rent captures tenant profit in equilibrium, making it a natural way to assess the value of a location. We work primarily with three relationships, in each case drawing on roughly 68,000 leases across 89 urban areas in the U.S. All of the leases were executed between January 2019 and October 2020, with just under 13,000 executed following the onset of COVID-19 (which we date as April 1, 2020).

Our first exercise regresses log of commercial rent per square foot per year on distance to the central business district. The estimated patterns are unique in the literature. Pre-COVID, rent declines 2.3 percent with each mile from a city center. In cities that are heavily dependent on rapid transit ("transit cities"), the gradient is 6.3%, while in other urban areas ("car cities"), the gradient is 0.9%. In the second approach, we regress log rent directly on zipcode employment density. This abstracts from spatial structure, but directly addresses the underlying fundamental idea that local density matters. Before COVID-19, doubling zipcode employment density was associated with an 8.4% increase in rent. Again, the effects are heterogeneous, with the local density rent premium for transit cities equal to 13.4%, versus 4.6% for car cities. For transit cities we also estimate a third sort of spatial model: the rent premium associated with proximity to subway and light rail transit stops which provide fast access to the rest of the city. Estimates indicate a strong station proximity premium.

These results are the foundation for our analysis of the effects of COVID-19 on the value of access to city centers, employment density, and proximity to a transit station. Commercial leases are long-term instruments, with a median term of roughly 60 months (see Table 1). Our estimates of post-COVID effects, therefore, encompass both current conditions and expectations of future events, including fear of disease risk, potential for renewed public health restrictions such as lockdowns, and a structural increase in work from home. In this sense, our data allow us to address whether COVID-19 has reduced the degree to which downtowns, local density, and transit station proximity are valued by commercial establishments.

COVID-19 changes these relationships. We continue to see premiums for access to city centers, transit stations, and density, but the relationships tend to weaken. Among car cities, the post-COVID rent gradient is essentially unchanged. Among transit cities, the commercial rent gradient is flatter and the transit station proximity premium falls within one-half mile. Among both types of city, the post-COVID elasticity of rent with respect to density is roughly 2 percentage points lower, although it takes a few extra months for this effect to become apparent for the car cities. The bottom line is clear: COVID-19 weakened the attraction of city centers and reduced the value of density, but both density and city centers remain attractive.

The paper contributes to several lines of research. Research on agglomeration considers the advantages of spatial concentration (Combes and Gobillon, 2015; Behrens and Robert-Nicoud, 2015; Liu et al (2020)). Given our focus on downtowns/city centers, research on spatial concentration at a small geographic scale is most relevant here. See Rosenthal-Strange (2003, 2020), Arzaghi and Henderson (2008), or Ahlfeldt et al (2015). Research on urban spatial structure (Duranton-Puga, 2015) has focused primarily on the residential sector. We follow the theoretical analysis in Ogawa-Fujita (1982) in considering commercial rent. While there are many estimates of residential rent gradients in the tradition of Alonso (1964), Mills (1967), and Muth (1969), our estimates of commercial rent gradients based on a large, multi-city sample of recently executed leases are unique.[1] The paper also contributes to research on the economics of commercial real estate. Liu et al (2018) show that in tall office buildings, commercial rent rises with the scale of nearby activity and exhibits a u-shaped vertical pattern, with high rent at ground level and on floors high up in a building. Liu et al (2020) provide complementary analysis of vertical employment density patterns. Gould et al (2005) consider the relationship between commercial rent and the composition of shopping malls.

We also contribute to research on the impacts of COVID-19. Chetty et al (2020) document COVID-19's significant economic impacts. Desmet and Wacziag (2021) show a more serious COVID-19

[1] Until very recently, other estimates of commercial rent gradients of which we are aware use very small samples for a single city and focus on industrial/warehouse properties. See Schmenner (1981) or Dunse et al (2004). Ahlfeldt and Barr (2021) provide some welcome recent estimates of office rent gradients. Another line of research considers land or building values instead of rents. See Adams et al (1968), Peiser (1987), Lockwood and Rutherford (1996), Buttimer et al (1997), and McMillen (1996).

shock in dense areas, while Almagro and Orane-Hutchinson (2021) find that exposure to crowded spaces (e.g. subways) is especially hazardous. Brueckner et al (2021) and Delventhal et al (2021) consider the impact of working-from-home. While no paper in this literature addresses the effect on commercial rents, several papers are related. Ling et al (2020) show that COVID-19 led to a decrease in the prices of commercial real estate by looking at REITs containing properties in places impacted by COVID-19. Wang and Zhou (2020) show that the tenants impacted most by COVID-19 are those where working at home is viable. Liu and Su (2021) show a shift in housing demand away from dense locations, while Gupta et al (2021) and Huang et al (2021) establish that the residential market sees a flattened residential rent gradient.

The rest of the paper details our methods and conclusions.

II. Theory

This section presents a theory of the relationship between interactions and commercial real estate. The starting point is the standard market clearing condition for a competitive real estate market: competition among potential tenants sets rent at a level that generates zero economic profit. In this setting, rent will have the properties of a firm's gross profit function.

Formally, suppose that tenant profit depends on workplace interactions, n, according to the gross profit function $\pi(n)$, which is increasing and concave. Market interactions depend on numerous characteristics of the local environment, including residential and employment density and local infrastructure. Rent will be high where conditions favor interactions. Suppose specifically that workplace interactions are a decreasing function of distance the city center, $n(d)$. The rent gradient will be driven by this relationship, with $r'(d) = \pi'(n)n'(d) < 0$. If interactions decline rapidly, then rent will decline rapidly as well. It is worth noting that all of this is consistent with fully specified models of spatial interactions such as Ogawa-Fujita (1980). We will consider empirically the relationship of rent with density, infrastructure, and distance to the city center.

COVID-19 has the potential to affect both $\pi(n)$ and $n(d)$. There are several reasons that $\pi(n)$ might fall. Social distancing restrictions restrict elevator use, impacting the ability to interact in buildings. Lockdowns restrict interactions in restaurants and coffee shops. The fear of disease will lead tenants to choose to be less interactive. All of these would give lower profit for a given level of activity at a location. Working-from-home means that the level of market interactions will fall at dense locations and rise elsewhere. This fall will presumably be larger near transit stations, since transit exposes people to greater disease risk. Together, these effects will result in rents falling at dense locations and in rent gradients becoming smaller, with a flatter equilibrium rent function and lower intercept at the city center. It is these relationships that we consider empirically.[2]

III. Empirical design and summary statistics

A. Data

Our primary data comes from CompStak Inc., which provides detailed information on individual commercial leases across the United States.[3] We focus on 68,638 office sector and retail leases signed between January 1, 2019 ,and October 31, 2020 in 89 distinct U.S. urban areas. Of these, 12,857 were executed after April 1, 2020, which we characterize as the post-COVID period. The CompStak data include information on space leased, rent per square foot, lease term, street address, latitude and longitude of the building, building quality (Class A, B and C), and more.[4] Throughout the analysis, we work with effective rent, a standard measure in the commercial real estate industry that includes monthly rent and other payments between landlord and tenant converted to a monthly basis.[5] The primary purpose of the leased suite (e.g., retail, office) is also reported, but standard industry classification of the tenant is not.

Using building addresses for the leases, we merged in 2018 zipcode employment data from the US Census Bureau along with information on zipcode land area. This enabled us to compute employment density for each zipcode in which a lease is present.

