A First Look at the Impact of COVID-19 on Commercial Real Estate Prices: Asset-Level Evidence

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Abstract

This is the first paper to examine how the COVID-19 shock transmitted from the asset markets to capital markets. Using a novel measure of the exposure of commercial real estate (CRE) portfolios to the increase in the number of COVID-19 cases (*GeoCOVID*), we find a one-standard-deviation increase in *GeoCOVID* on day *t*-1 is associated with a 0.24 to 0.93 percentage points decrease in abnormal returns over 1- to 3-day windows. There is substantial variation across property types. Local and state policy interventions helped to moderate the negative return impact of *GeoCOVID*. However, there is little evidence that reopenings affected the performance of CRE markets. (*JEL* I10, G11, G14, D80, R10)

The COVID-19 pandemic is having a devastating impact on economic activity. Real gross domestic product (GDP) decreased at an annual rate of 32.9% in the second quarter of 2020 according to the "advance" estimate released by the Bureau of Economic Analysis. This has produced a rapidly growing literature, some of which focuses on how stock returns have responded to changes in investors' information and expectations (e.g., Alfaro et al. 2020; Gormsen and Koijen 2020; Ramelli and Wagner 2020). Most of these studies provide evidence at the *index* or *firm* level. However, movements in a firm's stock price are largely driven by the perceived current and future productivity of the firm's *underlying assets*; therefore, it is important to understand how the COVID-19 shock transmits to the equity markets from a firm's asset base. The goal of this paper is to help fill this gap in the literature.

We focus on the commercial real estate (CRE) assets owned by listed U.S. equity real estate investment trusts (REITs). This setting is advantageous to the study of the impact of COVID-19 at the level of the firm's assets for several reasons. First, the prices of liquid stocks quickly capitalize information about investors' short-run and long-run expectations of the future cash flows likely to be generated by the underlying asset portfolio. In addition, REITs are subject to a set of restrictive conditions that ensure that equity REITs invest primarily in income-producing real estate and distribute a large percentage of their cash flow in the form of dividends.[1] Also, listed REITs typically acquire and dispose of CRE in a parallel private market, in which valuations of comparable properties can be observed. Thus, the CRE assets owned by REITs are relatively easier to locate and value than the tangible (e.g., plant and equipment) and intangible assets (e.g., intellectual property) owned by many conventional firms. Although the illiquidity and opacity of private CRE markets limit our ability to detect rent and (especially) price movements in "real time," we argue that the effects of COVID-19 we observe in highly liquid stock markets are indicative of the effects occurring in the private CRE market.

To examine how the growth rates of COVID-19 cases affect firms differently through their asset holdings, we construct a novel firm-level measure of geographically weighted COVID-19 growth

[1] A "qualified" REIT may deduct dividends paid from corporate taxable income if the REIT satisfies a set of restrictive conditions on an ongoing basis. Fully 75% of the value of the REIT's assets must consist of real estate assets, cash, or government securities. Moreover, at least 75% of the REIT's gross income must be derived from real estate assets. A REIT must pay out 90% of its annual taxable income in dividends.

(*GeoCOVID*) that varies daily during our sample periods. This variable is the weighted average of the daily growth rates of COVID-19 cases in counties in which the firm owns properties. The weights are the percentages of the firm's portfolio (based on book value) allocated to each county prior to the pandemic outbreak at the end of 2019. Given that the testing capacity and, perhaps, the accuracy of COVID-19 tests may vary across locations over our sample period, our measure of geographically weighted COVID-19 case growth is likely measured with error. However, these growth rates are reported daily and widely discussed and therefore are reasonable proxies for the information investors had available on a day-to-day basis about the spread of the pandemic.

To evaluate firm-level stock performance across property types, we first calculate abnormal returns over 1-, 2-, and 3-day windows using a sample of 11,210 firm-day observations for 198 equity REITs from January 21 through April 15, 2020. These returns are risk-adjusted based on the S&P 500 index and the FTSE-NAREIT All Equity REITs index. In our univariate analyses, we find that REITs that focus their investments on data center, cell tower, self-storage, and warehouse properties produced positive abnormal returns during the early stages of the pandemic. In contrast, the worst performers were hospitality and retail REITs.

In our multivariate analysis, we regress 1-, 2-, and 3-day abnormal returns on each firm's *GeoCOVID* on day *t*-1. Our baseline results suggest that a one-standard-deviation increase in *GeoCOVID* is associated with a 0.24 percentage point decrease in abnormal returns on the next day. This return reduction is equivalent to 40% of the sample mean (-0.6 percentage points) of abnormal returns. A one-standard-deviation increase in *GeoCOVID* is associated with a 0.80 and 0.93 percentage point decrease in abnormal returns over 2- and 3-day windows, respectively. Our findings also suggest that the strong negative association between our geographically weighted measure of the growth in COVID-19 cases and abnormal returns is not simply driven by the national trend in reported cases. Our results are robust to using the "hump-shaped" period of rapid-and-then-decelerating growth in COVID-19 cases from February 27 to April 13, 2020, as well as an extended sample period that runs through June 30, 2020.

Understanding the connection between local nonpharmaceutical interventions (NPIs), such as shelter-in-place orders (SIPOs), and stock price reactions to COVID-19 might be helpful in assessing the effectiveness of NPI policies. Investors likely expected such policies to flatten the epidemic curve and therefore produce long-term benefits, but at the expense of reduced economic activity, at least in the short run. We find that investors initially react negatively to the announcement of state of emergency declarations (SOEs) and SIPOs. To examine how NPIs affect investors' reactions to COVID-19 growth, we construct a geographically weighted measure, *GeoNPI*, of each firm's time-varying exposure to NPIs at the asset level. We find that firm's with property portfolios more exposed to NPIs perform better over time and that more exposure (larger *GeoNPI*s) diminishes the negative return impact of *GeoCOVID*. These results indicate that investors place more weight on the expected long-term benefits of these policies than their short-run costs.

Using an extended sample through June 30, 2020, we also investigate the impact of reopenings on abnormal returns using another asset-level measure, *GeoReopen*, to capture a firm's geographically weighted exposure to reopenings. Our event studies and regression analysis both suggest that reopenings had little impact on abnormal returns. This finding is consistent with several existing studies (e.g., Chetty et al. 2020; Bartik et al. 2020; Villas-Boas et al. 2020).

Taken together, our findings highlight the importance of the asset-level attributes of a firm's portfolio to stock price reactions to the pandemic. Specifically, the key drivers are the property type (business) focus of the firm, the geographic allocation of assets (proxied by *GeoCOVID*, *GeoNPI*, and *GeoReopen*), and the interaction between these two attributes.

Most of the existing studies on the COVID-19 shock focus on either index-level returns (e.g., Alfaro et al. 2020; Gormsen and Koijen 2020; Sinagl 2020) or firm-level returns without controlling for the location of the firm's underlying assets (e.g., Ramelli and Wagner 2020; Ding et al. 2020; Hassan et al. 2020; Gerding, Martin, and Nagler 2020). Ours is the first paper to examine how the COVID-19 pandemic has affected stock returns through a firm's underlying assets. Given the extraordinary nature of this pandemic, researchers are finding that existing models may no longer be adequate (Barro, Ursúa, and Weng 2020; Alfaro et al. 2020) and are therefore exploring new measures that better capture firm-level exposures to epidemics (e.g., Hassan et al. 2020). Our paper contributes to this literature on firm-level exposures by constructing a geographically weighted COVID-19 growth variable at the asset level.

We are the first to examine how the outbreak of the COVID-19 pandemic affects the real estate market.[2] More broadly, our study is related to the extensive literature on the economic effects of pandemics and health shocks (e.g., Bleakley 2007; Weil 2007; Nunn and Qian 2010; Correia, Luck, and Verner 2020; Ambrus, Field, and Gonzalez 2020; Francke and Korevaar 2020; Farboodi, Jarosch, and Shimer 2020; Forsythe et al. 2020). Outside of the pandemic literature, our study contributes to the growing literature on the geography of firm assets and the extent to which "local" information about the productivity of a firm's assets is capitalized into stock prices (e.g., Parsons, Sabbatucci, and Titman 2020; García and Norli 2012; Bernile, Kumar, and Sulaeman 2015; Jannati 2020; Smajlbegovic 2019; Ling, Wang, and Zhou 2019, 2020; Wang and Zhou 2020).

1. Data

Figure 1 plots monthly indexes for the S&P 500, Russell 2000, and the FTSE-NAREIT All Equity REITs index from 2015 through April 23, 2020. Each index is set equal to 100 at year-end 2014. During March of 2020, the total return index on the S&P 500, equity REITs, and the Russell 2000 declined 16%, 23%, and 26%, respectively. This decline in REIT share prices far exceeds the reduction that can be explained by a temporary loss in rental income.[3]

Figure 2 plots NAREIT subindexes for office, industrial, retail, residential, health care, and lodging/resort REITs from 2015 through April 23, 2020. Even before the onset of the pandemic, returns varied substantially by the property type focus of the REIT. During March 2020, the cumulative total return index for retail REITs declined by 49%. This March decline was closely followed by lodging/resort REITs (-44%) and health care REITs (-41%); again, with significant day-to-day variation. The total return indexes for office and residential REITs also declined sharply in March 2020: 25% and 26%, respectively. Of the six major types included in Figure 2, industrial (primarily warehouses) was the best performer during this

[2] Milcheva (2020) examines REIT returns across a few Asian countries and the United States during the COVID-19 pandemic and finds that the global COVID-19 shock propagates to real estate markets through financial channels. Van Dijk, Thompson, and Geltner (2020) document substantial drops in transaction volumes in the private commercial real estate markets. D'Lima, Lopez, and Pradhan (2020) provide evidence of the effects of the COVID-19 shutdown and reopening orders in the housing market.

