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 109 urban areas, commercial rent on newly executed long-term leases declines 2.1 percent with each mile from the CBD and increases 7.7 percent with a doubling of zipcode employment density. These relationships are strongest for large, dense "transit cities" that rely heavily on subway and light rail. Post-COVID, spatial patterns weaken by roughly 20% in transit cities including a premium for proximity to transit stops, but there is little change in other cities, establishing heterogeneous impacts of COVID-19.

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I. Introduction

Density is fundamental to productivity in cities because it allows agents to interact in beneficial ways. These include agglomeration economies, peer effects, preference externalities, and a range of other spatial interactions (see Ahlfeldt and Pietrostefani, 2019). 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 led to the realization that working at home can be productive. For all these reasons, COVID-19 may reduce the value that firms place on dense locations, weakening their attraction to city centers.

The possibility that COVID-19 would negatively impact cities has been the subject of considerable speculation in the media. 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 dimming of city lights in the future. See, for instance, the Linkedin post by Altucher (2020), the rebuttal by Jerry Seinfeld (2020), or the more cautious discussion in Kim (2020).

This paper will address 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 city centers. We work primarily with three versions of the rent-density relationship. In the first, we regress log of commercial rent per square foot per year on distance to the CBD, drawing on over 55,000 leases in 109 urban areas across the U.S. The leases were executed between January, 2019 and October, 2020 and yield estimates of commercial rent gradients that are unique in the literature.

Estimates indicate that pre-COVID, rent declines 2.1 percent with each mile from a city center but in a manner that is heterogeneous across cities. In metropolitan areas that are heavily dependent on rapid transit, the gradient is 6.3%, while in other urban areas – which we will refer to as car cities – the gradient is 0.9%. This heterogeneity will be important throughout the analysis. In the second approach, we regress log rent directly on zipcode employment density. This abstracts from spatial structure, but is more tightly linked to the underlying fundamental principle that local density matters. Before COVID-19, doubling zipcode employment density was associated with a 7.7 percent increase in rent. Again, the effects are heterogeneous, with the local density rent premium for transit cities equal to 12.9%, while the estimate is 4.2% for car 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. We estimate the model only for the transit cities. For these cities, we find a strong station proximity premium.

These results are the foundation for our analysis of the effects of COVID-19 on the value of density and access to city centers, local employment density, and proximity to a transit station. The leases are long-term instruments, with an average term of 59 months (see Table 1). The new leases that we analyze are, therefore, capturing much more than just the most recent events. Instead, post-COVID effects are an amalgam of both current and expectations of future effects, including the negative effects of disease and disease risk, as well as of the economic effects of public health measures such as lockdowns. In this sense, our data do not allow us to identify mechanisms, but they do allow us to address whether COVID-19 has reduced the degree to which downtowns, local density, and transit station proximity – all aspects of the general phenomenon of density – are valued by commercial establishments.

Post-COVID, while we continue to see businesses pay premiums for density and its correlates, we also see a clear reduction in the value of density in some circumstances. Among car cities, post-COVID patterns are largely the same as pre-COVID. Among the six metropolitan areas that rely most heavily on rapid transit, however, the commercial rent gradient is flatter and the rent-density relationship is sharply lower. The rent gradient falls by 1.2 points from its pre-COVID level of 6.3% per mile, while the local density rent premium falls by 2.7 points from a pre-COVID base of 12.9%. Companies also place less value on locations within one-half mile of a transit station, an easy walking distance for most adults. The bottom line is clear: COVID-19 does weaken city centers, but they still remain attractive, and the weakening is only in the largest and most dense cities.

