Changes in the Zip-code Level Rent Distribution under COVID-19 and the Bid-rent Theory

Aiqi Sun Yuan Yuan

University of North Carolina at Chapel Hill

September 2021

Abstract

This paper aims to examine COVID-19's impact on urban rent distribution based on the classical bid-rent theory. Using data from Zillow, NBER, and CUSP, we quantify the effect of COVID-19 on rental markets across US cities. We find three key results. First, the pandemic flattens the bid-rent curve and reduces the gap between downtown and suburban rents. We rationalize this finding by noting that people are less dependent on the city center for working and other reasons during the pandemic, and the valuation of living closer to the city center falls. Second, COVID-19's impact on the 12 most populous cities is of smaller magnitude than the relatively less populous cities. Third, during periods of Stay-at-home, rents on average increased, and downtown rents rose relative to suburban rents compared to periods in pandemic without lockdown.

This project was supported by the Matthew Guest Family Fund and made possible by the UNC Economics Department. We would like to thank Samuel Barker for his invaluable support and guidance as our advisor.

1 Overview

The internal structure of urban areas has been evolving. The service industry in populated cities in the US, for example, has transformed from being low-skill-intensive to becoming skill-intensive and information-intensive (Eckert et al., 2020), which loosens the restriction of the workplace and makes a high ratio of remote work possible (Althoff et al., 2020; Dingel & Neiman, 2020). Meanwhile, the outer areas around the American metropolis have emerged and captured critical masses of leading urban activities from the central city that spawned it, enhancing the attractiveness of suburban areas (Muller, 1997).

These phenomena undermine the traditional land rent model, which assumes a negative correlation between rent and the distance from the Central Business District (CBD). People are willing to pay more to reside closer to the CBD since they can save the opportunity costs of commuting (Alonso, 1960). However, if telecommuting becomes the mainstream, the need to go to the workplace no longer exists, liberating people from choosing residence around the CBD. As Leamer et al. (2014) and Moeckel (2017) predicted, with the increase in the share of time a person telecommutes, employees are more likely to move to suburban and rural areas for more habitable houses surrounded by a better environment. Land rent theory is a model that uniquely integrates political and economic perspectives for analyzing urban phenomena (Jäger, 2003). Because of this, it is expected to change as time passes.

Until recent years, the high potential for remote work was inconsequential since it was not widely used (Bloom et al., 2013). However, since 2020, with the spread of SARS-CoV-2, the hypothesis around remote work has a chance to be tested by reality. To prevent the aggravation of the COVID-19 pandemic, state governments enacted several measures to restrict people's mobility, including State of Emergency (SOE) and Stay-At-Home (SAH) (Moreland et al., 2020). According to Brynjolfsson et al. (2020) and Bick et al.(2020), about half of all employed persons worked entirely or partly from home in May 2020, and a work-from-home ratio of around 20 percent is most likely to stay in the future (Barrero, Bloom, & Davis, 2020).

Motivated by the change in reality and the legitimacy of the bid-rent theory, this study aims at understanding the differential impact of COVID-19 on rental prices in large cities by distance to the city center, taking the trend over time into account. Using zip-code-level data, including rental index from Zillow and geographical distances between the city center and each region, we discovered that COVID-19 had a moderate effect on shrinking the gap in relative rental prices of urban versus suburban housing. This result is consistent when using a simple post-March 2020 indicator or the State of Emergency status to model the pandemic.

2 Literature Review

2.1 Urban Development

Extensive literature has documented transitions in the US urban area from multiple aspects, including colonization, industrial expansion, population turnover, liberal immigrant laws, and other political and cultural relations (Gottdiener, M., Hohle, R., & King, C. 2019). Skilled workers have increasingly chosen to live in expensive urban areas close to work, lowering the skilled wage premium and amplifying the wage and employment polarization (Moretti, 2013;

Autor & Dorn, 2013). Moretti (2013) also argues that cities' productive spillovers and amenity values account for the steep relationship between real estate prices and distance, which is vital for the skilled workers living near the city centers.

Apart from that, other researchers highlighted that large cities and small cities differ in the pattern of economic growth. Due to the preexisting comparative advantage of cities in skilled services and the increasingly reliable resources in information and communication technology, the largest cities in the US have grown the fastest (Eckert, Ganapati & Walsh, 2020) and also enjoy a higher potential of the rising work-from-home ratio (Althoff, 2021). Moreover, large and small metropolises have different trends in the geographical sprawling. Hajrasouliha, Amir, and Hamidi (2017) investigate in all 356 Metropolitan Statistical Areas in the US and report that polycentricy emerges primarily in large and medium metropolitan regions, while small metropolitan regions tend to be monocentric. These disparities between big and small cities imply the rent distribution in the most populous cities, and the relatively small cities may perform differently under the COVID-19 shock.

2.2 Bid-Rent Theory

A rigorous yet straightforward economic model of urban spatial structure, known as bid-rent theory, has been popularized and widely used since 60 years ago (Brueckner, 1987). This model explained the principal regularities observed in the urban landscape, including the decreasing intensity of urban land-use along with the distance from the city center and the higher building in urban areas with a larger scale. It derived from Alonso (1964) and was refined by Mills (1967) and Muth (1969). In 1960, Alonso first introduced the bid-rent function from the rural to urban land market in America, claiming that an individual resides where the commuting costs are balanced against the advantages of cheaper land and the satisfaction of more living space. While Alonso implied that individuals consume land directly, Mills and Muth regarded land as an intermediate good, and the final consumption for individuals is housing, which is more realistic (Brueckner, 1987). Gross and his colleagues (1990), Ahlfeld (2010), Narvaez, Penn and Griffiths (2013), and Bochnovic (2014), and Albouy, Ehrlich, and Shin (2018) have supported the validity of this theory based on empirical studies in the American cities.

Nevertheless, the Alonso-Mills-Muth model has been criticized as an oversimplified model. Egan and his colleagues (2000) also argued it ignores various attributes to the actual land development propensity in a complex urban land market context, such as fixity, costless supply, and immobility. Most of the criticisms are induced by the assumptions: (1) the city is monocentric, and all employment opportunities are located at the city center; (2) every urban resident earns equal wages. Although the effects of relaxing these assumptions are likely to be inconsequential because employment locations within the city can be endogenized (Mills, 1972; Fujita & Ogawa, 1982), and many of the critical properties of the model are unaffected by income heterogeneity—though it may add curvature to the initially linear bid-rent curve (Jaffe et al., 2019). Chances are that the further one lives away from the city center, the less likely one is dependent on the city center for work and living. Rosen (1972) rationalized this idea by establishing a Hedonic pricing model to quantify the relationship between the amenity value and the urban residence location. Lambin and Meyfroidt (2010) and Gao et al.