[3] Green Street Advisors estimates that a typical property that experiences a loss of all its operating income in the next year would decline in market value by just 5% to 6% (Green Street Advisors 2020b).

bear period. Industrial REITs experienced a decline in their total return index of just 10% and recovered a modest 3% through April 23.

Although property type indexes are a substantial improvement over aggregate industry-level index, they still mask significant variation across firms in the exposure of their CRE portfolios to the COVID-19 pandemic. To measure time-varying, firm-level exposure to the growth in confirmed COVID-19 cases in each county, we collect the following data from the S&P Global Real Estate Properties (formerly SNL Real Estate) database for each property held by a listed equity REIT at the end of 2019Q4: property owner (institution name), property type, geographic (county) location, book value, initial cost and historic cost. This produces a REIT-property-level data set containing 73,406 property observations for 201 unique equity REITs. We first calculate, for each REIT, the percentage of its property portfolio, based on depreciated book values, invested in each county at the end of 2019.[4] We then match these portfolio allocations with the daily growth rates of county-level COVID-19 confirmed cases, which are obtained from the Coronavirus COVID-19 Global Cases database at Johns Hopkins University.[5] These county-level growth rates are then value-weighted by the percentage of the CRE portfolio invested in each county. This produces an estimated daily COVID-19 exposure (*GeoCOVID*) for each firm.

The black dash-dotted line in Figure 3 represents the trend of *GeoCOVID* since the first reported case in the United States on January 21, 2020. The horizontal axis represents the number of *trading* days since the first outbreak. The average daily increase in reported cases was approximately zero until day 27 (February 27, 2020), consistent with the nationwide trend of reported cases. We also compare *GeoCOVID* with a simple average of growth rates in 2,572 counties in which REITs own properties. In untabulated results, we find that the simple average of daily COVID growth rates was also about zero from January 21 to February 27, 2020, except for few "spikes." This is because for each county the growth rates in the first few days since the first reported case are relatively high. For example, the growth rate from 1 to 2 cases is higher than the growth from 10 to 20. In general, REITs own properties in dense population counties; the

[4] The use of book values in place of unobservable true market values may understate (overstate) the value-weighted percentage of a CRE portfolio invested in regions that have recently experienced a relatively high (low) rate of price appreciation.
[5] https://github.com/CSSEGISandData/COVID-19

virus spread from counties with higher population densities to those with lower population densities. Therefore, the property weights smooth out the spikes by placing less weight on high growth rates in counties with less population. Thus, *GeoCOVID* has, on average, a smaller mean and standard deviation than the simple average of county-level COVID-19 growth.

Another important takeaway from Figure 3 is the hump-shaped pattern of *GeoCOVID* from day 27 to day 58 (February 27 to April 13, 2020). Given the reduced growth of COVID-19 cases after April 13, 2020, our initial sample period runs from January 21 to April 15, 2020. However, our results are robust to extending of our sample period to June 30 or when we restrict our analysis to the hump-shaped period of *GeoCOVID* from February 27 to April 13, 2020.

We require nonmissing values for the following items for each REIT at the end of each day from January 1, 2019, to April 15, 2020: firm identifier (SNL Institution Key), total return, stock price, property type, and stock market capitalization. The initial sample includes 224 unique equity REITs traded on NYSE, AMEX, and Nasdaq in 2019Q4. S&P Global and NAREIT classify CRE portfolios into 12 major property types, including office, industrial, retail, residential, diversified, hospitality (lodging/resorts), health care, self-storage, specialty, timber, data center, and infrastructure. Because of a small number of firms, we include timber REITs in the specialty category and combine infrastructure and data center REITs into a "technology" category.[6] Table A2 in the appendix summarizes property type descriptions. Quarterly accounting data and daily returns on individual REITs and on our broad-based market indexes are obtained from the S&P Global Companies database. The 30-day U.S. Treasury rate is downloaded from the Federal Reserve System website.[7] After merging with *GeoCOVID*, our sample includes 198 equity REITs and 11,210 firm-day observations.

To calculate daily abnormal returns, we estimate return sensitivities for each firm using a simple market model and data from January 1, 2019, to January 20, 2020. We use two stock market indexes: the S&P 500 index and the FTSE-NAREIT All Equity REITs index. The estimated firm-level return

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[6] The FTSE-NAREIT All Equity REITs index contained only 4 timber REITs, 5 infrastructure (primarily cell tower) REITs, and 5 data center REITs as of February 29, 2020. See *REIT Watch*, March 2020 (www.nareit.com).

[7] See https://www.federalreserve.gov/releases/h15/

sensitivities are used to compute daily abnormal returns for the baseline period between January 21, 2020, and April 15, 2020.

We first use *GeoCOVID* reported on day t -1 to predict stock returns on day t. However, because the news contained in the number of new cases of COVID-19 reported on day t-1 may take more than the subsequent day to be fully incorporated into stock prices, we also use $GeoCOVID_{t-1}$ to predict cumulative returns over the subsequent 2 days (day t and day t+1). Finally, because investors may be able to partially predict reported COVID-19 growth using epidemiological models, we use $GeoCOVID_{t-1}$ to predict aggregate stock returns over a 3-day window: day t-1, day t, and day t+1. These multiple-day return measures are constructed using nonoverlapping return horizons (days) so that each observation of the dependent variable is independent of the prior and subsequent observation (Harri and Brorsen 2009).

To analyze investors' responses to policy interventions, we construct *GeoNPI* and *GeoReopen* to capture the exposure of a firm's portfolio to NPIs and reopenings, respectively. *GeoNPI* (*GeoReopen*) is measured as the percentage share of a firm's portfolio (in total adjusted cost) exposed to county-level NPIs (state-level reopenings). Because reopenings nullify NPIs, we also construct a composite exposure measure, *GeoNetExp*, defined as the percentage share of a firm's portfolio exposed to NPIs, net of reopenings, both measured at the state level.

Wheaton and Thompson (2020) propose the use of a power function to measure the cumulative number of confirmed COVID-19 cases across the major U.S. counties from January 21, 2020, to the end of March 2020. They calibrate the power parameters using a log-linear regression equation. Among the parameters, days since the onset of the pandemic in that county and the population density of the county predict the cumulative number of confirmed cases. Similar to Wheaton and Thompson (2020), we define *Days since outbreak* as the number of days since a COVID-19 case was reported in any county in which the REIT owns property. To account for the expected nonlinearity in the growth rate of COVID-19 cases, we also include *Days since outbreak*^{2} in our analysis.

Population density impedes social distancing and therefore increases the likelihood the virus will spread. To test this conjecture, we construct *GeoDensity*, which is equal to the average of county-level population densities per square mile in 2019, weighted by the percentage of the firm's portfolio invested in the corresponding county at the end of 2019Q4. County-level population densities come from the S&P Global Geographic Intelligence database.

Our control variables include determinants of daily stock returns identified in the prior literature (e.g., Brennan, Huh, and Subrahmanyam 2013; Giannini, Irvine, and Shu 2018; Patel and Welch 2017). These variables are measured as of the end of 2019. *GeoHHI* and *PropHHI* are Herfindahl-Hirschman indexes (HHI) that capture the degree to which the firm concentrates its property portfolio on counties or property type.[8] *Leverage* is the total book value of debt divided by the book value of total assets, *Cash* is the sum of cash and equivalents divided by lagged total assets, *Size* is the reported book value of total assets, and *Tobin's q* is the market value of equity, plus the book value of debt, divided by the book value of total assets. *LAG3MRET* is defined as the firm's cumulative return during 2019Q4, *InstOwn* is a REIT's institutional ownership percentage, *Investment* is defined as the growth rate in noncash assets over the fourth quarter of 2019, and *EBITDA/AT* is EBITDA divided by the book value of assets.[9] Table A1 in the appendix defines all variables and lists data sources.

2. Results

2.1 Summary statistics

Table 1 reports summary statistics. During our sample period from January 21, 2020, to April 15, 2020, the average 1-day abnormal return based on the S&P 500 (FTSE-NAREIT All Equity REITs index) is -0.6% (-0.8%). The average 2-day cumulative abnormal return is -1.3% (-1.5%). The number of observations in our 2-day return sample is approximately half of the 1-day sample because of the nonoverlapping return horizons. The average 3-day cumulative abnormal return is -1.9% (-2.2%). The standard deviation of 1-day abnormal returns for both the S&P 500 and the FTSE-NAREIT All Equity REITs benchmarks are about 10 times their means, reflecting the extreme stock market volatility during the early stages of the pandemic.