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). 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. Gould et al (2005) consider the relationship between commercial rent and the composition of shopping malls. Finally, we contribute to research on the impacts of COVID-19. While

[1] The only 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). 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).

no paper in this literature addresses the effect on downtown, two 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.[2]

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 market interactions, m, according to the gross profit function $\pi(m)$, which is increasing and concave. Market interactions depend on numerous characteristics of the local environment. Interactions decrease as distance d to the downtown or central business district (CBD) rises. Interactions are likely to be higher when immediately local activity, a, is greater. Interactions will also rise with the quality of local infrastructure, q. Access to subways or other rail transit is one example. All of this gives market interactions as a function, $m(d,a,q)$, with $\partial m/\partial d < 0$, $\partial m/\partial a > 0$, and $\partial m/\partial q > 0$. This immediately gives the following relationships for commercial rent, r:

$$\partial r/\partial d = \partial\pi/\partial d = \partial\pi/\partial m \, \partial m/\partial d < 0, \tag{2.1}$$

$$\partial r/\partial a = \partial\pi/\partial a = \partial\pi/\partial m \, \partial m/\partial a > 0, \tag{2.2}$$

$$\partial r/\partial q = \partial\pi/\partial q = \partial\pi/\partial m \, \partial m/\partial q > 0, \tag{2.3}$$

It is worth noting that all of these are consistent with fully specified models of interactions in downtowns such as Ogawa-Fujita (1980). We will consider all of these relationships empirically. Before doing so, we must consider how COVID-19 changes the costs and benefits of interactions

COVID-19 affects all of these relationships. Access to the downtown/CBD may have lost value for a number of reasons. Increases in work-from-home have reduced the agglomeration experienced at or near the downtown in a quantitative way: less activity nearby. Restrictions on movement within buildings due to social distancing in elevators have reduced the interaction qualitatively. This implies that $\partial\pi/\partial m$ falls, while $\partial m/\partial d$ becomes larger. These both work to raise $\partial\pi/\partial d$ (a weaker negative relationship). Similar arguments imply that $\partial\pi/\partial a$ falls (a weaker positive relationship). Regarding q, crowded indoor spaces are believed to facilitate transmission. Subways present indoor crowding risks, which is part of

[2] See also Kuchler et al (2021), Almagro and Orane-Hutchinson (2021), and Liu and Su (2021) for other perspectives on COVID-19.

why ridership fell so much at the onset of COVID-19 (roughly 90% in New York City, Cohen, 2020). Even as of this writing, much later in the pandemic, subway ridership remains significantly down, even in places that have "crushed the curve", an example of which is Taiwan (Chen et al, 2020). This implies that COVID-19 reduces $\partial\pi/\partial q$, with subway and rail access worth less. In sum, we anticipate seeing a post-COVID increase in $\partial\pi/\partial d$, a decrease in $\partial\pi/\partial a$, and a decrease in $\partial\pi/\partial q$.

III. Empirical design and summary statistics

A. Data

Our primary data is obtained from CompStak Inc., which provides detailed information on individual commercial leases across the United States. We focus on 56,765 leases signed between January 1, 2019 and October 31, 2020 in 109 distinct urban areas across the U.S. The CompStak data includes 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.[3] Throughout the analysis, we work with effective rent, a standard measure in the commercial real estate industry that includes monthly rent and fixed payments between landlord and tenant converted to a monthly basis. Also reported is whether the primary purpose of the leased suite is for retail or office uses.

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.

City planning authority data were also merged for select "transit" cities in large, dense metropolitan areas that rely heavily on light rail and subway systems. In order of rail/subway ridership, these MSAs include NYC, Washington DC, Chicago, Boston, San Francisco, and Philadelphia.[4] 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 of the car cities have rail and/or subway service, but to a far lesser degree than the transit cities. The planning authority data allow us to compute the distance from each lease to the closest transit station.

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

[3] For 19.6 percent of the 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 in which we control for building class.

[4] 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).

B. Organization of leases into urban areas

In order to assess the appeal of city centers, we must identify city centers and then organize leases according to the nearest city center. In this way, we create pseudo-monocentric cities. We proceed in a three-step process. In the first, we determine the zipcode in which each lease is situated and the associated employment density in that zipcode (omitting any area covered by water). In the second step, 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 often 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.

We 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. We then repeat this procedure omitting previously assigned leases and continue to repeat until all leases in the sample are assigned to a core city. This yielded 109 core cities across the United States. 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 that is further away than the closest core city. The Dallas-Fort Worth area is an example. Dallas and Fort Worth are both distinct, important cities with downtowns just over thirty miles apart. However, because Dallas has higher density, in Step 2 a circle is first drawn around the Dallas CBD that captures many leases that are closer to the center of Fort Worth. To address this issue, in a third and final step, we *reassign* all leases to the closest core city identified in Step 2.