(2020) also show that a convex curve between distance-to-center and rent is closer to the factual situation instead of a monotonic linear decrease.

2.3 COVID-19 and Housing Market

A growing amount of literature investigates the impact of COVID-19 on the US housing market. Zhao (2020) claimed that under COVID and relevant monetary policies, the development in housing price, demand, and supply are similar across urban and suburban areas. Yilmazkuday (2020) found that having a monthly increase of 1,000 in COVID-19 cases within a county caused about $20 reduction in housing prices. Su and Liu (2020) proposed that the pandemic has shifted housing demand away from neighborhoods with high population density. Ramani and Bloom (2021) reported that COVID-19, along with the rise of the Work-From-Home ratio, has affected migration patterns and the rents within the US cities, hollowing out the city center and raising the surrounding suburbs. They named this phenomenon the "donut effect" generated by COVID-19. They also discovered that the "donut effect" is primarily a large city phenomenon: the top 12 cities, measured by population, see the most substantial donut effects, while the following 13-50 cities see more minor effects. Gupta et al. (2021) similarly found a flatter bid-rent curve in the top 30 US metros by using high-frequency location data from cell phone pings. The significance of effects also increases with higher work-from-home ratio or lower housing supply elasticity in metros.

Building on previous research, we expand on these findings in the two following ways: firstly, most of the literature omitted the time trend, and the rent distribution within cities will change even without the COVID-19, like the difference in agglomeration effect (Hajrasouliha, Amir, and Hamidi, 2017) and industrial structure (Eckert, Ganapati & Walsh, 2020) across large and small cities. In our model, we allow the time trend to vary by distance to city center by introducing an interaction term between time and distance. Secondly, rather than the simple indicator approach, we use State of Emergency and Stay-at-home orders to capture the intensity of the pandemic and its impact on residents more precisely. Stay-at-home orders also hint at limited access to urban amenities, which helps us examine the validity of the Hedonic pricing model. In addition, we attempt to examine the distinct impacts of COVID-19 on cities of different population sizes and reproduce Ramani and Bloom's findings (2021) that the "donut effect" is more significant in the 12 most populous cities.

3 Data

This study uses three categories of data regarding each facet of the project: the rental indices of zip-code areas, the characteristics of the zip-code areas, and state-level COVID-19 policies. First, we obtained monthly zip-code level residential property rent data between January 2014 and June 2021 from Zillow Group's Zillow Observed Rent Index (ZORI) data set. ZORI is a smoothed, current-dollar-value index that measures changes in asking rents for properties that remain listed across multiple periods, controlling for changes in the quality of the available rental stock. The ZORI data set includes zip-code level rent data for the US's 100 largest Metropolitan Statistical Areas. It is worth noting that Zillow may decide not to publish its index for a specific zip code or in a specific month if they are alarmed by the quality of the data. Unavoidably, the lack of some populous zip codes in several cities may affect the accuracy of our regression results. We give more details about this in appendix section A.

Table A: Summary Statistics of Rent Index

Variable	Before March 2020	Since March 2020	State of Emergency	Stay-at-home
Rent	1654.66	1813.33	1781.58	2150.07
	(711.23)	(633.30)	(633.06)	(748.87)
log(rent)	7.33	7.45	7.43	7.61
	(.39)	(.33)	(.33)	(.36)

Plot A: Rental Price Distribution (Source: Zillow)

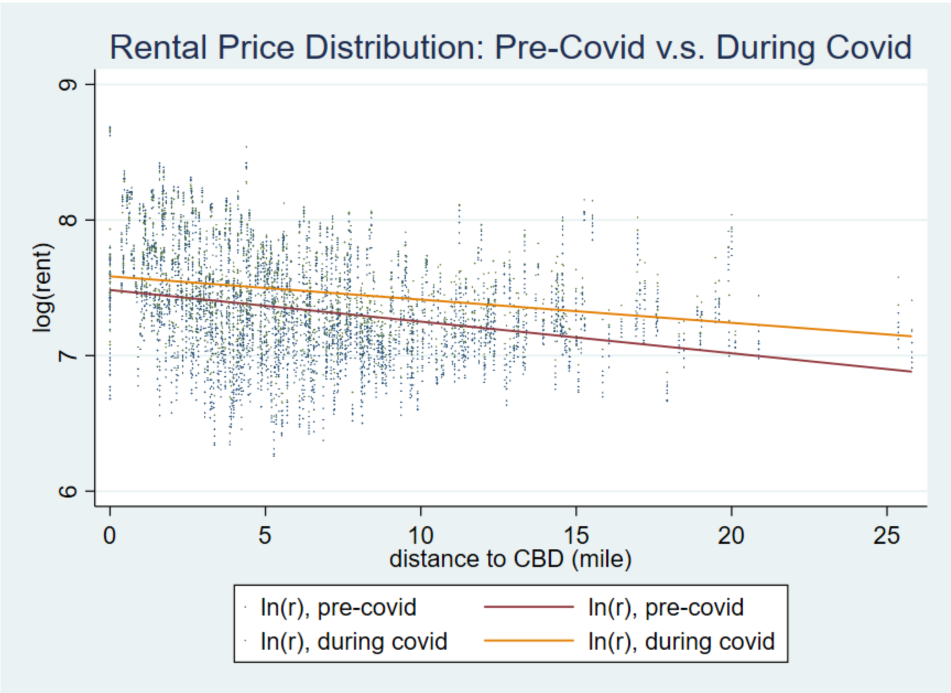


Table B: Summary Statistics by City (Source: Zillow)