As discussed above, we will partition the cities in our data into "transit" and "car" cities. The former are large, dense metropolitan areas that rely heavily on light rail and subway systems. In order of rail/subway ridership, the associated MSAs are NYC, Washington DC, Chicago, Boston, San Francisco, and Philadelphia.[6] All other cities in our sample are referred to as "car" cities because of their greater reliance on car transport, but this is an approximation. Many car cities have rail and/or subway service,

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[2] The key result of rent capturing the value of access would persist in models with less competition among tenants than the standard model that we employ. If rent is instead determined by bargaining over the surplus from a random tenant-landlord match, rent will still depend on the tenant valuation of the space.

[3] CompStak data include leases provided by commercial real estate agents in exchange for opportunities to examine other leases in the CompStak database that may be helpful when working with clients. As such, the CompStak sample is not designed to be representative of all commercial leases in a given urban area.

[4] For 18.7 percent of leases building class is not reported. In these instances, we created an additional 1-0 dummy ClassNA with 1 equal to missing. This was then interacted as ClassNA x Retail and ClassNA x Office, where Retail and Office denote the use of the leased space. These additional terms are included in all models where we control for building class.

[5] Effective rent is measured with error, which works against finding precise patterns in the data. Additionally, there have been media reports of concessions made by landlords in dense locations. To the extent that our data do not capture this, our results would understate the effects of COVID-19.

[6] In 2019, unlinked transit passenger trips in millions were 2,274.9 for New York, 237.7 for Washington DC, 218.47 for Chicago, 152.34 for Boston, 123.51 for San Francisco, and 90.24 for Philadelphia (see American Public Transportation Association, Transit Ridership Report, Fourth Quarter 2019).

but to a far smaller degree than the transit cities. For the transit cities, we use city planning authority data for the transit cities to compute the distance from each lease to the closest transit station

A detailed list of data sources used in the paper is provided in the Online Appendix.

A. Organization of leases into urban areas

In order to assess the appeal of city centers, we must organize leases into distinct, non-overlapping urban areas, each with a well-defined city center. In doing so, we seek to create pseudo-monocentric cities. In part, our approach is guided by lessons from a series of recent papers that have sought to delineate urban borders (see Duranton (2021) for a review). Duranton emphasizes that there is no single correct delineation procedure but instead it is desirable where possible to delineate areas in a manner relevant to the questions being addressed. In our case, a monocentric structure is natural for the questions we consider.

We organize our leases into distinct urban areas with a three-step process. First, we determine the zipcode in which each lease is situated and the associated employment density in that zipcode (omitting areas covered by water). Second, we use an iterative procedure to define a set of urban areas in the United States. These areas do not follow pre-set jurisdictional boundaries and indeed often cross municipal lines. For convenience, however, in the discussion to follow, we use the term "core city" when referring to the urban area to which a lease is assigned, in part a reference to the incorporated city at the center of the urban area.

Our iterative procedure begins begin by determining the zipcode with the highest employment density from among all leases in our sample, which happens to be situated near Grand Central Station in New York City. A 25-mile radius circle is drawn around the geographic centroid of the target zipcode and all leases within the circle are assigned to the core city to which the target zipcode belongs, in this first case New York City.[7] We then repeat this procedure, omitting previously assigned leases and continue until all leases in the sample are assigned to a core city. At this stage, it is important to recognize that the 25-mile boundaries of some urban areas will overlap. Also, some leases will be assigned to a core city where the city center is further away than that of another city center. The Dallas-Fort Worth area is an example. Dallas and Fort Worth are both distinct, large cities with city centers just over thirty miles apart. However, because Dallas has higher density, in Step 2 a circle is first drawn around the Dallas city center that captures many leases that are closer to the center of Fort Worth. To address this issue, in a third step, we *reassign* all leases to the closest core city identified in Step 2.

[7] We also experimented with drawing 20- and 30-mile radius circles. Results were similar.

In a final adjustment, we drop leases in core cities with fewer than 100 leases present before any further cleaning of the data. We then drop outlier leases including those with rent per square foot per year below \$2 or above \$2,000, and leases for less than 100 square feet or for more than 1 million square feet. The list of core cities included in the estimating sample is provided in Table A1 of the Online Appendix.

Assigning leases to urban areas as above ensures that employment density is highest in the center of each core city, leases are assigned to the closest city center, and core cities do not overlap. Step 3 of our procedure can also yield complicated shapes for core city boundaries that differ from circles because of the reassignment of leases to the closest core city. The procedure above organizes our data into approximate monocentric cities, despite the tendency for large cities to be ringed by suburban employment subcenters. Panel A of Figure 1 confirms this is the case. The figure plots employment density for car and transit cities as one moves away from the city center out to 15 miles. For both groups of cities, there is a largely monotonic decline in density that is steep at first and then quickly moderates, attributes characteristic of a monocentric city.

B. Summary statistics

Table 1 presents summary statistics. We report values just for those leases within 15 miles of a city center, which includes roughly 93 percent of our sample. This same restriction is imposed when we estimate models of the effect of distance to the city center to help mitigate the effect of suburban employment subcenters. Summary measures for the full sample as used for the density and transit stop models (Panel C of Table 2 and Figure 2, respectively) are similar. In Table 1, Panel A reports measures for all cities grouped together including the pre- and post-COVID periods. Panels B and C display separate summary measures for car cities and transit cities, respectively, with separate measures for the pre- and post-COVID periods.

Newly executed leases in transit cities are situated in larger, denser, and more expensive zipcodes that are closer to the city center. Pre-COVID, in car cities, average zipcode employment, density and rent were, respectively, 31,809 workers, 11,006 workers per square mile, and 26.86 dollars per square foot per year. In transit cities, the corresponding values were 59,824, 154,345 and 59.67. For transit cities, median and mean pre-COVID distance to the CBD are 1.68 and 3.81 miles compared to 7.26 and 7.22 miles, respectively, in the car cities. For both the car and transit city samples, summary measures in Table 1 are similar pre- and post-COVID. Regarding lease term, the most important point to make is that these are long term instruments, with mean lengths in months of 57.40. They become slightly shorter post-COVID, falling from 53.50 to 45.19 for car cities and from 76.32 to 68.03 for transit cities. Finally, Table 1 reports the cumulative death rate from COVID-19 over the sample period: death rates were roughly twice as high in transit cities, averaging 1.13 per 1,000 individuals compared to 0.60 in car cities.

D. Regression model

All of the regression models to follow are of the following general form,

$$y = \theta_j + X \cdot \theta_1 + s(d) + \varepsilon. \qquad (3.1)$$

In most models y is log of commercial rent per square foot on an annual basis, θ_j are location fixed effects for core city or the closest rapid transit station, X includes building quality (e.g. Class A, B or C) and zipcode employment density, and $s(d)$ captures the influence of distance, d, where d can be distance to the city center or a nearby transit station. In some models we impose a linear form on $s(d)$ with $s(d) = d \cdot \theta_2$. In other instances we allow $s(d)$ to be of an arbitrary form, in which case (3.1) is estimated as a partial linear regression using Robinson's (1988) double error approach with $s(d)$ estimated non-parametrically.[8]

IV. Results

A. Commercial rent gradients and the local density rent premium

Panel A of Table 2 revisits the rate at which log of employment density declines with distance to the city center. As in Panel A of Figure 1, the sample is restricted to leases within fifteen miles of the city center in order to reduce the influence of suburban subcenters. Core city fixed effects are included to help control for the influence of city size, industrial composition, and other unobserved city-specific attributes. A linear form for the distance function $s(d)$ is imposed to simplify presentation and also because this helps to clarify some of the other patterns to follow.