Assigning leases to urban areas as above ensures that employment density is highest in the center of each urban area, leases are assigned to the closest core city, and urban areas do not overlap. This also 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 CBD 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 that are characteristic of a monocentric city with a dominant central business district.[5]

[5] We also estimated all of the models in this paper using 20 and 30-mile radius circles to define urban areas. Results were robust.

C. Summary statistics

Table 1 presents summary statistics for different groupings of leases in the sample. In considering the summary measures, it is important to remember that the CompStak sample is not designed to be representative of all leases throughout a given urban area. Instead, it is designed to give market practitioners accurate information on relevant "comparable" leases, a feature we make use of by controlling in various ways for the characteristics of a given property.

To simplify presentation of the summary measures, we report values just for those leases within 15 miles of a city center. This includes roughly 93.5 percent of our sample and is a restriction that we impose when estimating models of the effect of distance to the CBD. Summary measures for the full sample are similar. Observe also that 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 the car cities, average zipcode employment, density and rent were, respectively, 26,074 workers, 3,227 workers per square mile, and 26.61 dollars per square foot per year. In the transit cities, the corresponding values were 63,183, 166,516 and 62.81. Transit city leases are in nicer buildings: pre-COVID, the share of leases in Class A buildings is 45% versus 34% in car cities. For transit cities, median and mean pre-COVID distance to the CBD are 1.54 and 3.48 miles compared to 6.97 and 6.93 miles, respectively, in the car cities. Also of note, for both the car and transit city samples, summary measures in Table 1 are very similar pre- and post-COVID.

D. Regression model

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

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

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 sometimes 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 CBD 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.[6]

[6] 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

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 from the CBD. As in Panel A of Figure 1, the sample is restricted to leases within fifteen miles of the CBD 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 -19.5%. For car cities the gradient is -14.0% and for transit cities -37.3%. These values are all precisely estimated and provide further support that our data are organized into pseudo-monocentric cities. Moreover, if density is valued, 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 CBD. As above, the sample is restricted to leases within 15 miles of the CBD in order to mitigate the effect of employment subcenters in outlying areas. Controls are included for core city fixed effects, building quality (Class A is omitted), and quarterly dummies for 2019:Q1 through March, 2020. April through October of 2020 is grouped into a single post-COVID dummy that is also interacted with distance.[7] Only the main controls of interest are reported to conserve space and the first quarter of 2020 is treated as the omitted time period. Specified in this fashion, the post-COVID dummy captures the effect of the pandemic on commercial rent in the heart of the downtown. The interaction between the post-COVID dummy and distance measures the effect of COVID-19 on the rent gradient relative to the five quarters prior to April of 2020.

Grouping all cities together (column 1), the pre-COVID rent gradient is -2.12% and significant. For the car and transit cities the corresponding estimates are -0.88% and -6.31%, with t-ratios of -2.19 and -4.21, respectively. As anticipated, transit cities exhibit a steeper rent gradient.

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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:

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

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).

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

Also evident, the direct effect of COVID-19 is negative for the transit cities, implying a post-COVID decline in rent in the city center, and the gradient flattens: the coefficient on the interaction term is positive 1.16% with a t-ratio of 2.18. This suggests that for each mile from the CBD, the post-COVID rent gradient in the transit cities declined 1.16 percentage points less relative to a pre-COVID base of 6.31%. The pattern is different for car cities. The direct effect of the post-COVID dummy is positive 4.00% (with a t-ratio of 2.19) while the interaction term is negative, small, and not significant.

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 rotated the rent function downward, suggesting a tendency for lower post-COVID rents further from the CBD, different from 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.

The estimates above 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 urban areas. 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 possibility, Panel C of Table 2 replaces the distance measure with zipcode level employment density while retaining all other controls in Panel B. The sample also now includes leases out to 25 miles of the center since this model abstracts from a specific spatial pattern.