[8] For example, *GeoHHI* is the property-level HHI, calculated as the sum of squared proportions of the total book value of a CRE portfolio located in counties where the firm owns properties.
[9] EBITDA is earnings before interest, taxes, depreciation, and amortization expenses.

Firm-level, geographically weighted COVID-19 growth averaged 6.6% per day with a standard deviation of 9.4% during our sample period. Because we track firms' portfolio exposures since the first reported U.S. case on January 21, 2020, more than 25% of our firm-day observations are associated with no growth in reported cases. The geographically weighted growth rate in firms' exposure also varies substantially across firms; for example, more than 25% of firms experienced daily growth in COVID-19 cases in excess of 11.7%. The mean (and median) *Days since outbreak* is 33 days. On average, 24% of a REIT's portfolio is exposed to local nonpharmaceutical interventions (NPIs). In the extended sample that runs through June 30, 2020, 37% of the average REIT portfolio is exposed to reopenings, resulting in 29% net geographic exposure to NPIs.

Geographically weighted population density, *GeoDensity*, averages 4,887 persons per square mile. The summary statistics for other control variables are comparable to prior studies. The average firm in our sample has a property type concentration (HHI) of 0.788, a geographic concentration of 0.119 (measured using county data), a leverage ratio of 49%, cash holding of 3.7%, a book value of assets equal to $6.6 billion, and a *Tobin's q* of 1.5. The percentage of stock owned by institutional investors averages 81%. The percentage growth rate in noncash assets during 2019Q4 (*Investment*) averaged 9.2% but varies substantially across firms. The ratio of EBITDA to the book value of total assets has a mean of 2.1%. Nineteen percent of REITs focus on retail properties, 14% on hospitality properties, and 11% on office assets and health care properties.[10]

2.2 Stock performance across property types

Figure 4 displays the means and 95% confidence intervals of abnormal returns by property type. We observe similar patterns for different return horizons (1-, 2-, and 3-day), and for the S&P 500 and equity REIT market models (panels A and B, respectively). The best performing property types were technology, self-storage, and warehouses. Cell towers that transmit data communications and high-tech facilities that

[10] The disaggregation of CRE portfolios by major property type may mask some variation across subproperty types. For example, Green Street Advisors (2020a) disaggregate "residential" properties into apartments, student housing, single-family rental, and manufactured home parks.

host Cloud servers are in high demand because many people are working remotely from home. The worst performers were hospitality and retail REITs, likely because of the combined effects of canceled travel, imposed closures, and shelter-in-place orders in most cities and states. Diversified REITs also underperformed as a sector because many hold retail and multiuse properties. Owners of specialty REITs (e.g., casinos, golf courses, timber, and agriculture) were also negatively affected by reduced demand. Office and residential properties were less negatively affected over our sample period, perhaps because of longer-term leases and relatively inelastic demand. The results are little changed when the FTSE-NAREIT All Equity REITs index is used as our market benchmark instead of the S&P 500.

Figure 5, panel A, visualizes a heatmap of average daily COVID-19 growth at the county level during our sample period. In panels B–D, we show the geographic distribution of selected REIT portfolios as of 2019Q4. These geographic patterns are depicted in terms of percentiles. Although retail and health care REITs display a similar geographic pattern, these two sectors performed quite differently, as shown in Figure 2. Although COVID-19 growth is highly correlated with overall CRE property holdings, substantial variations can be spotted across firms, making geographic asset allocation an important factor in explaining stock returns.

To gain further insight, we next plot correlations between abnormal returns and geographically weighted COVID-19 growth by the property type focus of the firm. Figure 6 revealsthat the correlations are mostly negative, suggesting a firm's exposure to COVID-19 is negatively correlated with its stock performance. Again, the correlation pattern across property types is different from the return pattern displayed in Figure 2. For example, health care and technology REITs display a positive correlation, even though abnormal returns for these property types are mostly negative. Overall, these correlations suggest that a focus on both property location and property type affect the sensitivity of a firm's returns to the COVID-19 pandemic.

2.3 Baseline results: Abnormal returns and geographically weighted COVID-19 growth

We begin our multivariate analysis by estimating the relation between the daily growth rate in reported COVID-19 cases and abnormal returns, *Ret*. Columns 1 to 3 of Table 2, panel A, report the 1-day “market model” results. Columns 4 to 6 report the results for the 2-day model. Finally, columns 7 to 9 report the 3-day results. Our main test variable is $GeoCOVID_{t\text{-}1}$.

As an initial baseline, we regress 1-day abnormal returns on *GeoCOVID*. Property type fixed effects are included in this pooled, cross-sectional regression with 11,210 observations. Standard errors are clustered at the firm level. In column 1, the estimated coefficient on *GeoCOVID* is negative and highly significant, indicating that an increase in a firm’s portfolio exposure to COVID-19 cases on day *t*-1 is associated with significantly lower abnormal returns on day *t*.

Next, we add *Days since outbreak* and *Days since outbreak*^{2} to our baseline specification. *GeoDensity* is included in the specification to control for variation in the population density of counties in which the REIT owns properties. Finally, we include our set of firm-level control variables defined above, as well as property type fixed effects. Column 2 of Table 2, panel A, reports the results from estimating this expanded regression. The estimated coefficient on *GeoCOVID* remains negative and highly significant. Economically, a one-standard-deviation increase in *GeoCOVID* on day *t*-1 is associated with a 0.24 percentage point decrease (=-0.026×0.094) in abnormal returns on day *t*. This economic magnitude is equivalent to more than 40% of the sample mean decrease in returns (-0.6 percentage points).

The estimated coefficient on *Days since outbreak* is negative and highly significant. This suggests that 1-day abnormal returns are significantly related to the duration of the firms’ exposure to COVID-19 cases. However, the estimated coefficient on *Days since outbreak*^{2} is positive and highly significant. This suggests investors understand the concept of “flattening the curve.” The estimated coefficient on *GeoDensity* is positive and highly significant, indicating that CRE portfolios in dense population areas perform better.

Among the firm-level control variables, the estimated coefficient on *Leverage* is negative and significant at the 1% level, suggesting investors expect firms that employ more financial leverage to underperform during the market downturn. Although a repeat of the credit crisis that occurred during the Global Financial Crisis is unlikely, highly leveraged firms are more likely to experience financial distress during the pandemic. The estimated coefficient on *LAG3MRET* is positive and highly significant. We also find weak evidence that *Ret* is negatively related to the extent to which a firm concentrates its portfolio by property type (*PropHHI*) and geography (*GeoHHI*), consistent with Hartzell, Sun, and Titman (2014).

Next, we estimate our 1-day abnormal return regression using firm fixed effects in place of our set of firm-level explanatory variables. Column 3 of panel A reports these results. The estimated coefficients on *GeoCOVID* remain negative and highly significant. These results suggest that the large and significant coefficient estimates we observe for *GeoCOVID* are not being driven by an omitted (time-invariant) firm characteristic.

The results from the estimation of our 2- and 3-day market models are reported in columns 4 to 6 and 7 to 9. Although this 2-day (3-day) return window decreases the number of independent return observations from 11,210 to 5,510 (3,800), the magnitude and significance of the estimated coefficients on *GeoCOVID* are larger in all specifications than in the corresponding 1-day regression model. A one-standard-deviation increase in *GeoCOVID* is associated with a 0.8 (0.9) percentage points decrease in abnormal returns based on 2-day (3-day), which represents 62% (49%) of the mean abnormal return. Moreover, the estimated coefficients on *Days since outbreak*, *GeoDensity*, *Leverage*, and *LAG3MRET* retain their significance. Overall, the widening of the abnormal return window has little effect on our coefficient estimates or conclusions about the impact of *GeoCOVID* on the pricing of CRE portfolios.

We redo the analysis using the total returns on the FTSE-NAREIT All Equity REITs index in place of the S&P 500. Panel B of Table 2 reports these results. The use of this alternative benchmark has little effect on the magnitude or statistical significance of the estimated coefficients on *GeoCOVID*, *Days since outbreak*, *Days since outbreak*^{2}, or *GeoDensity*. The lack of sensitivity of our results to the change in the market benchmark is at least partially attributable to the high correlation (0.94) of daily returns on the FTSE-NAREIT All Equity REITs index and the S&P 500 index during March and April of 2020.

2.4 Abnormal returns by property type

Given the strong negative relation between abnormal returns and geographically weighted COVID-19 growth we uncover, we next investigate the extent to which this relation varies across property types. As discussed earlier, different property sectors face different COVID-19 exposures and show a striking variation in terms of abnormal returns (Figure 4) and correlations between returns and COVID-19 growth (Figure 6). We therefore augment the regressions reported in Table 2 with interactions between *GeoCOVID* and our property type dummies. We suppress the intercept and saturate the model with all combinations of property type dummies and *GeoCOVID* interactions. The estimated coefficients on the interaction terms can be therefore interpreted as the property-type specific effects of *GeoCOVID*. As before, we include our full set of firm-level controls.