Grouping all cities together (column 1), the density gradient is -19.9%. For car cities the gradient is -137% and for transit cities -37.8%. These values are all precisely estimated and provide further support that our data are organized into pseudo-monocentric cities. Moreover, the steeper density gradient in transit cities suggests that the rent gradient in transit cities should also be steeper. This is confirmed in Panel B.

Panel B presents estimates of the rate at which log rent declines with distance from the city center. As above, the sample is restricted to leases within 15 miles. Controls are included for core city

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[8] The partial linear model was estimated using the semipar user provided routine in Stata (Verardi and Debarsy, 2012). The model yields consistent estimates of the linear and nonlinear parts of (3.1) and works as follows. Take expected values of (3.1) conditioning on d: $E(y|d) = E(\theta_j|d) + E(X|d)\theta_1 + E(s(d)|d) + E(\varepsilon|d)$. Differencing from (3.1) and assuming ε is orthogonal to d yields:

$$y - E(y|d) = (X - E(X|d))\theta_1 + \varepsilon . \qquad (N.1)$$

The terms $E(y|d)$ and $E(X|d)$ are then estimated non-parametrically (using the lpoly routine in Stata) and inserted into (N.1) which is estimated by OLS. This yields a consistent estimate of θ_1 without having to specify $s(d)$ while bootstrapping provides correct standard errors. Having obtained $\hat{\theta}_1$, $s(d)$ is estimated by regressing $[y - \theta_j - X \cdot \hat{\theta}_1]$ on d non-parametrically using the lpoly routine in Stata.

fixed effects, building quality (Class A is omitted), and quarterly dummies for 2019:Q1 through March, 2020. In columns 1-3, April through October of 2020 is grouped into a single post-COVID dummy that is also interacted with distance.[9] In columns 4 and 5, we divide the post-COVID period in two, with separate time-dummies and interaction terms for April 1 to June 30 and July 1 to October 31. This allows us to consider whether COVID-19 effects became more severe as the pandemic continued. In all cases, 2020:Q1 is the omitted period. As specified, the post-COVID dummies capture the effect of the pandemic on commercial rent in the heart of the downtown. The interaction terms measure the effect of COVID-19 on the rent gradient relative to the five quarters prior to April of 2020. To conserve space, only the main controls are reported.

Grouping all cities together (column 1), the pre-COVID rent gradient is -2.27% and significant. For the car and transit cities the corresponding estimates are equal to -0.92% and -6.33%, with t-ratios equal to -2.46 and -5.00, respectively. As anticipated, transit cities exhibit a steeper rent gradient.

The direct effect of COVID-19 is negative for the transit cities (-0.086 with a t-ratio of -2.32), implying a post-COVID decline in rent in the city center, and the gradient flattens: the coefficient on the interaction term is positive 0.94% with a t-ratio of 2.20. For each mile from the city center, the post-COVID rent gradient in the transit cities declined roughly 1 percentage point less relative to a pre-COVID base of 6.3%. The pattern differs for car cities. The direct effect of the post-COVID dummy is close to zero while the interaction term is negative, small, and insignificant. Estimates in columns 4 and 5 indicate that for both city groupings COVID-19 effects were similar for both post-COVID periods.

Panels B and C of Figure 1 explore these patterns further. Pre- and post-COVID non-parametric estimates of the distance function $s(d)$ in (3.1) are plotted having stratified the sample by time period and city grouping (car versus transit cities), while still controlling for core city fixed effects and building quality. For the car cities, the more general approach in Figure 1 suggests that COVID-19 reduced rents and rotated the rent function clockwise, suggesting a tendency for lower post-COVID rents further from the city center, unlike the linear model estimates in Panel B of Table 2 (column 2). For the transit cities, the plot in Panel C of Figure 2 suggests an approximate parallel downward post-COVID shift in the rent function, approximately consistent with estimates in Panel C of Table 2.

These estimates make clear that access to the center commands a rent premium in all cities, but the effects of COVID-19 differ between the car and transit cities. One possible explanation for this heterogeneity is that localized spatial variation in density may be confounding the estimated distance patterns even given our attempt to organize leases into pseudo-monocentric cities. To address this, Panel C of Table 2 replaces the distance measure with zipcode level employment density while retaining all

[9] We experimented with other plausible dates for the COVID-19 shock. The pattern of results did not change.

other controls in Panel B. The sample also now includes leases out to 25 miles from the center since this model abstracts from a specific spatial pattern.

Estimates of pre-COVID effects in Panel C echo those in Panels A and B. The elasticity of rent with respect to density is 8.35% for all cities combined (column 1), 4.58% for car cities and 13.38% in the transit cities. These estimates are also highly significant with t-ratios roughly between 5 and 7. Unlike the gradient, however, COVID-19 appears to have reduced the value of density in both car and transit cities. Moreover, the effect grew as the pandemic progressed. In columns 4 and 5, the coefficients on the interaction terms for the April-June period are equal to -0.66% and -1.53% for car and transit cities, respectively, with t-ratios of 1.20 and 2.02. For the July to October period both estimates increase to roughly -2% with t-ratios of 2.64 and 3.49.

Overall, a clear pattern emerges from Table 2. Pre-COVID, businesses value both access to the city center and density. This is seen in the gradient models that assume a monocentric structure and in the local density premium models that consider only the immediate environment. These relationships are strongest in the large, dense, and more monocentric transit cities. As conjectured, COVID-19 reduces the value of density. Moreover, that effect grew as the pandemic progressed and is also reflected in a flatter rent gradient in the transit cities. At the same time, despite these effects, city centers and density retain considerable appeal in both car and transit cities.

In the Online Appendix, we consider several possible explanations for the post-COVID patterns in Table 2. One is that pre-trends may contribute to patterns observed after April, 2020. To address this, we estimate the specification in Table 2 using only 2019 data and treat the second half of the year as a placebo post-COVID period. Evidence of pre-trends is absent (see Table A2). Another possibility is that our results might be driven by Los Angeles and New York, the two giant cities among the car and transit city groupings. In fact, while New York shows a rent decline at the city center, Los Angeles does not, and we do not see a change in gradient or in the employment density premium in either city (see Table A3). A third possibility is that employment subcenters may be confounding estimates of the post-COVID distance gradients in Panel B of Table 2. To check this, we estimated using samples with leases restricted to within 10 miles of the city center and also including leases out to 25 miles (see Table A4). For both car and transit cities, pre-COVID rent gradients steepen when we restrict samples to leases closer to the city center. Among transit cities, we again find a flatter post-COVID gradient, but for car cities COVID-19 effects are absent as before.

B. Extensions

One might wonder if the results described above could be driven by the highly vulnerable retail sector. They are not. Table 3 presents models that divide the sample into the retail and office leases.[10] The results are reported only for the transit cities given the stronger gradient patterns for those cities in Table 2. Pre-COVID it is clear that retail places greater value on central, dense locations: this is evident in the steeper gradient (columns 1 and 2) and larger density effect (columns 3 and 4). It is also clear that both the retail and office sectors were hit by COVID-19. The office sector rent gradient is reduced as is the density premium (both estimates are significant). These effects are larger in the retail sector but the density effect is not significant. Overall, weakened attachment to city centers is found in both the retail and office sectors.

Table 3 also considers the differences between new tenant leases and renewals for existing tenants. Suppose there are two tenants, differing only in the probability of rental default. Despite the heavy protections in commercial leases, this is costly to landlords and especially so for the most valuable properties. In the hypothetical two-type case, the landlord strictly prefers the low-risk tenant. In our data, the best way to characterize risk is whether the tenant is a renewal (known, lower risk) or a new tenant lease (less known). We thus re-estimate the gradient and local density models from Table 2 separately for renewals and new tenant leases.