Estimates in Panel C echo those in Panels A and B. The elasticity of rent with respect to density is 7.67% for all cities combined (column 1), 4.24% for car cities and 12.88% in the transit cities. T-ratios on these estimates are all above 4. Also as above, for car cities COVID-19 does not appear to have affected the value of density – the coefficient on the interaction term is just -0.33% with a t-ratio of -0.60. Among the transit cities, however, the coefficient on the interaction term is -2.72% with a t-ratio of -3.21. This suggests that COVID-19 reduced the value of density by 21%.

Overall, a clear pattern emerges from Table 2. Pre-COVID, businesses consider density to be valuable. This is seen in the gradient models that assume a monocentric structure and also 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, but (a) not in the less monocentric car cities and (b) not to a degree that eliminates the value of density, even in the transit cities. City centers show less appeal, but the effects are heterogeneous and considerable appeal remains.

There are several potential explanations for these patterns. The transit cities had early and serious COVID-19 outbreaks relative to the car cities, possibly contributing to greater public awareness of threats from COVID-19, along with more dramatic changes in individual behavior (e.g. social distancing) and adoption of stricter lockdowns. The differences could also reflect differences in density between the two sets of cities. From Ogawa-Fujita (1980), if density becomes less valued, denser, more monocentric cities should experience sharper changes in the rent gradient in response to COVID-19. Reduced appeal of rapid transit further increases the tendency of transit cities to be more adversely affected by COVID-19, a point we return to shortly.

B. Extensions

One might wonder if the results described above are driven by the highly vulnerable retail sector. They are not. Table 3 presents models that divide the sample into the retail and office leases.[8] The results are reported only for the transit cities given the stronger patterns for those cities in Table 2.[9] It is clear that both the retail and office sectors were hit by COVID-19. The office sector sees a smaller rent gradient and a reduction in the density premium. The retail sector experienced an even greater flattening of the rent gradient and no significant change in the density premium. The weakened attachment to city centers is found in both the retail and office sectors.

Table 3 also considers the differences between new leases and renewals for existing tenants. Our model in Section II makes no distinction between these types, with rent determined by competitive bidding and the landlord renting to the high bidder. In a richer setting, 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 lease (less known). We thus re-estimate the gradient and local density models from Table 2 separately for renewals and new leases.

Results are shown in the last four columns of Table 3 and once 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 (6.4% new; 6.2% renewal), and so are the density premium estimates (13.1% new; 12.8% renewal).

This symmetry is broken post-COVID. For renewals, the gradient flattens by 1.7 points, while the local density premium falls by 3.4 points. The post-COVID coefficients are smaller for new leases (0.46

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

[9] Table 3 estimates for car cities mirror those of Table 2 with little evidence of post-COVID effects.

points in the gradient model and 2.2 points in the density specification with t-ratios of 0.41 and -1.79, respectively). 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 that provide rapid access to business centers. We carry out this analysis for transit cities only with estimates based on expression (3.1), allowing the effect of distance to a transit station to vary non-parametrically. The sample of leases is restricted to 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 distance 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. Observe also, post-COVID, the rent function is relatively flat within roughly 0.75 miles, rents are lower relative to pre-COVID conditions inside of 0.5 miles, and rents are higher between 0.5 and 1.25 miles (after which rent is similar pre- and post-COVID).

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. Higher post-COVID rents beyond 0.5 miles requires a different explanation. Once again going beyond the model in Section II, entrepreneurs may care about proximity to both home and transit station when choosing where to locate their business, analogous to Rosenthal and Strange (2012) where home and workplace locations are jointly modelled for female and male business owners. If post-COVID entrepreneurs place increasing weight on proximity to home, equilibrium rent functions between home and transit station could rotate in ways that could support higher post-COVID rents beyond 0.5 miles from a transit station.

In Panel B, controls are added for zipcode employment density. Results are qualitatively the same as in Panel A but more muted. This suggests that transit access has intrinsic value even after differencing away benefits associated with the scale of activity close to a transit station.