Table 3 displays the results of these tests. We continue to find a negative relation between *GeoCOVID* and abnormal returns for most of the property types. Retail and residential REITs experienced the largest negative abnormal returns, followed by office and hospitality REITs. For retail REITs, a one-standard-deviation increase in *GeoCOVID* is associated with a reduction in 1-day abnormal returns of 0.69 percentage points (-0.073 × 0.094), which represents 64% of the mean abnormal return for retail REITs (0.69% ÷ 1.08%). The cumulative 2- and 3-day effects for retail properties are even larger, ranging from 1.72 to 2.15 percentage points. For residential REITs, a one-standard-deviation increase in *GeoCOVID* corresponds to a return reduction of 0.62 to 1.57 percentage points, depending on the return window and risk adjustment methods. Given that the mean value of abnormal return for residential REITs is -0.45%, the impact of a one-standard-deviation increase in *GeoCOVID* corresponds to 138% to 349% of the mean. Hospitality REITs also experienced a large impact: a one-standard-deviation increase in *GeoCOVID* corresponds to a return reduction of 0.24 to 1.88 percentage points, representing 22% to 171% of the mean (-1.09 percentage points).

In contrast, the estimated *GeoCOVID* interactions for specialty REITs cannot be distinguished from zero in any of the six regression specifications, and the interaction term for industrial REITs is negative and significant in the 2-day return specifications, but otherwise indistinguishable from zero. However, CRE portfolios focused on health care and technology properties display positive (or zero) coefficients on the interaction terms. Using abnormal returns based on the S&P 500, a one-standard-deviation increase in *GeoCOVID* is associated with a 0.4 percentage point increase in 1-day returns in both sectors.

2.5 The importance of asset allocation

The results reported in Table 2 demonstrate that *GeoCOVID* predicts future abnormal returns. Given that prior studies using a nationwide growth rate of COVID-19 also find negative stock price responses (e.g., Ding et al. 2020; Alfaro et al. 2020), we investigate whether our geographically weighted COVID-19 growth measure is simply picking up the national trend. To investigate this issue, we rerun our baseline results using daily national COVID-19 growth rates (*USCOVID*) in place of *GeoCOVID*. Columns 1–3 of Table 4 report the results. Consistent with prior studies, this nationwide measure is negatively related to abnormal returns. Next, we include both *GeoCOVID* and *USCOVID* in our pooled, cross-sectional regressions. Columns 4–6 report the results. We find that, after controlling for the national trend, investors still react negatively to increases in our geographically weighted measure of COVID-19 growth. Comparing the economic significance of these two variables, we find that the effect of a one-standard-deviation increase in *GeoCOVID* on abnormal return is comparable to that of *USCOVID* in the 2-day window and slightly higher than that of *USCOVID* in the 1- and 3-day windows.[11]

Although our geographically weighted measure of COVID-19 growth provides increased explanatory power, the relative ability of national rates of growth in COVID-19 cases to explain the cross-section of abnormal returns is somewhat surprising. As discussed above, equity REITs must invest primarily in income-producing real estate; moreover, these real assets are relatively easier to locate. Our analysis clearly reveals that investors have been able to differentiate the future income-generating ability of the various property types (e.g., industrial vs. retail). We would also expect that marginal investors in REIT stocks would be able to accurately identify CRE portfolios heavily weighted toward areas hit hard in the early days of the pandemic and punish those stocks relatively more than others with portfolios less tilted toward COVID-19 "hot spots." However, it is widely known that the panic selling associated with sudden and substantial stock market downturns causes the return comovement of all stocks to increase. We

[11] The standard deviation of *USCOVID* and *GeoCOVID* is 0.63 and 0.94, respectively. Therefore, a one-standard-deviation increase in *USCOVID* is associated with a reduction in abnormal return of 0.12, 0.47, and 0.51 percentage points over 1-, 2-, and 3-day windows, respectively. Similarly, a one-standard-deviation increase in *GeoCOVID* is associated with a reduction in abnormal returns of 0.15, 0.41, and 0.53 percentage points over 1-, 2-, and 3-day windows, respectively.

conjecture that CRE portfolios less tilted toward COVID-19 hot spots will outperform during the eventual recovery of the broader stock market.[12]

Table 5 reports the results of robustness checks using only the hump-shaped period of *GeoCOVID* from February 27 to April 13, 2020 (as shown in Figure 3 and discussed in Section 1), as well as an extended period from January 21 to June 30, 2020. The coefficient estimates on *GeoCOVID* remain negative and highly significant in all model specifications. We conclude that our results are robust to alternative sample (sub)periods.

2.6 The impact of nonpharmaceutical interventions

An intense debate rages among researchers about the appropriate policy responses to contain and prevent the spread of COVID-19. The debate illuminates the obvious trade-off between instituting policies intended to slow the spread of the virus and foster economic activity. For example, Correia, Luck, and Verner (2020) find that NPIs mitigated the negative effects of the 1918 influenza pandemic on economic growth. In contrast, Lilley, Lilley, and Rinaldi (2020) suggest that NPIs have no effect on economic growth. An investigation of investors' responses to these NPIs helps us understand how changes in expectations about the efficacy of these policies affect firms differently. For example, if NPIs enhance investors' confidence, we expect that firms with more assets exposed to NPIs perform better in response to growth in COVID-19 cases.

NPIs have been passed at different administrative levels (e.g., city, county, and state). We therefore start with open-source data collected by Jataware, a machine learning company that automates the collection of news articles and detects whether an article mentions a COVID-19 NPI using natural language processing (NLP) classifiers (Bidirectional Encoder Representations from Transformers (BERT)).[13]

[12] We also examine the impact of population density, property type concentration, and geographic concentration. By creating a dummy variable for above-median values and interacting it with *GeoCOVID*, we find weak evidence for population densities, but not for concentration measures. Specifically, the coefficient estimate for the interaction term of population density and *GeoCOVID* is negative and significant at the 5% level or higher in all three return windows, suggesting the sensitivity to *GeoCOVID* increases and returns are more negatively affected if the firm allocates more assets to areas with high population density.

[13] The NPI data are available at https://github.com/jataware/covid-19-data.

As pointed out by Cui, Heal, and Kunreuther (2020), a policy enacted by one jurisdiction might influence other jurisdictions to adopt a similar policy. Therefore, we identify the NPI event date as the earliest date the NPI was announced at the city, county, or state level. This allows us to manually compare our event dates with those used in Dave et al. (2020) and Mervosh, Lu, and Swales (2020). We also verify our NPI event dates using Google searches (e.g., Google Trends).[14]

Figure 7 displays the market's reactions to two sets of NPI events: the announcement date of potential interventions (panel A) and the announcement date of shelter-in-place orders (SIPO), stay-at-home orders, or mandatory school and business closures (panel B). These two sets of events are based on the earliest (announcement) date in one of the three states that contain the largest property holdings of the firm.[15] We use announcements of state of emergency declarations (SOEs) as the date of potential policy interventions. In most states, SOE preceded actual interventions. For example, the average gap between a SOE announcement and the announcement of a SIPO at the state level is about 10 days. Thus, investors likely anticipated SIPOs when SOEs were announced and, in fact, evidence suggests declines in local commuting begin after SOE announcements (Couture et al., 2020). SIPOs and stay-at-home orders require residents to remain home for all but essential activities (e.g., purchasing food or medicine, caring for others).[16]

An inspection of Figure 7, panel A, reveals that, on average, returns were negatively affected by SOE announcements. In addition, the pattern of cumulative average buy-and-hold abnormal returns (CAARs) by property type is consistent with our previous finding that the technology, self-storage, and industrial sectors have been the least affected by the pandemic. In contrast, the retail and hospitality sectors have experienced the largest stock price declines. A comparison of panel A to panel B suggests that CAARs started to decline before SIPO announcements. This validates our conjecture that, after the announcements of SOEs, investors anticipated NPIs, such as SIPOs.

[14] See, for example, Mervosh, Lu, and Swales (2020).
[15] We also investigate alternative definitions of announcement dates most relevant for each firm, including the earliest announcement date in any state in which a firm owns property and the date of the announcement in the firm's headquarters state. These results vary little from those displayed in Figure 7 and are available on request.
[16] Many states announced stay-at-home or safe-at-home orders that affect business activity in ways similar to SIPOs. We refer to all of these orders as SIPOs.

We show cumulative abnormal returns (CARs) by property type, based 3- and 11-day windows, in columns 1–4, Table A3 in the appendix. The average 11-day CAR for SOE announcements is -9% for all property sectors in our sample and -15% (-11%) for the hospitality (retail) sector. The corresponding CAR for technology sectors is 3%. The average CARs associated with SIPOs are even more negative.

Next, we investigate whether the sensitivity of returns to *GeoCOVID* is reduced after policy responses to the crisis are announced. We construct each firm's exposure to NPIs at the asset level.[17] *GeoNPI* captures the percentage share of a firm's portfolio (in total adjusted cost) exposed to county-level NPIs. As some NPIs was announced at city level, we manually match NPIs implemented by cities to the corresponding counties. By construction, *GeoNPI* equals zero for all firms before March 5, 2020, the date when the first NPI went into effect in our sample. A firm's *GeoNPI* remains zero until a property in its portfolio is exposed to a NPI. The mean value of *GeoNPI* increases rapidly in March from 0% to 66%. By April 15, roughly 67% of the value of an average firm portfolio in our sample had been exposed to NPIs. For ease of interpretation, we also replace *GeoNPI* with a dummy variable, *Post-NPI*, which equals one when *GeoNPI* is greater than zero.