Results are shown in the last four columns of Table 3, again for transit cities only. Columns (5) and (6) report estimates of the gradient model, while columns (7) and (8) present the local density premium model. For both, there is essentially no difference in the pre-COVID estimates. The gradients are nearly identical (6.6% new; 6.2% renewal), and so are the density premium estimates (13.6% new tenant; 13.2% renewal).

This symmetry is broken post-COVID. For renewals, the gradient flattens by 1.2 points, while the local density premium falls by 2.5 points. The corresponding coefficients for new tenant leases are roughly half as large (0.57 and 0.98 points, respectively with t-ratios of 0.1.53 and 2.17). This is consistent with the building managers valuing the greater certainty associated with known tenants in the renewal market.

C. Transit station proximity

We now explore a third sort of spatial model, dealing with proximity to the nearest subway and light rail stations. We carry out this analysis for transit cities only with estimates based on (3.1), allowing the effect of distance to a transit station to vary non-parametrically. The sample of leases is restricted to

[10] We include R&D/Office leases in the office category

those within three miles of a station, either subway or light rail. Beyond this distance, sample size is small making it difficult to obtain reliable measures. Separate estimates are obtained for the pre- and post-COVID periods.

Figure 2 plots the estimated rent functions. In Panel A, controls are included only for city fixed effects and building quality. Several patterns are apparent. First, as expected, pre-COVID the relationship between rent and station proximity is downward sloping, with rent falling sharply in the first mile and then largely flattening out. This is consistent with the idea of the "15 minute city" (*Financial Times*, July, 2020) where the distance that can be covered in a relatively short walk is a soft limit on what matters to an urban inhabitant. Post-COVID, the rent premium adjacent to a transit stop is reduced by roughly 10%, the rent function flattens for the first half mile, and thereafter rent is close to pre-COVID levels.

Multiple forces might explain these patterns. Transit requires crowding in subway and rail cars, and this is risky. This makes transit use less attractive. In addition, transit reticence will have second-round effects: being near a subway means being near other firms that make regular use of the subway. Transit avoidance by customers and clients of these other companies will reduce potential for fruitful interactions for all companies close to a transit station. Together, these direct and indirect forces likely account for the post-COVID decline in rent within easy walking distance of a transit station.

Panel B provides further insight by adding controls for zipcode employment density. Both rent functions, pre- and post-COVID, flatten as the influence of nearby employment density is removed. However, the post-COVID drop in rent adjacent to a transit stop persists and is close in magnitude to the estimate in Panel A.

Panel C goes even further. In this panel, transit station fixed effects are included in place of city fixed effects and zipcode employment density. The station fixed effects difference away much of what might be valued in the area surrounding a transit stop apart from the opportunity to utilize the transit system itself. The patterns in Panel C are striking. Pre-COVID, the rent function is largely flattened except for that portion within 0.5 miles of a transit stop, where the rent premium associated with close proximity to the station remains. Post-COVID, the rent function is nearly flat over the entire distance from the transit station out to three miles. Adjacent to a transit stop, rent is about 10% lower relative to pre-COVID levels.[11]

The estimates in Figure 1 confirm that COVID-19 reduced the rent premium close to transit stations. Moreover, after controlling for much of the observable environment in the neighborhood of a transit stop, post-COVID tenants do not appear to consider distance to the transit station to be relevant. This could be explained by COVID-19 leading to a reduction in the value of nearby transit or of those

[11] A parametric version of Panel C with linear distance yields a similar pattern. Post-COVID, the estimated rent function is flat and rent is 5.3% lower adjacent to a transit station with a t-ratio of 3.35.

businesses that are attracted to transit stations. Both forces are consistent with evidence that subway use fell more precipitously with COVID-19 than auto use and is recovering more slowly (e.g. *New York Times*, March 8, 2021; Chen et al, 2020).

V. Conclusions

This paper considers the impact of COVID-19 on the value of density, broadly conceived. It begins by documenting three key empirical relationships: a downward-sloping commercial rent gradient, a premium for local density, and a premium for proximity to a transit station. These relationships are all affected by COVID-19. Rent gradients associated with distance to city centers flattened in cities that rely heavily on rapid transit but not in car-oriented cities. In contrast, among both groups of cities, COVID-19 reduced the value of density by an important amount: the elasticity of rent with respect to local density fell by 2 percentage points.

Economic theory points to several forces that may have contributed to these patterns. The association of disease with density and crowding, lockdowns and other non-pharmaceutical interventions, and working-from-home all reduce in person interactions that are fundamental to why density is valuable. Our data and research design do not allow us to identify these mechanisms separately.

What do our results imply about the future of cities? It is clear that COVID-19 has heightened awareness and ability to work remotely and those lessons seem unlikely to be forgotten. Risk of future pandemics even once COVID-19 is past will also remain. Balanced against these decentralizing forces are longstanding arguments for the productivity benefits of in person interactions that have long been thought to help explain why cities themselves are productive places. Past history in residential markets also include examples of prices rebounding once contagious disease events are past (e.g. Francke and Korevaar, 2021). Ultimately we must wait for additional data to learn more. Until then, the forward looking behavior embodied in our multi-year lease contracts suggest that COVID-19 has reduced the value of density and city centers, but considerable value remains.