Panel C goes even further. In this panel, core city fixed effects and local employment density are replaced with transit station fixed effects. Once again, results are qualitatively similar to those in Panel A but even more muted. Station fixed effects control for a plethora of valued local attributes, including the level and composition of nearby employment, idiosyncratic advantages of accessing rapid transit from a given location, and more. Controlling for such an extensive set of local attributes should remove most of the value associated with proximity to a transit station, as the figure suggests.[10]

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, but in a nuanced way. First, we observe COVID-19 effects in large, dense cities that rely most heavily on rapid transit. We do not observe significant effects in car cities. Second, while density is less appealing post-COVID, there remains attraction to centers of activity. Rent gradients become flatter, but still have negative slopes. The local density premium remains large, as does the station proximity premium. In sum, the results show a clear effect of COVID-19 in the predicted direction, but one that weakens rather than eliminates the appeal of business centers.

What do our results imply about the future of cities? As noted previously, the change in rents that we document has many potential causes. These include an increase in the cost of interaction because of contagion risk, a decrease in the benefit of interaction because of the reduced density of business districts, a decrease in the productivity of physical infrastructure such as subways, and a newly discovered ability to work from home. The rent patterns we see reflect the market's expectations of how these effects impact tenant profits. Successful vaccination programs will reverse some but not all of these. While it is likely that COVID-19 will become less serious, other diseases may arise. Furthermore, the ability to work from home will continue to grow. This all suggests that some of the effects we find here are likely to persist. Ultimately, we must await additional data to answer questions regarding long term impacts of COVID-19 and other future contagious events.

[10] In Panel C, beyond 1.5 miles post-COVID rent is lower than pre-COVID levels. However, the post-COVID sample is thin beyond that distance (see Table 1, Panel C) and are viewed with caution.

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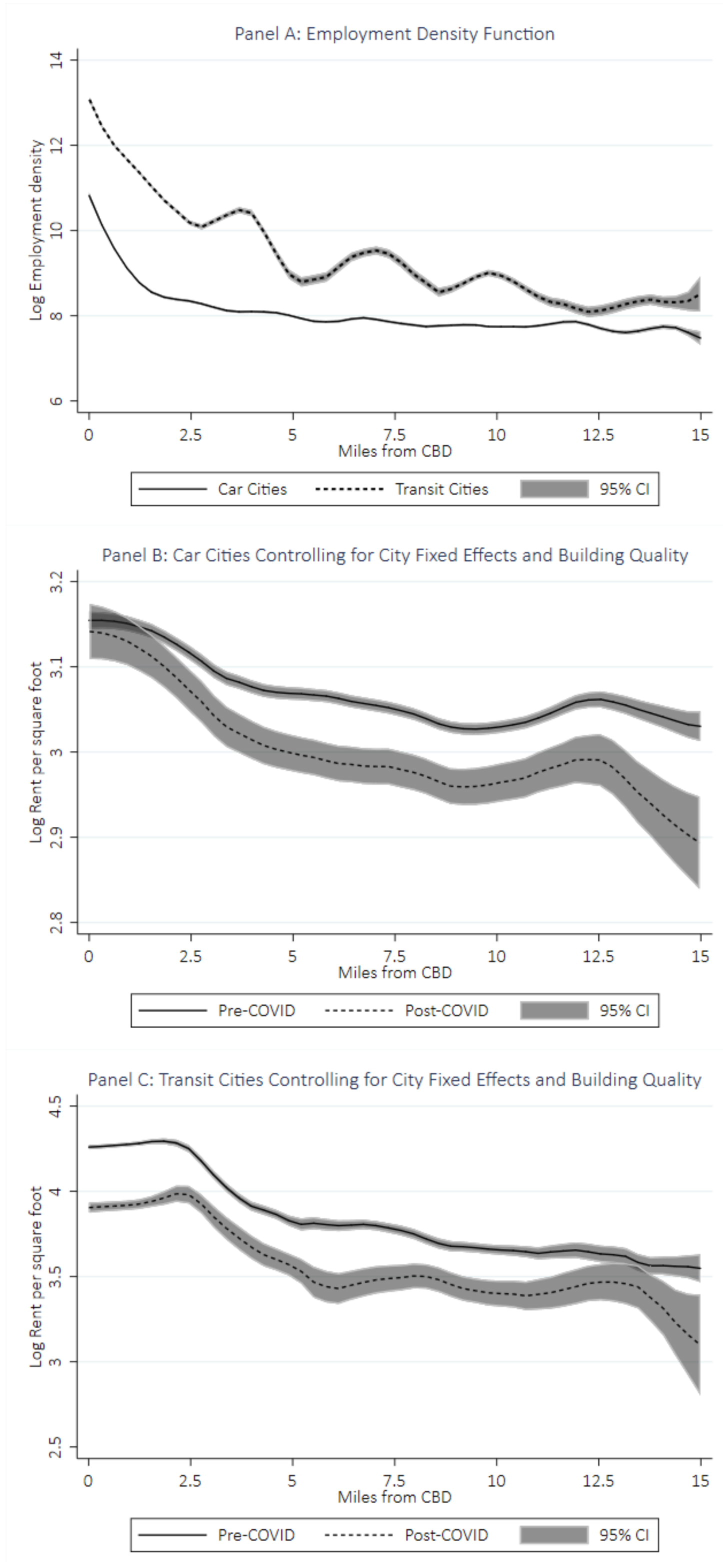
Figure 1: Density and Rent Functions Within 15 Miles of a CBD[a]