Results reported in columns 1–3 of Table 6 indicate that returns are higher after a firm is exposed to one or more NPIs. Moreover, the estimated coefficients on the interactions between *GeoCOVID* and *Post-NPI* are positive and statistically significant, indicating that returns respond less negatively to *GeoCOVID* after interventions. For example, the negative effect of a one-standard-deviation increase in *GeoCOVID* on 1-day abnormal returns is reduced by 0.63 percentage points (=0.067×0.094) in the post-NPI period. We find similar results when *GeoCOVID* is interacted with our continuous measure of *GeoNPI*. The stock price effects of NPIs are material. The average stock price reaction to *GeoCOVID* equals -0.026 (column 2 of Table 2). Compared to a firm with no exposure to NPIs, a firm with a 10% NPI exposure experiences a 1-day decline in stock returns that is 57% less [(-0.026+0.15×0.1)/(-0.026)-1]. The corresponding reductions in declines for 2- and 3-day stock return are 49% and 63%, respectively. These

[17] We thank an anonymous referee for this suggestion.

results strongly suggest investors respond less negatively to COVID-19 growth rates when public policies intended to reduce the spread of the virus are announced.

2.7 The impact of reopenings

We extend our sample through June 30, 2020, and examine the effects of lifting NPIs. Similar to the debate over NPIs, proponents of "reopening" argue that the cost of NPIs, such as reduced consumption and rising unemployment, are substantial. However, reopening opponents express serious concerns about a second wave of infections.

Unlike compulsory lockdowns, the decision to reopen a business is, ultimately, voluntary. Firms and businesses may choose not to open, or fully open, even after restrictions are lifted for several reasons. First, concerns about health risks for employees and customers may influence a firm's decision-making process about how or when to open. Consistent with this, Dave et al. (2020) find no evidence that the repeal of the SIPO affected social distancing. Goolsbee and Syverson (2020) find repealing SIPOs may not be an effective tool for restarting growth when people still fear the spread of the virus. Second, a firm may delay reopening if it expects customer demand will not return immediately (Balla-Elliott et al. 2020). Third, the supply chain disruptions created by the pandemic may prevent firms from immediately reopening (Papanikolaou and Schmidt 2020). Finally, state and local authorities typically announced reopening plans that included multiple phases of uncertain duration. Perhaps because of these complications and uncertainties, most studies (e.g., Chetty et al. 2020; Bartik et al. 2020; Villas-Boas et al. 2020) find that reopening policies have little immediate impact on local economic activity.

Similar to our analysis of NPIs, we first examine stock price reactions to the earliest reopening announcement in any of the three states in which a firm's portfolio is most heavily invested. We then calculate daily abnormal returns for each firm. Figure 8 plots averages of these returns by property type. We find no discernable pattern of market reactions to reopening announcements. CARs by property type over 3- and 11-day event windows are presented in columns 5 and 6 of Table A3 in the appendix. Mostly positive stock price responses occur from day -1 to day +1. However, from day -5 to day +5 we find no significant response overall, with some slight variation by property type. For example, the retail sector experienced large positive CARs during both 3- and 11-day windows. This is expected as the brick-and-mortar retailers were severely affected by lockdowns.

To analyze the impact of reopenings, we construct *GeoReopen* to capture the percentage share of a REIT's property portfolio exposed to a reopening plan. Similar to *GeoNPI*, a firm's *GeoReopen* takes on a value of zero until a property in its portfolio is exposed to a reopening. *GeoReopen* then increases with the proportion of a firm's portfolio exposed to state reopenings. Because the reopening of a local economy is a gradual process in which certain types of businesses in certain localities (e.g., essential industries) opened before others, it would be ideal to examine the effects phase by phase. However, there has been substantial variation across states in the precise form of reopening plans. In most states, governors issued guidance and orders as to which industries and places of congregation could reopen and under what conditions (Harris 2020). In addition, cities and counties have often had discretion over whether, and how, to reopen.[18]

Following Chetty et al. (2020), Nguyen et al. (2020), and Raifman et al. (2020), we define reopening as the date the state government allowed the first set of businesses to reopen. Similar results are obtained when we use the date a state lifted or eased stay-at-home orders. *GeoReopen* is equal to zero for all REITs before the first state (i.e., South Carolina) adopted a reopening policy on April 20. The mean of *GeoReOpen* increases to over 90% by May 18.

In the results presented in Table 7, we again include *Post-Reopen* in the first specification and *GeoReopen* in the second, along with their interactions with *GeoCOVID*. We conduct our analysis using both the extended sample period (April 15 to June 30) and the full sample (January 21 to June 30). Over the full sample, the estimated coefficient on the interaction of *GeoCOVID* and *Post-Reopen* cannot be distinguished from zero. Similarly, after April 15th, the estimated coefficient on the interaction of *GeoCOVID* and *GeoReopen* is not significant (column 2). Because this lack of significance could be due to reduced COVID-19 growth after reopenings (see Figure 3), we investigate whether the effects of reopenings differ for firms with larger portfolio allocations in more heavily affected areas or for firms with

[18] For example, in Washington, "each county can apply to State Secretary of Health John Wiesman for advancement through the different phases on a case-by-case basis, and Wiesman can modify the Safe Start plan to address the needs of different counties" (Wafai 2020).

greater NPI exposure prior to reopenings. In the results reported in column 3, we include *Severity (Apr 15)*, which is the percentage of each county's population that has tested positive, weighted by the percentage of each REIT's portfolio located in the county. We also include the firm's exposure to NPIs as of April 15th (*GeoNPI* (*Apr 15*)). The estimated coefficients on both *Severity* (*Apr 15*) and *GeoNPI* (*Apr 15*), as well as their interactions with *GeoReopen*, are not significant.

Finally, because reopenings are intended to nullify NPIs, we construct a composite measure of policy interventions, *GeoNetExp*, defined as the proportion of properties in each firm's portfolio exposed to NPIs, minus the proportion exposed to reopenings. Both proportions are measured at the state level.[19] The time-series trend of *GeoNetExp* based on a simple average across firms is shown in Figure 3 (gray dashed line). The inverse U shape corresponds to an increase in average NPI exposures until April 3, followed by a decline after April 20 as reopenings began to occur. Results in column 4 using data prior to April 15 are consistent those reported in Table 6: the estimated coefficient on *GeoNetExp* is positive and significant and the interaction between *GeoNetExp* and *GeoCOVID* is positive. However, after April 15 the estimated coefficient on *GeoNetExp* and its interaction with *GeoCOVID* are not significant (column 5). Lastly, results using a sample running from January 21 to June 30, which are reported in column 6, agree with pre-reopening results. Overall, these results suggest policy interventions that mandate social distancing helped mitigate stock price declines during this public health crisis. However, we find no evidence that reopenings boosted the expected performance of CRE markets.

3. Conclusion and Discussion

How does the shock of COVID-19 transmit to the equity markets from a firm's underlying assets? To answer this question, we employ asset-level data from the commercial real estate (CRE) market and construct a novel measure of geographically weighted exposure to COVID-19 growth (*GeoCOVID*) using a sample of equity REITs during the early stages of the pandemic from January 21, 2020, to April 15, 2020.

[19] *GeoNetExp* does not equal the difference between *GeoNPI* and *GeoReopen*, because the former is constructed at the county level, whereas the latter is measured at the state level.

Using different benchmarks for risk adjustment, different return windows, and different model specifications, we find a consistent negative relationship between abnormal returns and *GeoCOVID*, after controlling for the national growth rate of COVID-19 cases, a firms' property type and geographic concentrations, days since the outbreak, population density, and a comprehensive set of firm characteristics. In addition, firms focused on retail and residential properties react more negatively among all sectors. In contrast, the performance of the health care and technology sectors correlates positively with *GeoCOVID*.

Do nonpharmaceutical interventions (NPIs) and subsequent reopenings affect the pandemic-induced drop in stock prices? Using a firm's time-varying asset-level exposure to NPIs and reopenings, we find that a growing exposure to NPIs reduces the negative return impact of *GeoCOVID*. This indicates investors expected the effectiveness of these policies in slowing the spread of the virus to outweigh their expected economic cost. However, our findings suggest that lifting policies that closed business and mandated social distancing had no impact on stock performance.

Taken together, our results highlight the importance of asset-level attributes in explaining investors' reactions to the pandemic. Although our sample period is relatively short, movements in stock returns contain forward-looking information, and stock prices are based on prospective future earnings. Whether the shock of COVID-19 on CRE prices remains significant in the long run crucially depends on the resilience of the overall economy and, perhaps more importantly, how perceptions of risk change after the pandemic. For example, a few firms (e.g., Morgan Stanley, JPMorgan Chase, and Nielsen) currently occupying large amounts of office space in Manhattan have indicated that they expect to occupy considerably less space once the pandemic passes (Haag 2020). Dingel and Neiman (2020) conclude that 37% of jobs in the United States can be performed entirely at home. Permanent changes in work and lifestyle should differentially affect the rent generating ability and perceived risk of different types of business activities, as suggested by our finding of substantial variation across property types. These differential effects are certain to be observed across industry sectors outside of the CRE space.