City	Rent	Distance	Periods of SAH	Population	Number of Zip Codes
Albuquerque	1149.96	9.02	3	39877.4	5
Arlington	1414.48	6.76	1	39289.57	2
Atlanta	1464.53	6.75	1	29574.06	20
Austin	1409.18	6.36	1	34714.47	23
Baltimore	1393.68	4.47	2	37654.87	17
Boston	2534.09	3.17	2	28490.49	29
Charlotte	1295.91	6.53	2	39768.06	21
Chicago	1600.76	4.93	2	48352.26	33
Colorado Springs	1289.70	5.44	1	30597.64	14
Columbus	1079.58	4.46	2	31963.63	5
Dallas	1354.03	6.30	1	33943.59	12
Denver	1537.88	4.47	1	29964.22	17
Detroit	933.21	10.64	2	31554.25	5
El Paso	1077.87	9.38	1	83785	3
Fort Worth	1324.81	8.41	1	38843.67	12
Houston	1365.62	11.19	1	45479.93	16
Indianapolis	873.24	5.11	2	32783.02	11
Jacksonville	1220.55	9.28	1	36304.1	21
Kansas City	983.05	3.88	1	14657.55	5
Las Vegas	1200.36	9.78	1	37435.23	25
Long Beach	1641.65	4.75	11	48657.15	8

Los Angeles	2352.81	7.22	11	41443.62	21
Memphis	934.02	7.63	1	31723.9	7
Mesa	1182.23	7.46	2	43541.5	9
Miami	1901.67	9.14	2	36800.88	28
Minneapolis	1460.50	5.69	2	27547.4	10
Nashville	1480.53	6.41	1	31572.26	9
New York City	2719.16	5.20	3	50427.49	64
Oakland	2438.50	3.71	11	35616.92	4
Omaha	947.67	4.51	0	23744.87	5
Philadelphia	1470.22	2.88	2	34851.32	21
Phoenix	1132.56	10.28	2	36307.12	27
Portland	1473.44	4.54	3	32701.57	17
Raleigh	1220.81	7.75	2	42598.17	12
Sacramento	1536.57	6.55	11	35571.69	7
San Antonio	1186.84	11.76	1	40992.99	20
San Diego	2105.16	8.09	11	46548.3	23
San Francisco	3482.36	2.03	11	39129.86	13
San Jose	2790.43	5.61	11	48351.11	3
Seattle	1817.78	5.43	2	32285.87	19
Tucson	1024.62	8.69	2	35097.59	11
Virginia Beach	1597.32	7.79	2	55291.88	4
Washington D.C.	2076.41	2.78	2	36515.26	15

The two characteristics of a zip-code area of our interests are the distances from its residential properties to the city center and its population size. We first located each city's center using the address of each city's city hall, which is an efficient and accurate method, as Holian (2019) argued since governmental and business centers are usually located closely. In instances where it is clear that the location of a city hall does not represent its respective city center, we extracted information on central business districts (CBD) location from *Central Business Districts: 1982 Census of Retail Trade*, which was the US Census Bureau's final attempt to identify CBDs. Then we recorded the zip-codes of the locations of the residential rental properties and the proximate city centers and retrieved data on the distance between their zip-codes from the National Bureau of Economic Research (NBER)'s ZIP Code Tabulation Area (ZCTA) Distance Database. This database consists of the great-circle distances between zip codes calculated using the Haversine formula based on internal points in geographical areas. As for population, we obtained zip-code level 5-year estimates of population data from the American Community Survey (ACS) for the years 2014 to 2019, as this version is the most precise with small geographical areas, and it offers data unavailable in other surveys. We used population data for each zip-code area in 2019 to approximate 2020 and 2021 in its corresponding area. This approximation can be justified because population data is mainly used as the weights in our regression models across zip-codes and cities; the annual changes in population within one zip-code area are too minor to affect the results significantly.

To explore the influence of the pandemic, we first used March 2020 as the cut-off indicator of the advert of COVID-19 across the US. We then utilized an intensity measure of the pandemic using data of the periods of State of Emergency in each state, where the binary variable “State of Emergency” is equal to 1 if a city was under the State of Emergency in the particular month. We obtained data from the COVID-19 US State Policy (CUSP) database compiled by researchers at Boston University School of Public Health and Johns Hopkins Bloomberg School of Public Health. The CUSP documents the dates all 50 states and the District of Columbia implemented health and social policies to respond to the COVID-19 pandemic and its economic ramifications by searching government websites and media coverage for executive orders and directives pertaining to the specific policy in each state. It also kept a record of county-level variations within each state. We also used stay-at-home orders as defined by CUSP to test the effect of harsher shutdowns on rental prices. Similarly, the binary variable “Stay-at-home” is equal to 1 if the residents in a city were ordered to stay in their shelters in the particular month, whereas another continuous variable measures the number of months until the end of the local stay-at-home order. A ‘state of emergency’ or ‘stay-at-home’ order that was declared after the 15^{th} of a month is considered not to have impacted the corresponding month since most leases are signed on the 1^{st} or the 15^{th}. The motivation for this comes from an economic intuition about the relative importance of amenities to housing prices by location. For instance, it is reasonable to expect that an apartment downtown has more locational amenities than a suburban apartment. Thus, these downtown apartments may see a differentially significant impact on rental prices during a stay-at-home order. However, the exact meaning of a “stay-at-home” order is arguably ambiguous in the data. We noticed that CUSP classifies a stay-at-home order differently per state -- i.e., Florida’s ‘safer-at-home’ order is treated as a ‘stay-at-home’ order. However, we will continue to use the language coded in CUSP, and we utilize these data in this analysis as treatments that limit amenity access. We give more details about this in appendix section B.