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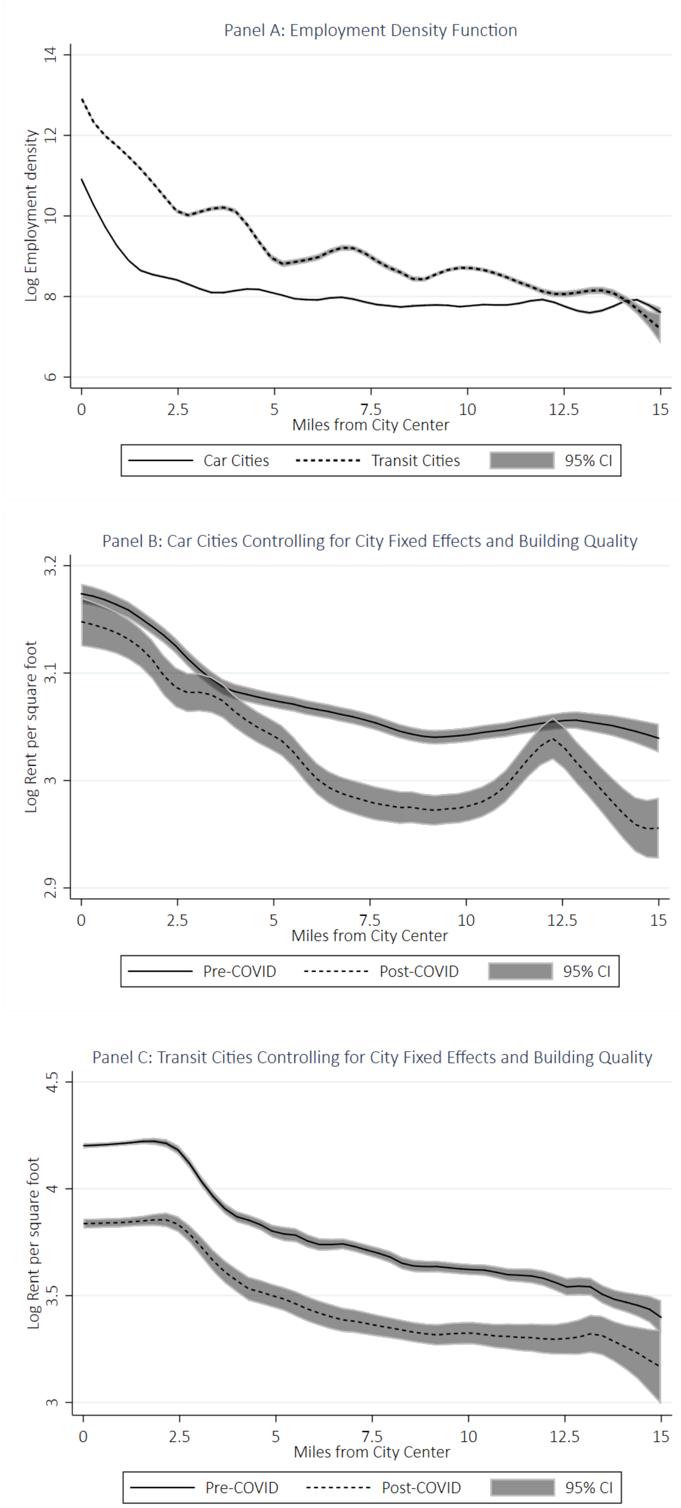
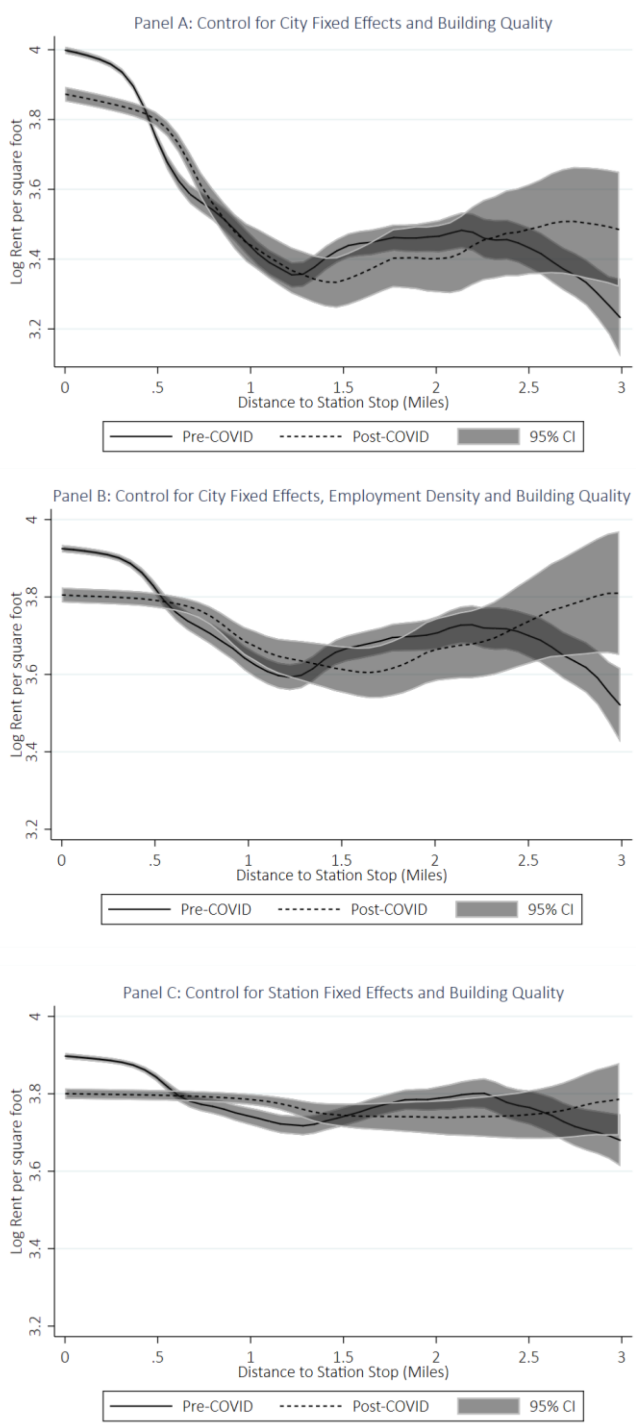
Figure 1: Employment Density and Rent Patterns Within 15 Miles of a City Center[a]



[a] Data are from CompStak and include leases executed between January 1, 2019 through October 31, 2020 that are within 15 miles of the city center for core cities defined using the 3-step process described in the text.

Figure 2: Rent Function and Distance to a Rapid Transit Station[a,b]



[a] Data are from CompStak and include leases executed January 1, 2019 through October 31, 2020 within 3 miles of a rapid transit station in NYC, Washington DC, Chicago, Boston, San Francisco and Philadelphia.

[b] A parametric version of Panel C with metro fixed effects and linear distance yields similar results. Pre-Covid, rent falls 5.61% with each mile from a metro stop (with a t-ratio of 2.44) but the gradient is close to zero post-COVID (the coefficient on a post-COVID interact with distance is 0.043 with a t-ratio of 1.83). Adjacent to the metro stop (distance equal to 0), rent is 5.31% lower post-COVID with a t-ratio of -3.35.

Table 1: Summary Statistics[a]

		Annual Rent Per Square Foot	Zipcode Employment	Zipcode Employment Per Square Mile	Miles to City Center	Miles to Closest Transit Station	Lease Term (number of months)	COVID Deaths per 1,000 inhabitants[b]
Panel A: All Cities								
Pre- and Post-COVID	p25	18.22	17,227	1,977	2.26	-	24	-
N = 63,886	p50	25.68	28,550	4,342	6.35	-	57	-
	p75	38.88	49,201	12,547	10.06	-	70	-
	Mean	34.04	38,465	45,177	6.43	-	57.40	-
Panel B: Car Cities								
Pre-COVID	p25	17.34	15,676	1,575	3.97	-	24	-
N = 38,820	p50	23.39	26,514	3,351	7.26	-	48	-
	p75	31.78	40,368	6,434	10.48	-	65	-
	Mean	26.86	31,809	11,006	7.22	-	53.50	-
Post-COVID	p25	16.00	17,675	1,807	4.27	-	12	0.267
N = 9,770	p50	21.00	27,300	3,694	7.36	-	36	0.473
	p75	29.00	39,487	6,138	10.45	-	62	0.780
	Mean	24.42	31,997	10,145	7.39	-	45.19	0.602
Panel C: Transit Cities								
Pre-COVID	p25	30.29	22,737	5,960	0.53	0.08	37	-
N = 12,995	p50	47.04	43,085	71,172	1.68	0.17	62	-
	p75	68.13	79,097	220,760	6.85	0.47	120	-
	Mean	59.67	59,824	154,345	3.81	0.76	76.32	-
Post-COVID	p25	28.62	22,480	5,259	0.49	0.09	36	0.915
N = 2,301	p50	43.50	42,118	45,270	1.68	0.18	60	1.128
	p75	62.47	69,865	220,760	7.28	0.51	96	1.469
	Mean	51.37	57,606	153,877	3.99	0.78	68.03	1.129

[a] Data are from CompStak and include commercial leases (office and retail) executed between January 1, 2019 through October 31, 2020. Summary measures reported here are based on leases within 15 miles of a city center having defined urban areas using 25-mile radius circles using the 3-step process described in the text.

[b] County level COVID deaths per 1,000 from the start of the pandemic through October 31, 2020. Source: USAFacts (2021).