Finally, the negative economic effects of social distancing are most severe among businesses that reply heavily on face-to-face communication or close physical proximity. As pointed out by Koren and Peto (2020), the agglomeration premium associated with conducting business in more densely populated areas may decline when firms find it less attractive to locate in high-density areas in a post-pandemic spatial equilibrium. This would suggest a reduced rent premium in highly desirable (prepandemic) urban areas, as suggested by our finding of negative return responses to increases in the growth of COVID-19 cases.

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Figure 1. Total return indexes: S&P 500, Russell 2000, FTSE-NAREIT

This figure depicts monthly indexes for the S&P 500, Russell 2000, and the FTSE-NAREIT All Equity REITs (FNER) indexes from 2015 through April 23, 2020. Each index is set equal to 100 at the 2014 year-end.

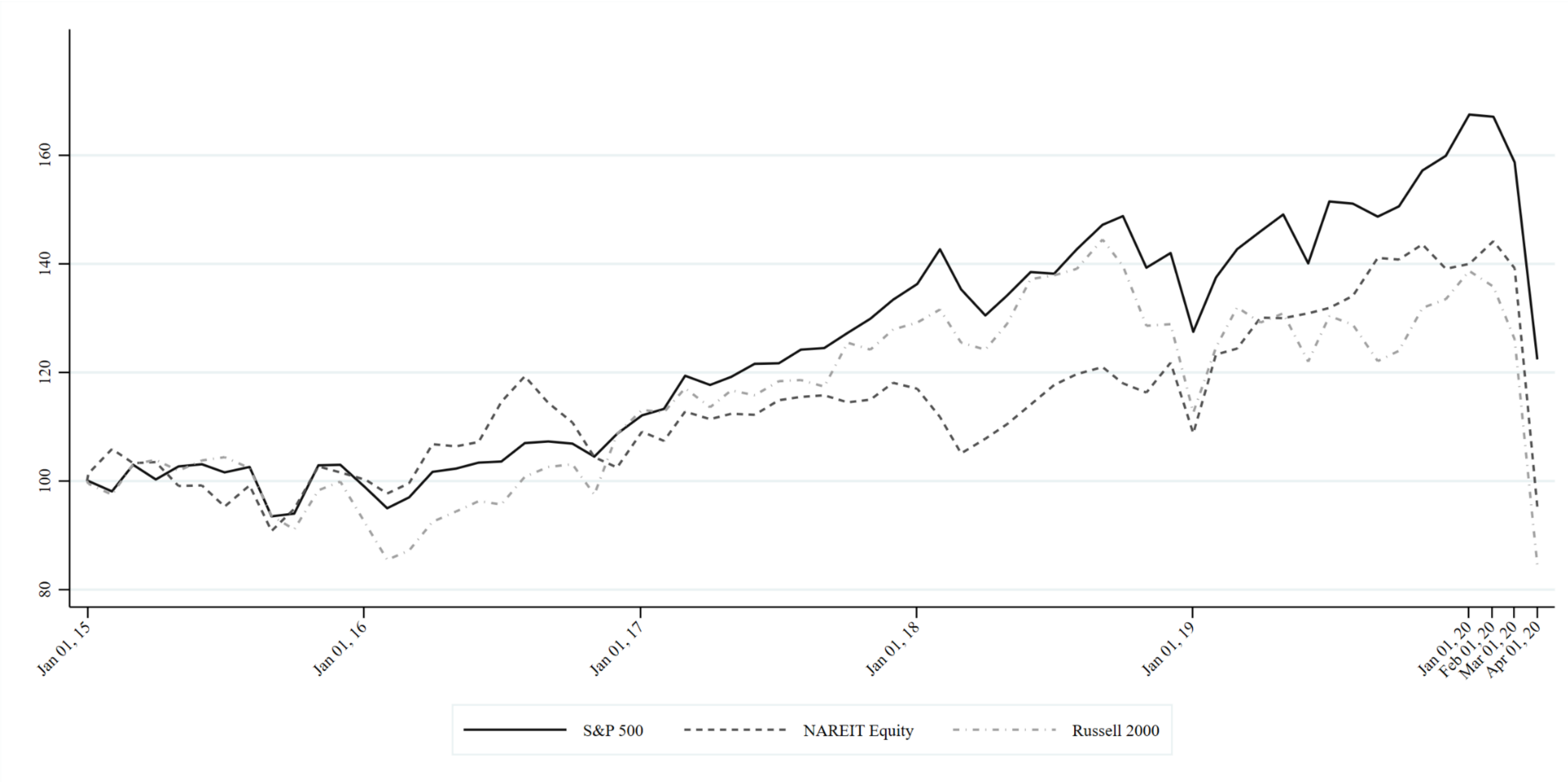


Figure 2. Total return indexes: REIT property types

This figure displays monthly return indexes for the FTSE-NAREIT All Equity REITs indexes for industrial, residential, office, health care, retail, and hospitality REITs from 2015 through April 23, 2020. Each index is set equal to 100 at the 2014 year-end.

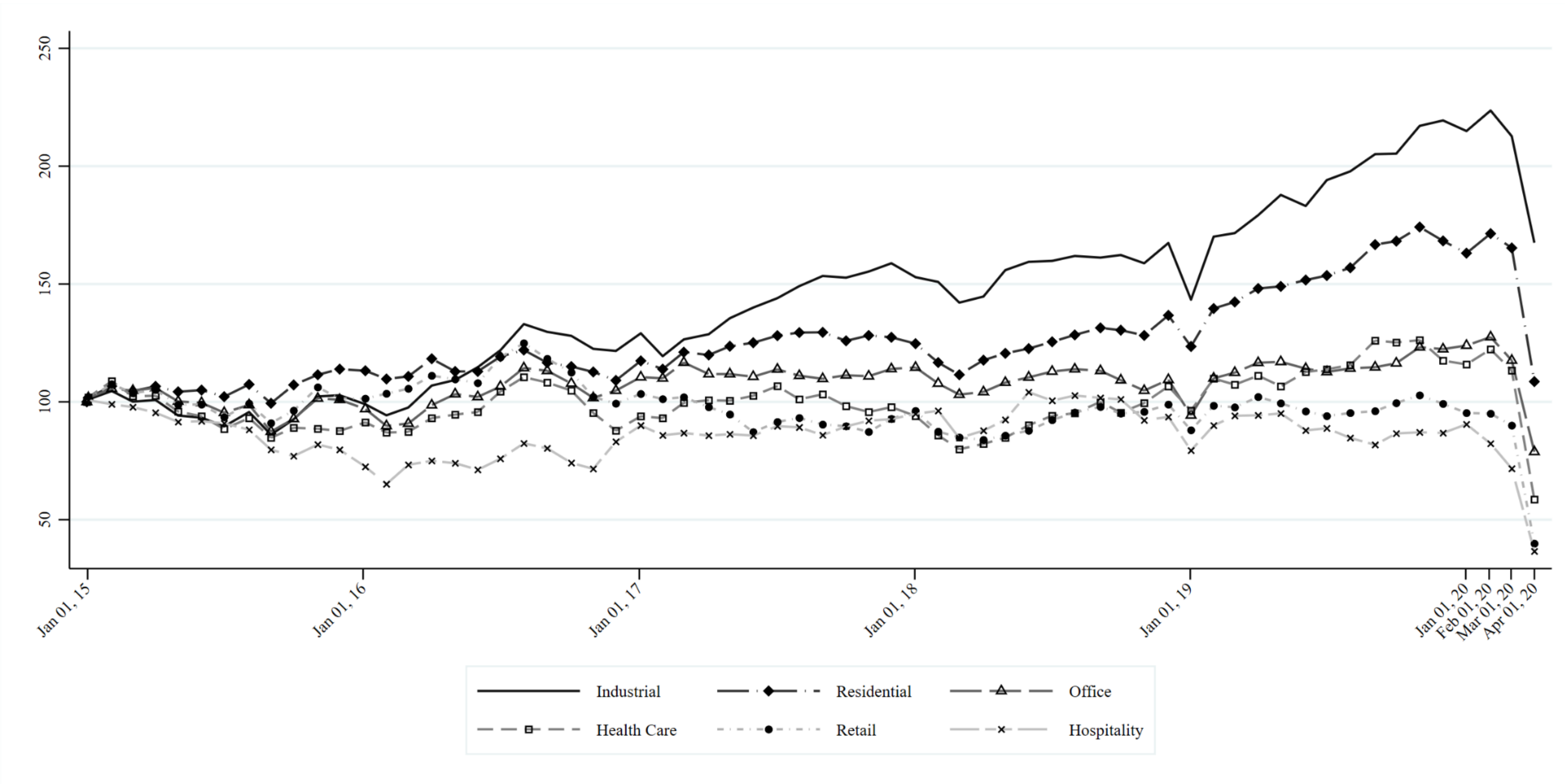


Figure 3. Trends in geographically weighted COVID-19 growth and nonpharmaceutical interventions

This figure shows the means of daily geographically weighted COVID-19 growth (*GeoCOVID*) and net geographic exposure to nonpharmaceutical interventions (*GeoNetExp*) for the period from January 21, 2020, through June 30, 2020. The horizontal axis is the number of *trading* days since the first outbreak in the United States on January 21, 2020. *GeoCOVID* is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of the firm's portfolio allocated to each county at the end of 2019Q4. *GeoNetExp* is the daily proportion of a firm's portfolio exposed to NPIs net of its exposure to reopenings.