4 Model

We begin with

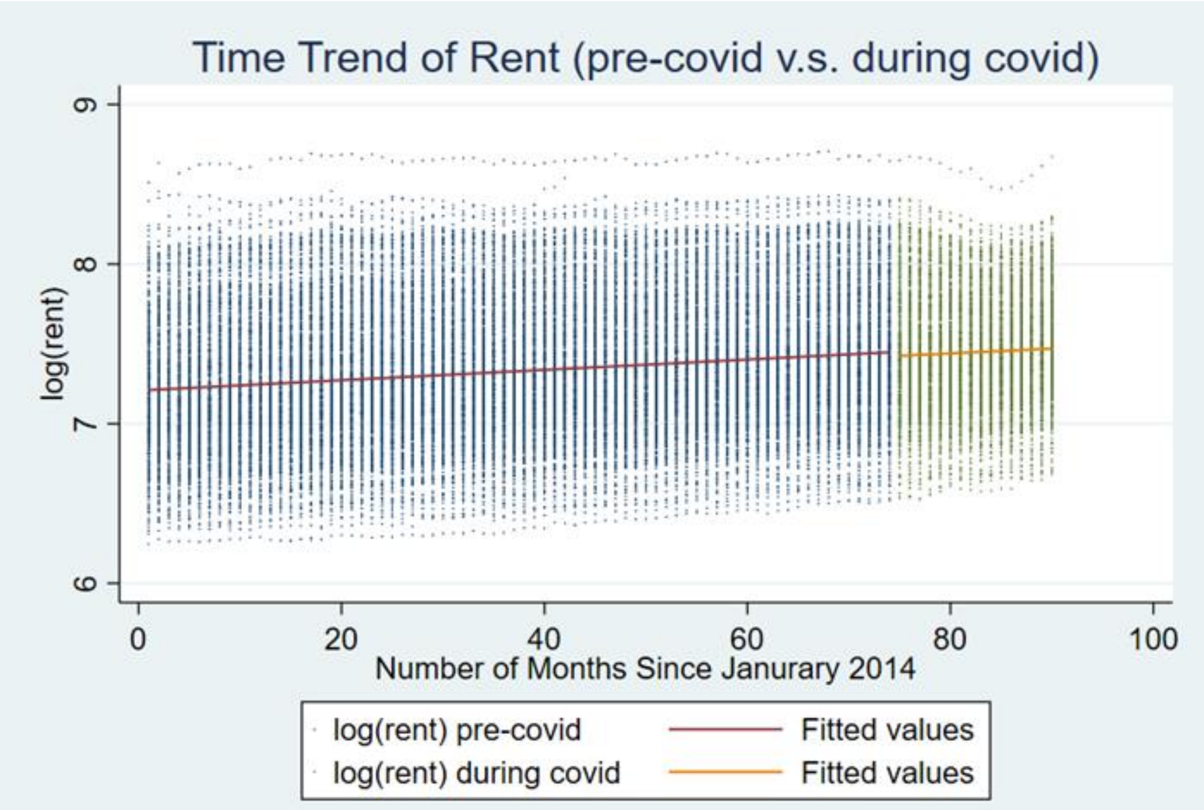
(1) $\boldsymbol{rent_{it} = \beta_1 + \gamma_1 distance + \varepsilon_{it}}$,

the classical Alonso bid-rent curve in which rent decreases proportionally as a property is located further and further from the CBD. The variable $distance$ is the distance between a zip code and the city center; therefore, γ_1 reflects the average valuation of living one mile away from the city center. We expect γ_1 to be negative as the bid-rent theory predicts. According to our expectations, the COVID-19 pandemic not only has created a shock to the rental market but also affected rental properties at different locations distinctively. We modify the Alonso model and estimate with robust OLS:

(2) $\boldsymbol{rent_{it} = \beta_1 + \gamma_1 distance_i + \gamma_2 covid_{it} + \gamma_3 (distance_i \times covid_{it}) + \varepsilon_{it}}$,

where $covid$ is a binary variable equal to one if the pandemic is present. The key coefficient is γ_3, the coefficient on the $distance_i \times covid_{it}$ interaction. We expect γ_3 to be positive if the pandemic has reduced the rent differential by distance to the city center, i.e., proximity to the CBD now plays a lesser influence in rent determination.

Plot B: Time Trend of Rent (Source: Zillow)



It is worth noting that while the bid-rent function can account for all differences in rent, in theory, the reality is not the oversimplified model in (1). The time trend also plays a significant role – plotting average rent against time shows a clear positive correlation between rent and the number of months since the starting period (i.e., January 2014). We also cannot assume the time trend is consistent across all distances away from the city center; the development of cities changes the opportunity cost of living further from downtown. We capture these effects by supplementing the model with $trend$ and $trend \times distance$. We estimate:

(3) $$\boldsymbol{rent_{it}} = \boldsymbol{\beta_1} + \boldsymbol{\gamma_1 distance_i} + \boldsymbol{\gamma_2 covid_t} + \boldsymbol{\gamma_3 (distancei \times covid_t)} + \boldsymbol{\gamma_4 trend_t} + \boldsymbol{\gamma_5 (trend_t \times distance_i)} + \boldsymbol{\varepsilon_{it}},$$

where the coefficient γ_5 on the interaction term $trend \times distance$ reflects the average trend in changes of urban rent distribution by location. A positive γ_5 would indicate that the rent gap between downtown and suburban apartments is gradually closing, and vice versa.

Additionally, each city has its own appeal in terms of climate, access to employment opportunities, public amenities, and people value an apartment in a city more if the city offers excellent value. We assume these traits do not vary between 2014 to 2021, and we estimate these locational fixed effects to control for variations in rent at city level. Meanwhile, it is evident from our database that rent differs by month, so we also introduce a month fixed effect control. We estimate:

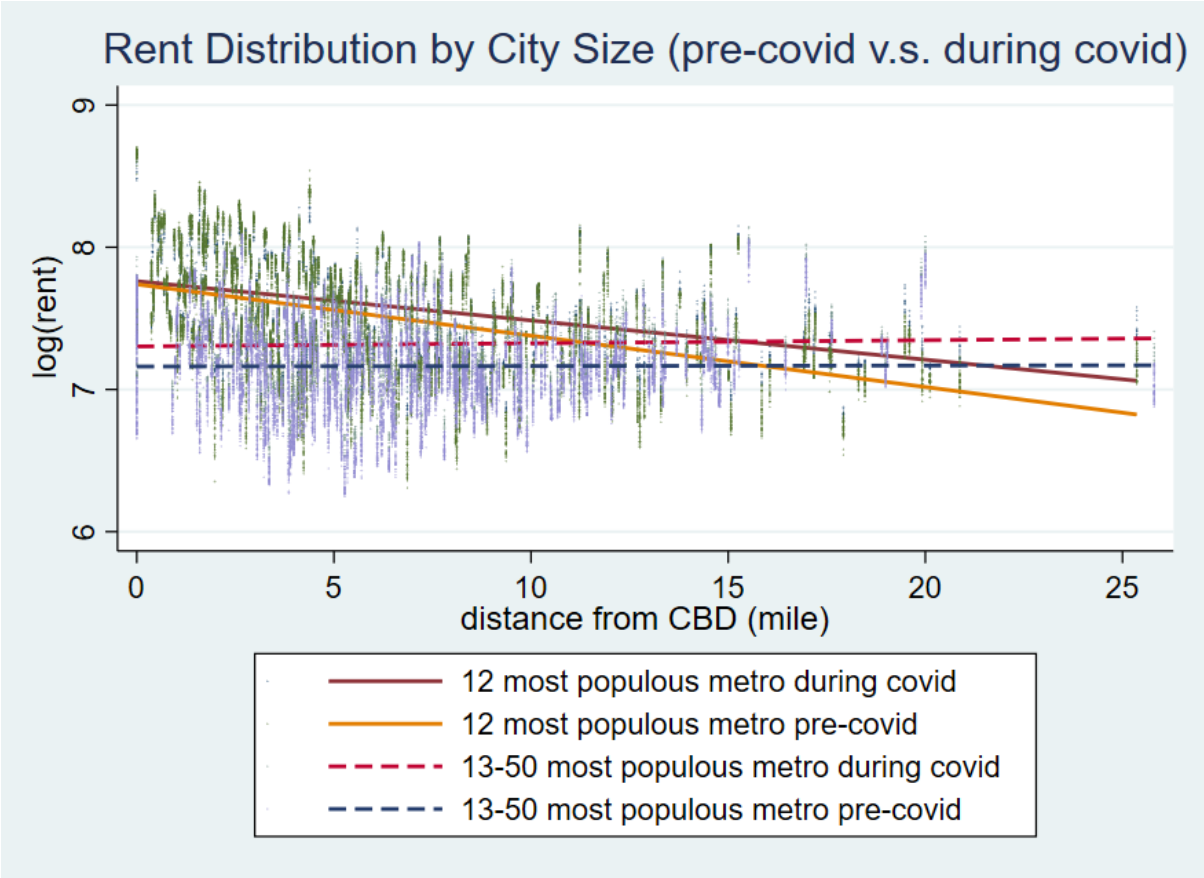
(4) $$\boldsymbol{ln(rent)_{it}} = \boldsymbol{\beta_1} + \boldsymbol{\gamma_1 distance_i} + \boldsymbol{\gamma_2 covid_t} + \boldsymbol{\gamma_3 (distance_i \times covid_t)} + \boldsymbol{\gamma_4 trend_t} + \boldsymbol{\gamma_5 (trend_t \times distance_i)} + \boldsymbol{\gamma_6 distance_i^2} + \boldsymbol{\beta_2 Z_{it}} + \boldsymbol{\varepsilon_{it}},$$

where Z_{it} is a vector that includes city fixed effects, month fixed effects, and their interactions with $covid$, $distance$, or $trend$ since the influence on rent caused by variations in cities and months may differ over time, across distance, or during the pandemic. Notice that the dependent variable is replaced with $ln(rent)$; this is on one hand because as we relax the assumption that everyone earns equal wages, the bid-rent curve becomes convex, and a natural log model can better fit the rent distribution (Jaffe et al., 2019). For the same reason, we added the $distance_i^2$ variable to model the gradually flattening shape of the curve, which could be a sign of the fading influence of the bid-rent theory as we move away from the city center – the further one lives away from the city center, the less likely one is dependent on the city center for work and living. In addition, the coefficient of a log-level model is interpreted as the percent difference in the dependent variable due to a unit change in the independent variable. Different cities have different valuations of the opportunity cost of living one mile further, and the nominal value of a 10% fall in the bid-rent coefficient is different in New York City and Raleigh. A log-level model allows us to overcome this issue by focusing on percent difference instead of dollar-value difference.

$$\textbf{(5)} \quad \boldsymbol{ln(rent)_{it} = \beta_1 + \gamma_1 distance_i + \gamma_2 Policy_{it} + \gamma_3 (distance_i \times policy_{it}) + \gamma_4 trend_t + \gamma_5 (trend_t \times distance_i) + \gamma_6 distance_i^2 + \beta_2 Zit + \varepsilon_{it}},$$

We employ an intensity measure of the pandemic and measure its severity using state-level policy data on the declaration of State of Emergency (SOE) and the issuing of stay-at-home (SAH) orders. This measure enables us to accurately extract the pandemic's impact on rental distribution while indirectly examining the relative importance of urban amenities to rental prices by location. We expect the indicators SOE and SAH to have a negative coefficient, and their interaction terms with $distance$ should have positive coefficients. In addition, we counted the number of months until the stay-at-home order expires in each city (labeled n_SAH in Table 3), and we expect that if residents value urban amenities, they will value urban apartments more as the stay-at-home order comes closer to an end, making the coefficient on n_SAH negative.

Plot C: Rent Distribution by City Size (Source: Zillow)



$$\textbf{(6)} \quad ln(rent)_{it} = \beta_1 + \gamma_1 distance_i + \gamma_2 covid_t + \gamma_3(distance_i \times covid_t) + \gamma_4 trend_t + \gamma_5(trend_t \times distance_i) + \gamma_6 distance_i^2 + populous_i + \beta_2 Z_{it} + \varepsilon_{it},$$

Finally, we provide another modification of (4) in which we include a binary variable $populous_i$ that indicates a city is one of the top 12 most populous cities in the US. It is intuitive from Plot C that the group of the 12 most populous cities and the group of the 13^{th} – 50^{th} most populous cities exhibit different distributions of rental prices across distance, before and during the pandemic. We intend to test if the 'donut effect' of COVID-19, the phenomena that real estate demand (measured by rental price) reallocates away from major city centers towards lower density areas on the outskirts of cities, is more significant in the most populous cities, as suggested by Ramani and Bloom (2021).

A test of the impact of the pandemic on rent distribution is a test that a fall in people's need and desire to visit the city center has changed the importance of the relative location to the city center in rent determination. It is a test that γ_3, the coefficient on the interaction term between $distance$ and $covid$, is not equal to zero (we cannot overlook the possibility that γ_3 turns out to be negative). Thus, our hypothesis tests are two-tailed tests (the ninety-fifth percentile of the t-distribution is 1.96).

5 Results

Table III presents results in which we use the time of March 2020 or the declaration of State of Emergency in each state to measure the COVID-19 pandemic. The sample is the top 50 most populous cities in the US, with at least two zip-codes of data available in the ZORI dataset (except in the final two columns). All models are modeled with population-weighted robust OLS. The first column is the Alonso bid-rent model, while the rest include pandemic indicators and their interactions with distance to the CBD. The first two columns have $rent$ as their dependent variable, whereas the rest have $log(rent)$. From column (4), the adjusted-R^2 reaches a significant level of more than 0.80, which proves the explanatory capability of our model.