Table 2: Distance to the City Center and Employment Density[a]

	(1)	(2)	(3)	(4)	(5)
Panel A - Employment density gradient: Dep var = Log zipcode employment density[b]	All Cities	Car Cities[c]	Transit Cities[c]	Car Cities with Delayed Effects[c,e]	Transit Cities with Delayed Effects[c,e]
Distance (miles) to City Center (D_{Center})	-0.1989	-0.1372	-0.3783	-	-
	(-8.59)	(-10.14)	(-18.26)	-	-
Core city fixed effects	89	83	6	-	-
Observations	63,886	48,590	15,296	-	-
R-squared	0.336	0.225	0.661	-	-

Panel B - Distance to City Center: Dep var = Log rent[b,d]	All Cities	Car Cities[c]	Transit Cities[c]	Car Cities with Delayed Effects[c,e]	Transit Cities with Delayed Effects[c,e]
Post Covid (April 1 – Oct 31, 2020)	-0.0395	0.0007	-0.0858	-	-
	(-1.47)	(0.04)	(-2.32)	-	-
Distance (miles) to City Center (D_{Center})	-0.0227	-0.0092	-0.0633	-0.0092	-0.0633
	(-3.54)	(-2.46)	(-5.00)	(-2.46)	(-5.00)
D_{Center} * Post Covid	0.0031	-0.0016	0.0094	-	-
	(0.96)	(-0.75)	(2.20)	-	-
D_{Center} * Post-Covid (Apr 1 – Jun 30, 2020)	-	-	-	-0.0019	0.0101
	-	-	-	(-1.07)	(2.02)
D_{Center} * Post-Covid (July 1 – Oct 31, 2020)	-	-	-	-0.0014	0.0092
	-	-	-	(-0.51)	(2.00)
Core city fixed effects	89	83	6	83	6
Observations	63,886	48,590	15,296	48,590	15,296
R-squared	0.140	0.140	0.258	0.140	0.258

Panel C - Valuing employment density: Dep var = Log rent[b,d]	All Cities	Car Cities[c]	Transit Cities[c]	Car Cities with Delayed Effects[c,e]	Transit Cities with Delayed Effects[c,e]
Post Covid (April 1 – Oct 31, 2020)	0.1280	0.1021	0.1194	-	-
	(2.61)	(1.93)	(2.98)	-	-
Log Employment per square foot (E_{Den})	0.0835	0.0455	0.1338	0.0455	0.1338
	(5.34)	(6.77)	(4.82)	(6.77)	(4.83)
E_{Den} * Post Covid	-0.0177	-0.0143	-0.0169	-	-
	(-3.07)	(-2.45)	(-3.73)	-	-
E_{Den} * Post-Covid (Apr 1 – Jun 30, 2020)	-	-	-	-0.0066	-0.0153
	-	-	-	(-1.20)	(-2.02)
E_{Den} * Post-Covid (July 1 – Oct 31, 2020)	-	-	-	-0.0197	-0.0190
	-	-	-	(-2.64)	(-3.49)
Core city fixed effects	89	83	6	83	6
Observations	68,638	52,490	16,148	52,490	16,148
R-squared	0.157	0.142	0.246	0.142	0.246

[a]Data are from CompStak for office and retail leases executed January 1, 2019 through October 31, 2020. Leases are assigned to core cities as described in the text. T-ratios are in parentheses with robust standard errors clustered at the core city level in all three panels.
[b]The estimating samples in Panels A and B are restricted to leases within fifteen miles of the core city center. No such restriction is imposed on the sample used in Panel C.
[c]The Transit City sample includes the six cities with the highest rate of rapid transit ridership, NYC, Washington DC, Chicago, Boston, San Francisco and Philadelphia. The Non-Transit sample includes all other defined core cities.
[d]Quarterly dummies are included for 2019:Q1 through 2019: Q4 but are not reported to conserve space. The omitted quarter in all of the models is 2020:Q1.
[e] Non-interacted post-COVID period dummies are included in the models but are not reported to conserve space.

Table 3: Retail Versus Office Establishments and New Arrival Versus Renewal Leases[a]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Retail	Office	Retail	Office	New Tenant Lease	Renewal Lease	New Tenant Lease	Renewal Lease
Post Covid (April 1 – Oct 31, 2020)[b]	-0.2673	-0.0444	0.1154	0.0734	-0.0589	-0.1197	0.0674	0.1757
	(-3.19)	(-2.04)	(0.62)	(1.49)	(-1.48)	(-2.51)	(1.26)	(2.35)
Distance (miles) to City Center (D_{Center})	-0.0942	-0.0571	-	-	-0.0655	-0.0617	-	-
	(-3.11)	(-8.20)	-	-	(-4.55)	(-5.38)	-	-
D_{Center} * Post Covid	0.0260	0.0057	-	-	0.0057	0.0118	-	-
	(2.56)	(2.40)	-	-	(1.53)	(2.22)	-	-
Log Employment per square foot (E_{Den})	-	-	0.2546	0.1164	-	-	0.1364	0.1319
	-	-	(4.39)	(7.60)	-	-	(4.44)	(5.27)
E_{Den} * Post Covid	-	-	-0.0230	-0.0099	-	-	-0.0098	-0.0250
	-	-	(-1.22)	(-2.19)	-	-	(-2.17)	(-3.01)
Core city fixed effects	6	6	6	6	6	6	6	6
Observations	2,772	12,524	2,889	13,259	6,438	8,858	6,798	9,350
R-squared	0.246	0.361	0.310	0.326	0.269	0.256	0.256	0.242

[a]Data are as for the corresponding models in Table 2 but restricted to just the six Transit cities (NYC, Washington DC, Chicago, Boston, San Francisco and Philadelphia). Estimating samples are stratified into Retail and Office activity based on the tenant's industry (columns 1-4) and also leases issued to new arrivals versus renewals (columns 5-8). T-ratios are in parentheses with robust standard errors clustered at the core city level. As in Table 2, the samples used for the gradient models (columns 1, 2, 5, and 6) are restricted to leases within 15 miles of the core city center. No such restriction is imposed on the density models (columns 3, 4, 7, and 8).

[b]Quarterly dummies are included for 2019:Q1 through 2019: Q4 but are not reported to conserve space. The omitted quarter is 2020:Q1.

Online Appendix

This not-for-publication appendix presents supplemental tables. Table A1 reports the set of 89 urban areas into which our leases are assigned and also the number of leases for each area. Table A2 presents estimates of Table 2's models using only 2019 data and treating the second half of 2019 as a placebo post-COVID period. Table A3 again revisits Table 2 but this time with alternate city samples. Table A4 presents models of the rent function allowing for distance to the city center, revisiting Panel B of Table 2. In this case, however, we experiment with two alternate sample restrictions. The first restricts leases to just those within 10 miles of the city center. The second includes leases out to 25 miles from the city center. Also reported to facilitate comparison is the model from Table 2, which includes leases out to 15 miles from the city center. Table A5 provides a complete list of all of the many data sources used in the paper.