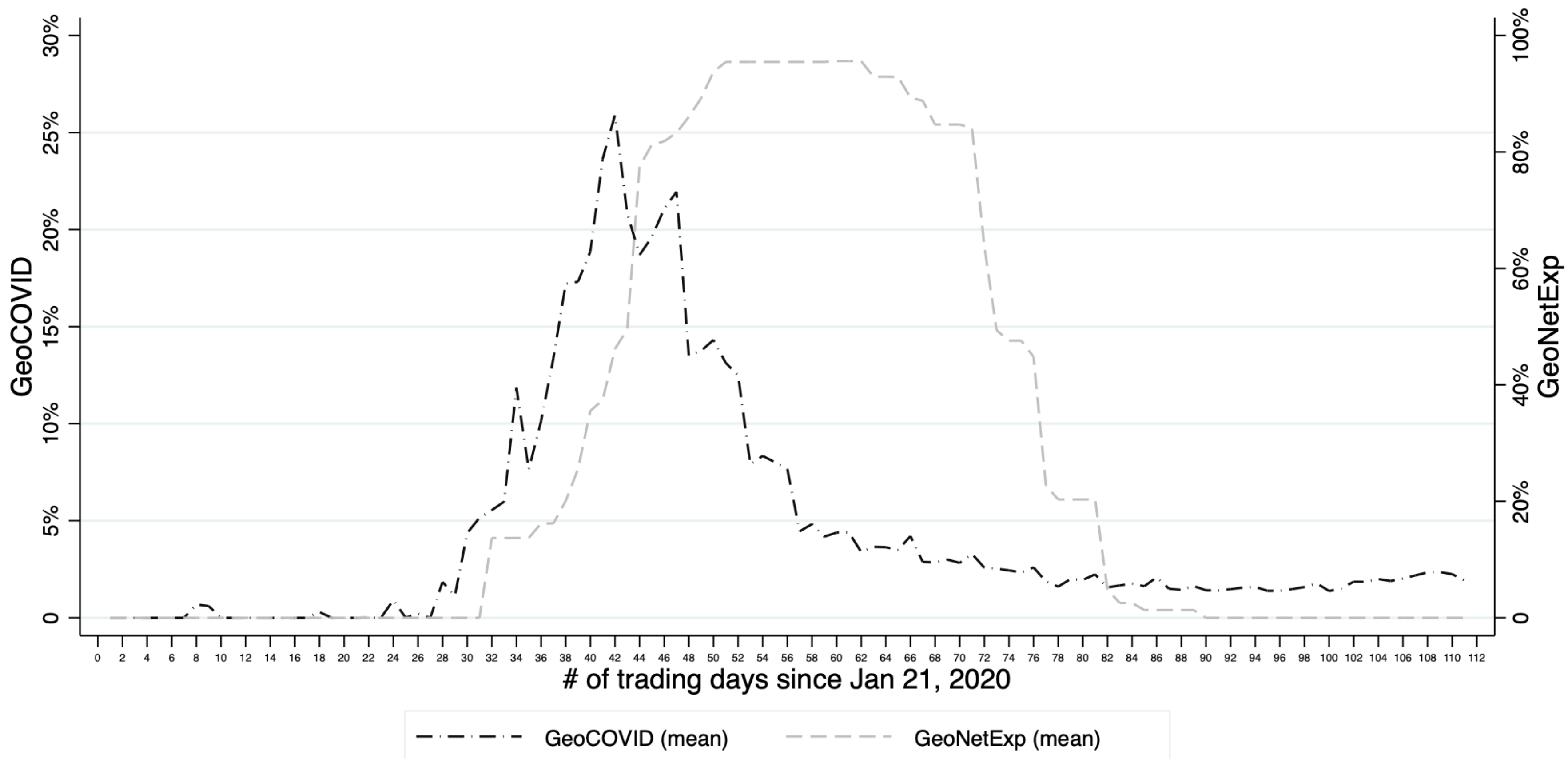
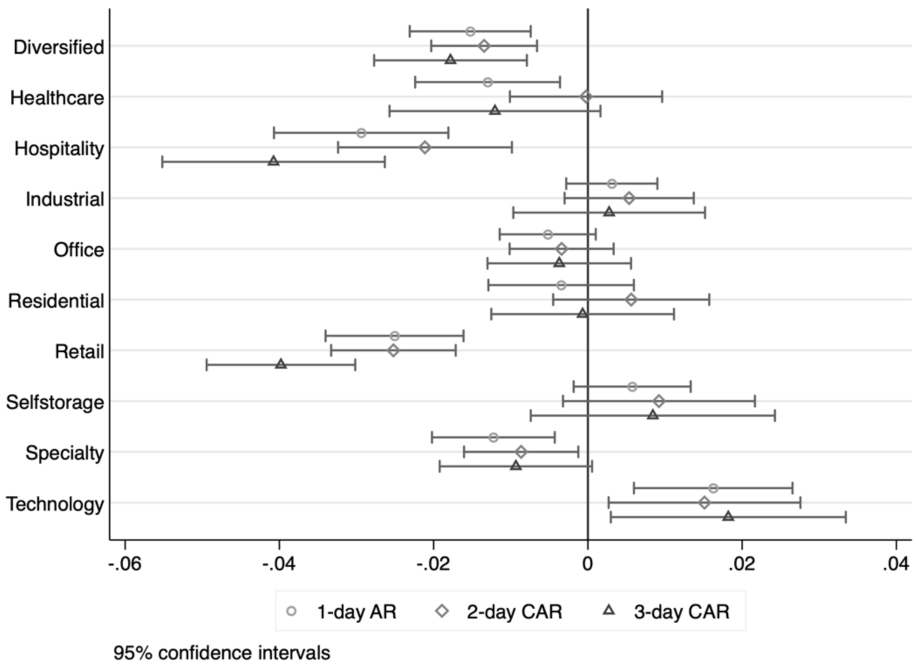


Figure 4. Abnormal return by property types

This figure shows the means and 95% confidence intervals of abnormal returns across property types for the period from January 21, 2020, through April 15, 2020. *1-day AR* are calculated as $R_{i,d} - \beta_i M_d$. β_i is estimated from the market model for firm i from the beginning of 2019 to January 20, 2020. $R_{i,d}$ denotes stock returns for firm i on day d. M_d denotes daily returns on either the S&P 500 index (panel A) or the FTSE-NAREIT All Equity REITs index (panel B). *2-day (3-day) CARs* are the nonoverlapping cumulative abnormal returns from day d (d-1) to day d+1. See Tables A1 and A2 in the appendix for variable descriptions and descriptions of property types, respectively.

(A) Abnormal returns based on the S&P 500 index



(B) Abnormal returns based on NAREIT Equity index

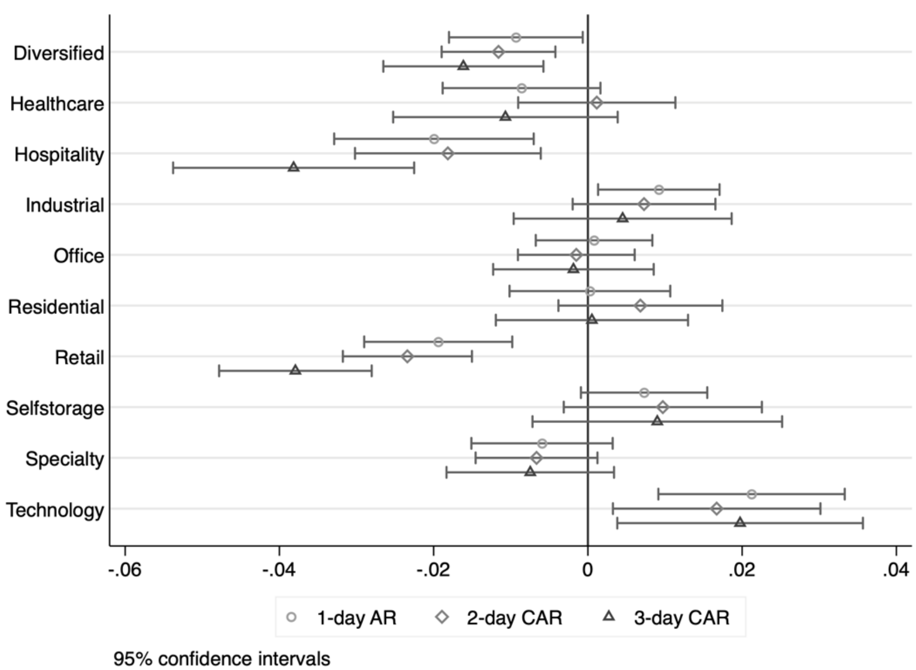
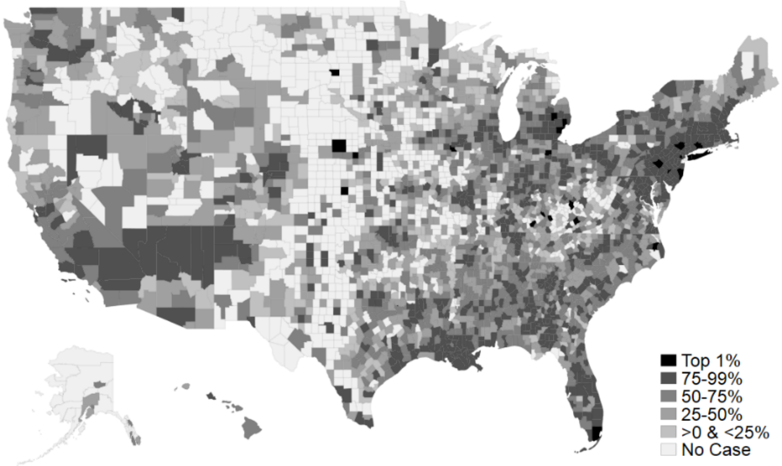