Our foundational assumption, the bid-rent function, is valid as proven by the statistics in column (1) of Table III, where the coefficient on the term $distance$ is -40.52 (with a

Table C Summary Statistics of Regression Results

	Dependent variable: rent		Dependent variable: log(rent)					
	Alonzo Model (1)	Covid*distance interaction with no covariate (2)	Time trend & t*d interaction (3)	Distance-squared & fixed-effects (4)	Intensity measure of the Pandemic (5)		Regression by population size (6)	
					SOE & SAH	SOE & n_SAH	12 most populous cities	13^{th}-50^{th} most populous cities
Distance to CBD (d)	**-40.52****	**-42.18****	**-.0212****	**-.0257****	**-.0257****	**-.0256****	**-.0388****	**.1554****
	(.6786)	(.7545)	(.0009)	(.0027)	(.0027)	(.0027)	(.0027)	(.0144)
Covid/SOE		**99.01****	**-.0556****	**-.0771****	**-.0829****	**-.0806****	**-.0827****	**-.0585****
		(14.95)	(.0107)	(.0056)	(.0058)	(.0057)	(.0065)	(.0096)
Covid/SOE * d Interaction		**8.997****	**.0045****	**.0098****	**.0106****	**.0103****	**.0054****	**.0108****
		(1.682)	(.0012)	(.0015)	(.0015)	(.0015)	(.0018)	(.0024)
Time trend (t)			**.0032****	**.0033****	**.0033****	**.0034****	**.0036****	**-.0037***
			(.0002)	(.0004)	(.0004)	(.0004)	(.0004)	(.0016)
t * d interaction			7.76e-06	-.00002	**-.00001****	-.00002	-.00002	**.0011****
			(.00002)	(.00005)	(.00005)	(.00005)	(.00005)	(.0002)
Distance Squared (d^2)				**.0011****	**.0011****	**.0011****	**.0017****	**.0004****
				(.00005)	(.00005)	(.00005)	(.00006)	(.00008)
Covid/SOE * d^2 interaction				**-.0003****	**-.0003****	**-.0003****	-.00002	**-.0004****
				(.00009)	(.00009)	(.00009)	(.0001)	(.0001)
SAH					**.0262****			
					(.0068)			
SAH * d interaction					**-.0039****			
					(.0009)			
number of months until SAH ends (n_SAH)						**.0042****		
						(.0013)		
n_SAH * d interaction						**-.0007****		
						(.0002)		
Observations	57,668	57,668	57,668	57,668	57,668	57,668	26,837	30,831
R^2	0.0725	0.0821	0.0967	0.8640	0.8640	0.8640	0.8629	0.8011

Regressions are weighted by ACS zip-code level population data.

** indicates that a coefficient is statistically significant at p=0.01; * indicates that a coefficient is significant at p=0.05

standard deviation of 0.6786). Thus, locating one mile away would decrease rent by $40.52. We also discover that across most models with a *time trend* covariate, the positive coefficient on the $time\ trend$ term is significant so that rental prices would still change in the absence of any other factors. One exemption was that when limiting the sample to the group of the 13^{th} -50^{th} most populous cities, their rents on average presented a 0.37% decreasing trend by month. Thus, using the time trend model as a control, we isolate the 'natural' changes in rent from the changes caused by COVID-19.

In all columns with the $distance \times covid$ interaction term, the coefficient on the interaction term is positive and statistically significant. This suggests that just as predicted, during the COVID-19 pandemic, the value of living closer to the city center falls, and the bid-rent curve flattens. According to columns (4) and (5), locating one mile away from the CBD during the pandemic would result in a 1% smaller fall in rent. The narrowing gap between CBD and suburban rental prices during the pandemic can also be inferred from the negative coefficient (-0.0003) on the $pandemic \times distance^2$ interaction term, which suggests that the rent curve is becoming less convex. The above results are consistent in employing a cut-off point or the State of Emergency orders to indicate the pandemic. This suggests that future research with monthly data can use March 2020 as an efficient estimate for the start of the pandemic. We acknowledge that COVID-19 is only a temporary shock to the market, and a permanent change in people's commuting habits could potentially cause a more substantial impact.

However, contrary to our assumptions, rent on average rose during lockdown periods by 2.62%. Moreover, despite stay-at-home orders prohibiting residents’ access to urban amenities, the rental price of suburbs fell relative to downtown, and the value of living one mile closer to the city center rose by 0.39% . It was also to our surprise to discover that rents were higher when the city entered lockdown than when the city was about to be freed from lockdown, as shown in column (5). One possible explanation for the increased rent is that ZORI measures only the asking rent, and homeowners did not collect as much because a large number of tenants nationwide could no longer afford rents while the eviction moratorium was in place. We advocate for future researchers to examine this phenomenon more closely.

In the final two columns, the sample is split into one group of the 12 most populous metros and the rest relatively less-populous metros. Noticeably, consistent with Plot C, the group with the 13^{th} – 50^{th} most populous cities did not follow Alonso's theory, and on average, the rent away from CBD is greater than the rent near CBD as shown by the positive coefficient on the distance term. One explanation for this outcome is that these cities with relatively smaller populations tend to have smaller sizes, and their business activities are less aggregated; therefore, not all residents need to commute downtown daily. Residents then may prefer to live in the suburban areas, where, as suggested by a hedonic model, they can have more access to open space amenities and avoid traffic congestion. We suggest that future research on the relationship between rent and (commuting) distance should look directly into the distribution of business and business activities. The group with the 12 most populous cities, on the other hand, exhibited a significant downward sloping bid-rent curve - rent decreases by 3.88% for every mile away from the CBD. The gradient of the two groups' rent-distance distributions diverges significantly. Interestingly, the two groups had the opposite time trend - rents are rising on average in the 12 most populous cities but falling in the rest of the cities. In addition, the suburban rental properties are becoming relatively more expensive in the relatively less populous metros. A probable interpretation is that economic activities in smaller cities are not centralizing, and the importance of city centers in these cities are gradually fading. We encourage researchers to replicate our modeling in the future to discover if these cities are becoming less agglomerated.