[a] Data are for leases executed between January 1, 2019 through October 31, 2020 that are within 15 miles of the CBD based on 25-mile circles to define urban areas using the 3-step process as described in the text.

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

[a] Data include leases executed between January 1, 2019 through October 31, 2020 that are within 3 miles of a rapid transit station in defined urban areas in the NYC, Washington DC, Chicago, Boston, San Francisco and Philadelphia metropolitan areas.

Table 1: Summary Statistics[a]

		Annual Rent Per Square Foot	Zipcode Employment	Zipcode Employment Per Square Mile	Miles to CBD	Miles to Closest Transit Station	Percent in Class A Buildings	Lease Term (number of months)
Panel A: All Cities								
Pre- and Post-COVID	p25	18.31	16,824	1,890	2.08	-	0.00	25
N = 53,092	p50	26.09	28,550	4,240	5.96	-	0.00	60
	p75	39.73	49,372	13,714	9.68	-	1.00	72
	Mean	34.91	38,852	47,265	6.12	-	0.37	58.93
Panel B: Car Cities								
Pre-COVID	p25	17.11	15,223	1,486	3.71	-	0.00	24
N = 36,836	p50	23.18	26,074	3,227	6.97	-	0.00	48
	p75	31.77	39,685	6,394	10.07	-	1.00	64
	Mean	26.61	31,242	10,404	6.93	-	0.34	53.50
Post-COVID	p25	17.00	16,137	1,576	3.61	-	0.00	24
N = 4,002	p50	23.00	27,175	3,493	6.69	-	0.00	40
	p75	31.10	41,659	6,471	9.94	-	1.00	65
	Mean	25.95	32,729	11,580	6.79	-	0.36	52.98
Panel C: Transit Cities								
Pre-COVID	p25	31.74	24,664	9,194	0.51	0.08	0.00	38
N = 10,963	p50	49.60	45,667	96,068	1.54	0.16	0.00	63
	p75	71.02	84,995	240,759	5.80	0.37	1.00	120
	Mean	62.81	63,183	166,516	3.48	0.54	0.45	77.81
Post-COVID	p25	31.70	27,599	10,887	0.42	0.08	0.00	36
N = 1,291	p50	48.22	52,707	115,591	1.38	0.16	1.00	61
	p75	67.30	107,798	325,733	4.63	0.32	1.00	115
	Mean	56.68	68,333	196,946	3.27	0.51	0.56	71.79

[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.