Table A1: List of Core Cities and Number of Leases

Core City	State	Number of Leases	Core City	State	Number of Leases
Acworth	GA	160	Malibu	CA	177
Allentown	PA	140	Marlborough	MA	198
Ann Arbor	MI	144	Miami	FL	734
Anthem	AZ	228	Minneapolis	MN	776
Atlanta	GA	2,360	Modesto	CA	99
Auburn	CA	366	Monee	IL	53
Auburn Hills	MI	440	Moreno Valley	CA	147
Austin	TX	1,033	New York	NY	5,032
Bakersfield	CA	63	North Attleborough	MA	92
Baytown	TX	419	Ogden	UT	235
Bolingbrook	IL	681	Orem	UT	530
Boston	MA	2,037	Oxnard	CA	52
Bound Brook	NJ	396	Palm Desert	CA	109
Canton	GA	421	Parsippany	NJ	576
Capitola	CA	79	Peachtree City	GA	103
Carlsbad	CA	635	Philadelphia	PA	1,090
Castle Rock	CO	95	Phoenix	AZ	1,765
Chicago	IL	1,613	Portland	OR	881
Colorado Springs	CO	223	Princeton	NJ	263
Concord	CA	555	Ramona	CA	207
Conyers	GA	73	Rancho Cucamonga	CA	374
Dallas	TX	6,172	Rohnert Park	CA	117
Denton	TX	94	Round Rock	TX	493
Denver	CO	2,413	Sacramento	CA	836
Detroit	MI	320	Salt Lake City	UT	1,302
Dumfries	VA	45	San Antonio	TX	1,426
Everett	WA	117	San Diego	CA	1,581
Fort Collins	CO	59	San Francisco	CA	3,169
Fort Lauderdale	FL	529	San Jose	CA	2,631
Fort Worth	TX	832	Schaumburg	IL	696
Fresno	CA	175	Seattle	WA	1,468
Frisco	TX	1,224	Shrewsbury	NJ	203
Gainesville	GA	79	Souderton	PA	323
Gary	IN	85	Sterling	VA	790
Gilbert	AZ	432	Stockton	CA	84
Harrisburg	PA	85	Tacoma	WA	212
Highland	CA	112	Temecula	CA	241
Houston	TX	3,395	The Woodlands	TX	815
Irvine	CA	1,946	Vacaville	CA	55
Katy	TX	174	Valencia	CA	224
Kenosha	WI	41	Victorville	CA	47
Lawrence	MA	211	Washington	DC	3,207
Livermore	CA	394	West Palm Beach	FL	224
Longmont	CO	120	Wilmington	DE	244
Los Angeles	CA	3,542			

Table A2: Year 2019 Pre-COVID Trends in Spatial Patterns[a]

	(1)	(2)	(3)
Panel A Distance to City Center: Dep var = Log rent[b]	All Cities	Car Cities[c]	Transit Cities[c]
Second Half 2019 (July 1 – December 31)[d]	0.0277	0.0396	0.0113
	(2.11)	(2.34)	(0.73)
Distance (miles) to City Center (D_{Center})	-0.0221	-0.0081	-0.0624
	(-3.31)	(-2.04)	(-4.82)
D_{Center} * Second Half 2019	-0.0005	-0.0013	-0.0005
	(-0.38)	(-0.91)	(-0.17)
Core city fixed effects	89	83	6
Observations	43,063	32,070	10,993
R-squared	0.141	0.144	0.257

Panel B Valuing employment density: Dep var = Log rent[b]	All Cities	Car Cities[c]	Transit Cities[c]
Second Half 2019 (July 1 – December 31)[d]	0.0569	0.0611	0.0141
	(3.04)	(1.65)	(0.28)
Log Employment per square foot (E_{Den})	0.0850	0.0459	0.1337
	(5.31)	(7.31)	(4.62)
E_{Den} * Second Half 2019	-0.0037	-0.0035	-0.0007
	(-1.67)	(-0.71)	(-0.17)
Core city fixed effects	89	83	6
Observations	46,374	34,774	11,600
R-squared	0.160	0.146	0.246

[a]Data are from CompStak for office and retail sector leases executed from January 1, 2019 through December 31, 2019. Leases are assigned to core cities using a 3-step process as described in the text. T-ratios are in parentheses with robust standard errors clustered at the core city level in all three panels.

[b]The estimating samples in Panels A and B are restricted to leases within fifteen miles of the core city center. No such restriction is imposed on the sample used in Panel C.

[c]The Transit City sample includes leases from the six core cities with the highest rate of rapid transit ridership including subway and above ground rail (NYC, Washington DC, Chicago, Boston, San Francisco and Philadelphia). The Non-Transit sample includes all other defined core cities, some of which have rapid transit but to a much more limited degree.

[d]A quarter dummy for 2019:Q2 is included in the model but not reported to conserve space. The omitted period is 2019:Q1.

Table A3: Distance to the City Center and Employment Density for Alternate City Samples[a]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A Employment density gradient: Dep var = Log zipcode employment density[b]	Car Cities	Los Angeles[d]	2^{nd} to 6^{th} Largest Car Cities[d]	Car Cities Other Than Los Angeles	Transit Cities[c]	New York City	Transit without NYC
Distance (miles) to City Center (D_{Center})	-0.1372	-0.1412	-0.1463	-0.1369	-0.3783	-0.4242	-0.3671
	(-10.14)	(-28.15)	(-19.10)	(-9.29)	(-18.26)	(-102.03)	(-17.03)
Core city fixed effects	83	-	5	82	6	-	5
Observations	48,590	3,099	13,998	45,491	15,296	4,991	10,305
R-squared	0.225	0.212	0.315	0.227	0.661	0.679	0.658

Panel B Distance to City Center: Dep var = Log rent[b]	Car Cities	Los Angeles[d]	2^{nd} to 6^{th} Largest Car Cities[d]	Car Cities Other Than Los Angeles	Transit Cities[c]	New York City	Transit without NYC
Post Covid (April 1 – Oct 31, 2020)[e]	0.0007	0.0280	-0.0174	-0.0055	-0.0858	-0.1168	-0.0448
	(0.04)	(0.43)	(-0.58)	(-0.32)	(-2.32)	(-3.52)	(-1.66)
Distance (miles) to City Center (D_{Center})	-0.0092	0.0151	-0.0125	-0.0114	-0.0633	-0.1106	-0.0503
	(-2.46)	(6.58)	(-2.67)	(-3.53)	(-5.00)	(-39.56)	(-7.53)
D_{Center} * Post Covid	-0.0016	-0.0030	0.0012	-0.0008	0.0094	0.0035	0.0048
	(-0.75)	(-0.43)	(0.80)	(-0.37)	(2.20)	(0.51)	(1.19)
Core city fixed effects	83	-	5	82	6	-	5
Observations	48,590	3,099	13,998	45,491	15,296	4,991	10,305
R-squared	0.140	0.078	0.231	0.153	0.258	0.332	0.296

Panel C Valuing employment density: Dep var = Log rent[b]	Car Cities	Los Angeles[d]	2^{nd} to 6^{th} Largest Car Cities[d]	Car Cities Other Than Los Angeles	Transit Cities[c]	New York City	Transit without NYC
Post Covid (April 1 – Oct 31, 2020)[e]	0.1021	-0.2052	0.1169	0.1094	0.1194	-0.1138	0.0557
	(1.93)	(-1.11)	(0.57)	(1.98)	(2.98)	(-0.80)	(1.20)
Log Employment per square foot (E_{Den})	0.0455	0.0589	0.0435	0.0441	0.1338	0.2165	0.1057
	(6.77)	(8.03)	(2.19)	(6.10)	(4.82)	(38.30)	(5.60)
E_{Den} * Post Covid	-0.0143	0.0209	-0.0148	-0.0153	-0.0169	0.0013	-0.0089
	(-2.45)	(1.05)	(-0.67)	(-2.49)	(-3.73)	(0.11)	(-1.88)
Core city fixed effects	83	-	5	82	6	-	5
Observations	52,490	3,542	14,339	48,948	16,148	5,032	11,116
R-squared	0.142	0.094	0.224	0.149	0.246	0.318	0.269

[a]Data are from CompStak for office and retail leases executed January 1, 2019 through October 31, 2020. Leases are assigned to core cities using the process described in the text. T-ratios are in parentheses with robust standard errors clustered at the core city level in all three panels.
[b]The estimating samples in Panels A and B are restricted to leases within fifteen miles of the core city center. No such restriction is imposed on the sample used in Panel C.
[c]The Transit City sample includes the six core cities with the highest rate of rapid transit ridership including subway and above ground rail (NYC, Washington DC, Chicago, Boston, San Francisco and Philadelphia). The Non-Transit sample includes all other defined core cities, some of which have rapid transit but to a much more limited degree.
[d]Measured by population, in order from largest to smallest, the six largest car cities are Los Angeles, Houston, Phoenix, San Antonio, San Diego and Dallas.
[e]Quarterly dummies are included for 2019:Q1 through 2019: Q4 but are not reported to conserve space. The omitted quarter is 2020:Q1.