In terms of the key $covid \times distance$ interaction term, we found that locating one mile away from the city center reduces rent by only 0.54% in the more populous group and by 1.08% in the less populous group; in other words, the pandemic had a less substantial impact on the rental distribution across distance of the 12 most populous cities in the US. Market rent is determined by the demand and supply of rental properties; as COVID-19 constrained the changes in the supply of rental properties, we can attribute much of the changes in rents to changes in market demand. As the groups with the most populous cities had a smaller coefficient on the $covid \times distance$ interaction term, we suspect that the fall in rental demand resulting from the pandemic was smaller in the group with the most populous cities relative to the other group. We, therefore, did not reproduce the findings made by Ramani and Bloom (2021), who discovered that the 'donut effect' was more significant in the top 12 metros by population. Our findings suggest the opposite - the 'donut effect' is a medium city phenomenon.

6 Conclusion

This research aims to examine the classical bid-rent theory under the COVID-19 pandemic in major US cities. Despite some data quality issues, our results support the predictions of traditional urban economics: in an environment where people's spending on commuting fall significantly, i.e., there is minimal commuting, the value of proximity to the city center decreases, and the relative rental price of downtown rental properties does indeed fall. Our estimates show that during the COVID-19 pandemic, the bid-rent curve is flattened and less convex and are in line with previous findings by Gupta et al. (2021), Su and Liu (2020), and Rosenthal, Strange, and Urrego (2021). In addition, we discovered that the rent distributions of the group of the 13^{th} – 50^{th} most populous cities do not comply with the Alonso Model, and they are further deviating from it. We also found that under the pandemic, the slopes of bid-rent curves of the most populous cities changed by a smaller magnitude than those of the relatively less populous cities, suggesting that the magnitude of the 'donut effect' is inversely associated with metro population size. Furthermore, our extended finding on the increased rent during stay-at-home orders suggests that the value of some urban amenities, such as bars, and cafes, behaved against the hedonic model and did not fall during COVID-19. Thus, our analysis not only confirms some theories from urban economics but also provides insight into how a future temporary interruption to economic activities would affect urban rent distribution. This paper also provides foresight into how the rental market may develop as commuting becomes less necessary, with the projection that substantial employment positions would remain partially online post-pandemic.

Bibliography

Ahlfeldt, Gabriel. "If Alonso was right: modeling accessibility and explaining the residential land gradient." *Journal of Regional Science* 51, no. 2 (2011): 318-338.

Albouy, David, Gabriel Ehrlich, and Minchul Shin. "Metropolitan land values." *Review of Economics and Statistics* 100, no. 3 (2018): 454-466.

Alonso, William. "A theory of the urban land market." Bobbs-Merrill Company, College Division, 1960.

Ambrose, Brent W., N. Edward Coulson, and Jiro Yoshida. "The repeat rent index." *Review of Economics and Statistics* 97, no. 5 (2015): 939-950.

Autor, David H., and David Dorn. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." AMERICAN ECONOMIC REVIEW 103, no. 5 (2013): 1553-97.

Bailey, Martin J., Richard F. Muth, and Hugh O. Nourse. "A regression method for real estate price index construction." *Journal of the American Statistical Association* 58, no. 304 (1963): 933-942.

Barrero, Jose Maria, Nicholas Bloom, and Steven J. Davis. *Why working from home will stick.* No. w28731. National Bureau of Economic Research, 2021.

Bick, Alexander, Adam Blandin, and Karel Mertens. "Work from home after the COVID-19 Outbreak." (2020).

Bloom, Nicholas, James Liang, John Roberts, and Zhichun Jenny Ying. "Does Working From Home Work? Evidence From a Chinese Experiment." *The Quarterly Journal of Economics* 130, no. 1 (2015): 165-218.

Bochnovic, Michael Andrew. *An Analysis of Bid-Rent curve variations across American cities*. Arizona State University, 2014.

Brueckner, Jan K. *Lectures on urban economics.* MIT press, 2011.

Brynjolfsson, Erik, John J. Horton, Adam Ozimek, Daniel Rock, Garima Sharma, and Hong-Yi TuYe. *COVID-19 and remote work: an early look at US data*. No. w27344. National Bureau of Economic Research, 2020.

Dingel, Jonathan I., and Brent Neiman. "How Many Jobs Can be Done at Home?" JOURNAL OF PUBLIC ECONOMICS 189 (2020): 104235. https://doi.org/10.1016/j.jpubeco.2020.104235.

Eckert, Fabian, Sharat Ganapati, and Conor Walsh. "Skilled Scalable Services: The New Urban Bias in Economic Growth." (2020).

Gottdiener, M., Hohle, R., & King, C. (2019). The New Urban Sociology (6th ed.). Routledge. https://doi.org/10.4324/9780429244452

Gross, David J., C. F. Sirmans, and John D. Benjamin. "An empirical evaluation of the probabilistic bid-rent model: The case of homogenous households." *Regional Science and Urban Economics* 20, no. 1 (1990): 103-110. http://doi.org/https://doi.org/10.1016/0166-0462(90)90027-Z

Gupta, Arpit, Vrinda Mittal, Jonas Peeters, and Stijn Van Nieuwerburgh. *Flattening the curve: pandemic-induced revaluation of urban real estate*. No. w28675. National Bureau of Economic Research, 2021.

Hajrasouliha, Amir H., and Shima Hamidi. "The typology of the American metropolis: monocentricity, polycentricity, or generalized dispersion?." *Urban geography* 38, no. 3 (2017): 420-444.

Holian, Matthew J. "Where is the City's Center? Five Measures of Central Location." *Cityscape* 21, no. 2 (2019): 213-226.

Jaffe, Sonia, Robert Minton, Casey B. Mulligan, and Kevin M. Murphy. *Chicago Price Theory*. Princeton University Press, 2019.

Jäger, Johannes. "Urban Land Rent Theory: A Regulationist Perspective." INTERNATIONAL JOURNAL OF URBAN AND REGIONAL RESEARCH 27, no. 2 (2003): 233-49.

Leamer, Edward E., and Michael Storper. "The economic geography of the internet age." In *Location of international business activities*, pp. 63-93. Palgrave Macmillan, London, 2014.

Moeckel, Rolf. "Working from home: Modeling the impact of telework on transportation and land use." *Transportation Research Procedia* 26 (2017): 207-214.