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

	(1)	(2)	(3)
Panel A – Employment density gradient: Dep var = Log zipcode employment density[b]	All Cities	Car Cities[c]	Transit Cities[c]
Distance (miles) to CBD (D_{CBD})	-0.1953	-0.1401	-0.3732
	(-8.38)	(-10.80)	(-14.03)
Core city fixed effects	109	102	7
Observations	53,092	40,838	12,254
R-squared	0.318	0.221	0.629

Panel B – Distance to CBD: Deb var = Log rent[b]	All Cities	Car Cities[c]	Transit Cities[c]
Post Covid (April 1 – Oct 31, 2020)[d]	-0.0057	0.0400	-0.0662
	(-0.19)	(2.19)	(-2.30)
Distance (miles) to CBD (D_{CBD})	-0.0212	-0.0088	-0.0631
	(-3.12)	(-2.19)	(-4.21)
D_{CBD} * Post Covid	0.0020	-0.0030	0.0116
	(0.53)	(-1.32)	(2.18)
Core city fixed effects	109	102	7
Observations	53,092	40,838	12,254
R-squared	0.139	0.148	0.237

Panel C – Valuing employment density: Dep var = Log rent[b]	All Cities	Car Cities[c]	Transit Cities[c]
Post Covid (April 1 – Oct 31, 2020)[d]	-0.1316	-0.0214	-0.2131
	(-2.12)	(-0.43)	(-3.96)
Employment per square foot (D_{EmpDen})	0.0767	0.0424	0.1288
	(4.84)	(6.14)	(4.19)
D_{EmpDen} * Post Covid	-0.0150	-0.0033	-0.0272
	(-2.17)	(-0.60)	(-3.21)
Core city fixed effects	109	102	7
Observations	56,765	43,716	13,049
R-squared	0.153	0.150	0.219

[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 three-step process as described in the text. All leases in core cities with fewer than 100 assigned leases are omitted. 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 CBD. 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]Quarterly dummies are included for 2019:Q1 through October, 2020. The period from April 1 through October 31, 2020 is grouped together. The omitted quarter is 2020:Q1. Coefficients for pre-COVID quarters are not reported.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Retail	Office	Retail	Office	New Lease	Renewal Lease	New Lease	Renewal Lease
Post Covid (April 1 – Oct 31, 2020)[b]	-0.1686	-0.0280	-0.0513	-0.1203	-0.0067	-0.1328	-0.1437	-0.3069
	(-4.75)	(-1.59)	(-0.18)	(-4.30)	(-0.17)	(-3.23)	(-1.81)	(-5.40)
Distance (miles) to CBD (D_{CBD})	-0.0994	-0.0542	-	-	-0.0643	-0.0622	-	-
	(-3.21)	(-7.01)	-	-	(-3.73)	(-4.66)	-	-
D_{CBD} * Post Covid	0.0211	0.0079	-	-	0.0046	0.0168	-	-
	(2.28)	(2.88)	-	-	(0.41)	(3.06)	-	-
Employment per square foot (D_{EmpDen})	-	-	0.2630	0.1058	-	-	0.1311	0.1276
	-	-	(4.96)	(6.39)	-	-	(3.83)	(4.62)
D_{EmpDen} * Post Covid	-	-	0.0034	-0.0170	-	-	-0.0221	-0.0343
	-	-	(0.09)	(-3.59)	-	-	(-1.79)	(-4.81)
Core city fixed effects	7	7	7	7	7	7	7	7
Observations	2,315	9,939	2,403	10,646	5,395	6,859	5,752	7,297
R-squared	0.267	0.327	0.329	0.288	0.241	0.240	0.220	0.224

[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 CBD. No such restriction is imposed on the density models (columns 3, 4, 7, and 8).

[b]Quarterly dummies are included for 2019:Q1 through October, 2020. The period from April 1 through October 31, 2020 is grouped together. The omitted quarter is 2020:Q1. Results for earlier quarters are suppressed to conserve space.

Online Appendix: 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.

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

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

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.

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.

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.

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.

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.

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.

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.

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.

Regional Rail Data and Highspeed Data. Southeastern Pennsylvania Transportation Authority (SEPTA). Downloaded on August 14th, 2020. http://septaopendata-septa.opendata.arcgis.com/.

Subway Entrances. Metropolitan Transportation Authority (MTA), NYC Open Data. Downloaded on June 24th, 2020. https://data.cityofnewyork.us/Transportation/Subway-Entrances/drex-xx56.

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

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

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.

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.

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.