Table A4: Log Rent Regression Including Leases Out To Different Distances of the City Center (10 miles, 15 miles, 25 miles)[a]

	(1)	(2)	(3)
Panel A: Within 10 miles of the city center[b]	All Cities	Car Cities[c]	Transit Cities[c]
Post Covid (April 1 – Oct 31, 2020)[d]	-0.0368	0.0102	-0.0751
	(-1.37)	(0.54)	(-2.63)
Distance (miles) to City Center (D_{Center})	-0.0319	-0.0147	-0.0752
	(-3.84)	(-2.62)	(-5.41)
D_{Center} * Post Covid	0.0024	-0.0047	0.0052
	(0.53)	(-1.20)	(8.54)
Core city fixed effects	89	83	6
Observations	47,520	34,130	13,390
R-squared	0.147	0.156	0.221
Panel B: Within 15 miles of the city center[b]	All Cities	Car Cities[c]	Transit Cities[c]
Post Covid (April 1 – Oct 31, 2020)[d]	-0.0395	0.0007	-0.0858
	(-1.47)	(0.04)	(-2.32)
Distance (miles) to City Center (D_{Center})	-0.0227	-0.0092	-0.0633
	(-3.54)	(-2.46)	(-5.00)
D_{Center} * Post Covid	0.0031	-0.0016	0.0094
	(0.96)	(-0.75)	(2.20)
Core city fixed effects	89	83	6
Observations	63,886	48,590	15,296
R-squared	0.140	0.140	0.258
Panel C: Within 25 miles of the city center[b]	All Cities	Car Cities[c]	Transit Cities[c]
Post Covid (April 1 – Oct 31, 2020)[d]	-0.0437	-0.0116	-0.0792
	(-1.82)	(-0.78)	(-2.08)
Distance (miles) to City Center (D_{Center})	-0.0169	-0.0058	-0.0468
	(-3.02)	(-1.45)	(-3.43)
D_{Center} * Post Covid	0.0030	-0.0002	0.0044
	(1.24)	(-0.12)	(1.17)
Core city fixed effects	89	83	6
Observations	68,638	52,490	16,148
R-squared	0.131	0.133	0.228

[a]Data are from CompStak for office and retail sector leases executed from January 1, 2019 through October 31, 2020. Leases are assigned to core cities using a 3-step process as described in the text. T-ratios are in parentheses with robust standard errors clustered at the core city level in all three panels.

[b]The estimating sample in Panel A is restricted to leases within ten miles of the core city. Panel B restricts the sample to leases within fifteen miles and Panel C uses all leases assigned to each core city out to 25 miles.

[c]The Transit City sample includes leases from the six core cities with the highest rate of rapid transit ridership including subway and above ground rail (NYC, Washington DC, Chicago, Boston, San Francisco and Philadelphia). The Non-Transit sample includes all other defined core cities, some of which have rapid transit but to a much more limited degree.

[d]Quarterly dummies are included for 2019:Q1 through 2019: Q4 but are not reported to conserve space. The omitted quarter is 2020:Q1.

Table A5: Data Sources

American Public Transportation Association – APTA (2020). Public Transportation Ridership Report, Fourth Quarter 2019. https://www.apta.com/wp-content/uploads/2019-Q4-Ridership-APTA.pdf.

Building Footprints (current). City of Chicago, Chicago Data Portal. Downloaded on June 23rd, 2020. https://data.cityofchicago.org/Buildings/Building-Footprints-current-/hz9b-7nh8.

Building Footprints. City and County of San Francisco, San Francisco Open Data. Downloaded on June 25th, 2020. https://data.sfgov.org/Geographic-Locations-and-Boundaries/Building-Footprints/ynuv-fyni.

Building Footprints. DC Geographic Information System (DC GIS) for the D.C. Office of the Chief Technology Officer (OCTO), Open Data DC. Downloaded June 23rd, 2020. https://opendata.dc.gov/datasets/building-footprints.

Cook County Assessor's Residential Property Characteristics. Cook County Assessor's Office, Cook County Open Data. Downloaded on June 15th, 2020. https://datacatalog.cookcountyil.gov/Property-Taxation/Cook-County-Assessor-s-Residential-Property-Charac/bcnq-qi2z.

Counties and Covid-19: Safer at home orders. National Association of Counties (NACo). Downloaded on July 26th, 2020. https://www.naco.org/resources/featured/counties-and-covid-19-safer-home-orders#go.

County Business Patterns: 2018. United States Census Bureau. Downloaded on August 7th, 2020. https://www.census.gov/data/datasets/2018/econ/cbp/2018-cbp.html.

CTA - 'L' (Rail) Stations. Chicago Transit Authority, Chicago Data Portal. Downloaded on June 25th, 2020. https://data.cityofchicago.org/Transportation/CTA-L-Rail-Stations-Shapefile/vmyy-m9qj.

Geospatial Data: Stations and Lines. Bay Area Rapid Transit (BART). Downloaded on June 24th, 2020. https://www.bart.gov/schedules/developers/geo.

Historic Data on DC Buildings. The DC Historic Preservation Office, Open Data DC. Downloaded on June 14th, 2020. https://opendata.dc.gov/datasets/historic-data-on-dc-buildings.

LA City Parcels. The Mapping and Land Records Division of the Bureau of Engineering, Department of Public Works, LA GeoHub. Downloaded on July 25th, 2020. https://geohub.lacity.org/datasets/la-city-parcels.

Land Use. San Francisco Department of Planning, San Francisco Open Data. Downloaded on July 22nd, 2020. https://data.sfgov.org/Housing-and-Buildings/Land-Use/us3s-fp9q.

MassGIS Data: Standardized Assessors' Parcels. Massachusetts Bureau of Geographic Information. Downloaded on July 22nd, 2020. https://docs.digital.mass.gov/dataset/massgis-data-standardized-assessors-parcels.

MBTA Rapid Transit Stops. Massachusetts Bureau of Geographic Information. Downloaded on June 25th, 2020. http://maps-massgis.opendata.arcgis.com/datasets/a9e4d01cbfae407fbf5afe67c5382fde_0

Metro Rail Lines Stops. City of Los Angeles Open Data, LA GeoHub. Downloaded on July 20th, 2020. https://geohub.lacity.org/datasets/metro-rail-lines-stops?geometry=-119.102%2C33.769%2C-117.368%2C34.168.

Metro Station Entrances (Regional). DC Geographic Information System (DC GIS) for the D.C. Office of the Chief Technology Officer (OCTO), Open Data DC. Downloaded June 23rd, 2020. https://opendata.dc.gov/datasets/556208361a1d42c68727401386edf707_111.

PLUTO and MapPLUTO version 20v4. Department of City Planning. Downloaded on June 21st, 2020. https://www1.nyc.gov/site/planning/data-maps/open-data/dwn-pluto-mappluto.page.

Railroad Stations in NJ. NJ Transit, New Jersey Office of GIS (NJOGIS), New Jersey Geographic Information Network (NJGIN) Open Data Portal. Downloaded on June 25th, 2020. https://njogis-newjersey.opendata.arcgis.com/datasets/railroad-stations-in-nj?geometry=-81.515%2C38.945%2C-67.640%2C41.872.

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