Moreland, Amanda, Christine Herlihy, Michael A. Tynan, Gregory Sunshine, Russell F. McCord, Charity Hilton, Jason Poovey et al. "Timing of state and territorial COVID-19 stay-at-home orders and changes in population movement—United States, March 1st–May 31st, 2020." *Morbidity and Mortality Weekly Report* 69, no. 35 (2020): 1198.

Moretti, Enrico, 2013, Real wage inequality, *American Economic Journal: Applied Economics* 5, 65–103.

Muller, Peter O. "The Suburban Transformation of the Globalizing American City." *The ANNALS of the American Academy of Political and Social Science* 551, no. 1 (1997): 44-58. https://doi.org/10.1177/0002716297551001004.

Narvaez, Laura, Alan Penn, and Sam Griffiths. "Spatial configuration and bid rent theory: How urban space shapes the urban economy." In *Proceedings of the 9th Space Syntax*

Symposium, Seoul, Korea, vol. 31. 2013. http://sss9sejong.or.kr/paperpdf/ussecp/SSS9_2013_REF089_P.pdf

Ramani, Arjun, and Nicholas Bloom. *The Donut Effect of COVID-19 on Cities*. No. w28876. National Bureau of Economic Research, 2021. http://doi.org/10.3386/w28876

Rosen, Sherwin. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." JOURNAL OF POLITICAL ECONOMY 82, no. 1 (1974): 34-55. https://doi.org/10.1086/260169

Yilmazkuday, Hakan. "COVID-19 and Housing Prices: Evidence from US County-Level Data." *Available at SSRN 3746552* (2020). http://dx.doi.org/10.2139/ssrn.3746552

Zhao, Yunhui. "US housing market during COVID-19: aggregate and distributional evidence." (2020). https://ssrn.com/abstract=3744679

Zillow Group. "Methodology: Zillow Observed Rent Index (ZORI),". Last modified May 20th, 2020. https://www.zillow.com/research/methodology-zori-repeat-rent-27092/

Appendix A: Monthly Rental Index by Zip-Code (Source: Zillow)

ZORI utilizes a repeated transaction methodology, which calculates the rental price changes for all units with more than one recorded sale by regressing changes in rent prices on the change in the time between two transactions, was first developed by Bailey, Muth, and Nourse (1963) and is similar to the approach described by Ambrose, Coulson, and Yoshida (2015). In addition, ZORI put more weight on observations underrepresented in the Zillow sample by comparing the stocks recorded in Zillow's data and that in the census in terms of construction year, structure type, and rental year.

Availability of zip codes in Houston, TX when released in June 2021 vs. July 2021

	June 2021	July 2021
Total Number of Zip Codes	33	17
Differences	77003 77004 77008 77018 77025 77030 77035 77040 77041 77047 77054 77056 77064 77066 77070 77072 77082 77089 77096	77073

Appendix B: Stay-at-home Order in the US by State (Source: CUSP)

Sample:

State	Stay-at-home/shelter in place	Stay-at-home order issued but did not specifically restrict movement of the general public	End Stay-at-home/shelter in place	Stay-at-home record in our data set
Arizona	3/31/2020	N/A	5/16/2020	Apr-May 2020
Arkansas	N/A	N/A	N/A	N/A
California	3/19/2020	N/A	1/25/2021	Apr 2020 - Jan 2021

Quality issues:

State	Stay-at-home/shelter in place	Stay-at-home order issued but did not specifically restrict movement of the general public	End Stay-at-home/shelter in place
Colorado*	3/26/2020	N/A	4/27/2020
Florida**	4/3/2020	N/A	5/18/2020
Georgia***	4/3/2020	N/A	5/1/2020

New Mexico****	3/24/2020	N/A	N/A
New York*****	3/22/2020	N/A	6/27/2020
North Carolina*****	3/30/2020	N/A	5/22/2020

* CO - Initial stay-at-home order replaced 4/27 with safer-at-home order, which does not mandate that individuals must Stay-at-home (therefore was not recorded). Yet, the safer-at-home order by the Florida State Governor is counted as a stay-at-home order.

** FL - Executive Order 90-21, while calling elders and other volatile populations to shelter in place and asking all Florida residents to limit their movement, only stated that it was 'safer-at-home'. In the CUSP data set, a 'safer-at-home' directive does not count towards a 'stay-at-home' order in other states. (For instance, in MA, the stay-at-home order was replaced 5/18 with safer-at-home advisory, and the state's stay-at-home record ended on 5/17 in the CUSP data set.)

*** GA - According to CUSP, only high-risk individuals were ordered to shelter in place. Nevertheless, official documents show that the governor ordered all residents to shelter in place.

**** NM - According to CUSP, New Mexico never lifted its stay-at-home order. This is partly because NM was constantly updating its criteria of ‘stay-at-home’, and non-essential businesses were gradually reopening under the ‘stay-at-home’ order. In addition, the New Mexico Department of Health record shows that the first ‘stay-at-home’ order in NM ended after June 2020, and a second order was in effect only between November 16th and November 30th.

***** NY & NC - CUSP measures the termination of the 'stay-at-home' order in the two states differently. NC's termination was consistent with the end of Phase 1 of reopening, whereas NY's termination was at the end of Phase 2, while many non-essential businesses in NY resumed businesses two weeks ago.

Appendix C: Summary Statistics

Summary Statistics of Rent by Year

Year	Mean	Std. Dev.	Min.	Max.	Freq.
2014	1486.605	664.76742	516	5626	7,236
2015	1568.1968	707.50137	525	5962	7,627
2016	1631.4067	709.67101	539	5801	7,730
2017	1678.1488	705.51016	564	5940	7,810
2018	1729.4278	708.75784	602	5978	7,827
2019	1792.1609	720.2195	625	6041	7,826
2020	1803.6535	665.13069	671	5894	7,812
2021	1833.7003	597.43655	730	5838	3,890

Summary Statistics by COVID Indicator

COVID-19 Status	Mean	Std. Dev.	Min.	Max.	Freq.
Pre-Pandemic	1654.66	711.23	516	6041	47,358
During Pandemic	1813.33	633.30	683	5846	10,400
Stay of Emergency declared	1812.50	631.54	683	5846	10,283
Stay-at-home order issued	2150.07	748.87	683	5846	1,885