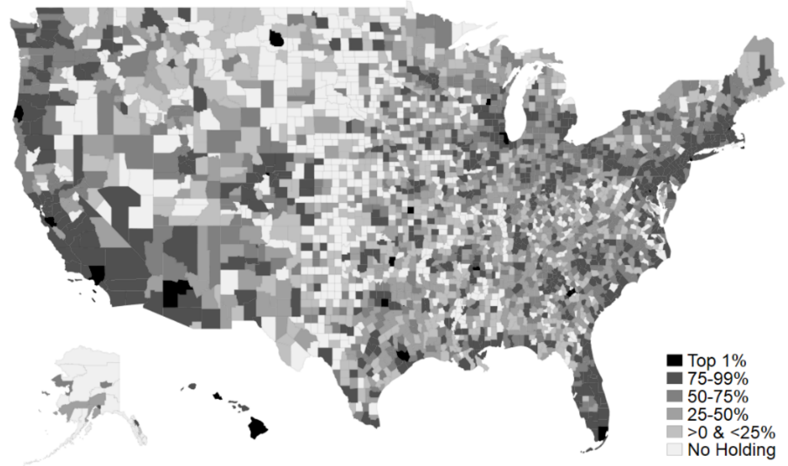
Figure 5. COVID-19 growth and property holdings

Panel A shows geographic patterns of the average daily growth rates of COVID-19 confirmed cases in the U.S. counties for the period from January 21, 2020, through April 15, 2020. Panels B–D show the geographic distribution of CRE portfolios as of 2019Q4. Geographic patterns are shown in terms of percentiles. Panel B is based on all property types. Panel C (D) is based on retail (health care). See Tables A1 and A2 in the appendix for variable descriptions and descriptions of property types, respectively.

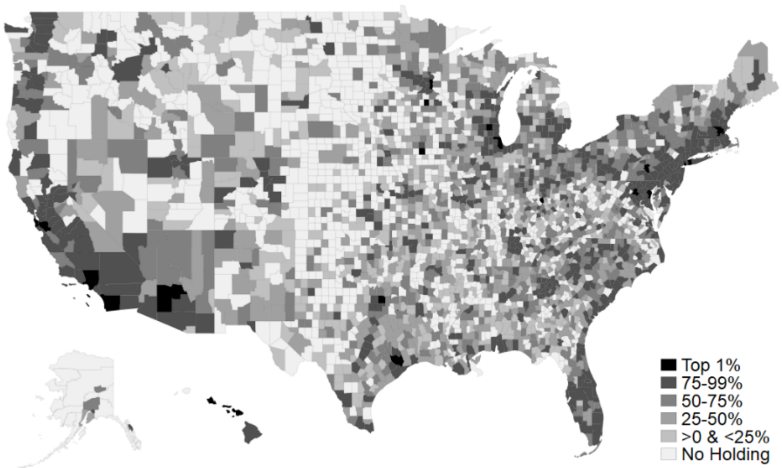
(A) COVID-19 growth



(B) Average property holdings



(C) Average property holdings (retail)



(D) Average property holdings (health care)

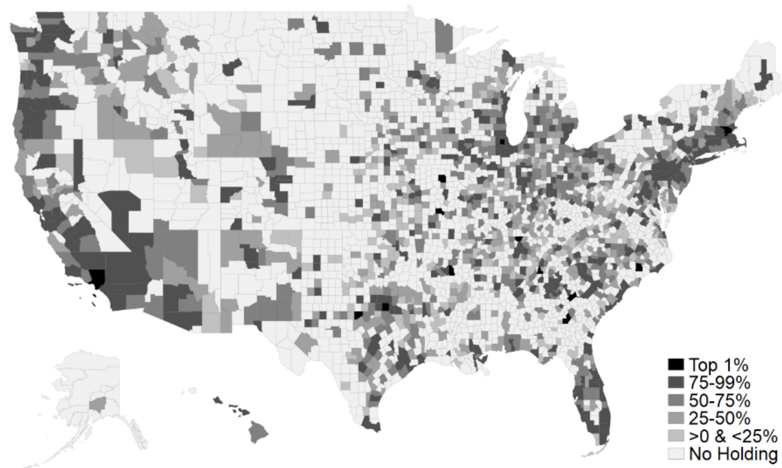


Figure 6. Correlations between abnormal returns and COVID-19 growth by property type

This figure presents the correlations between abnormal returns across property types based on the S&P 500 index and the growth rate of COVID-19 cases. See Tables A1 and A2 in the appendix for variable descriptions and descriptions of property types, respectively.

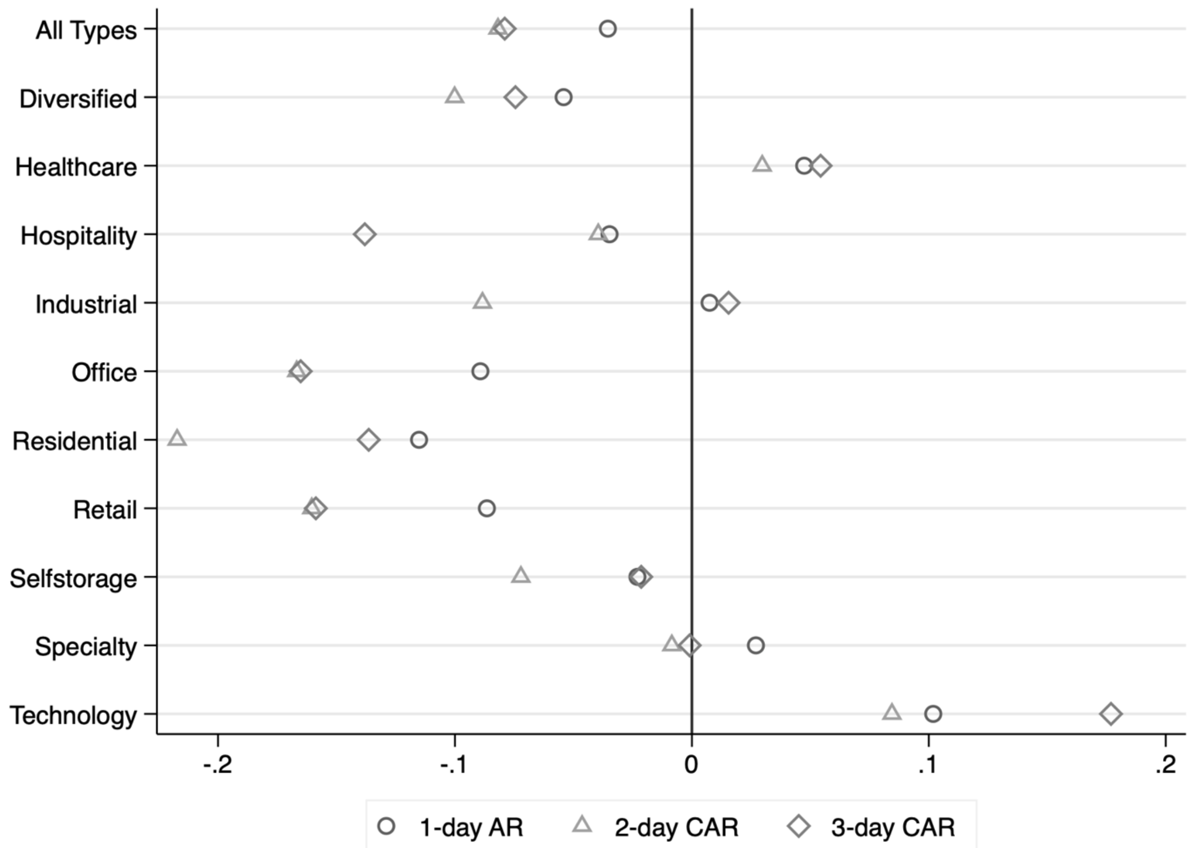
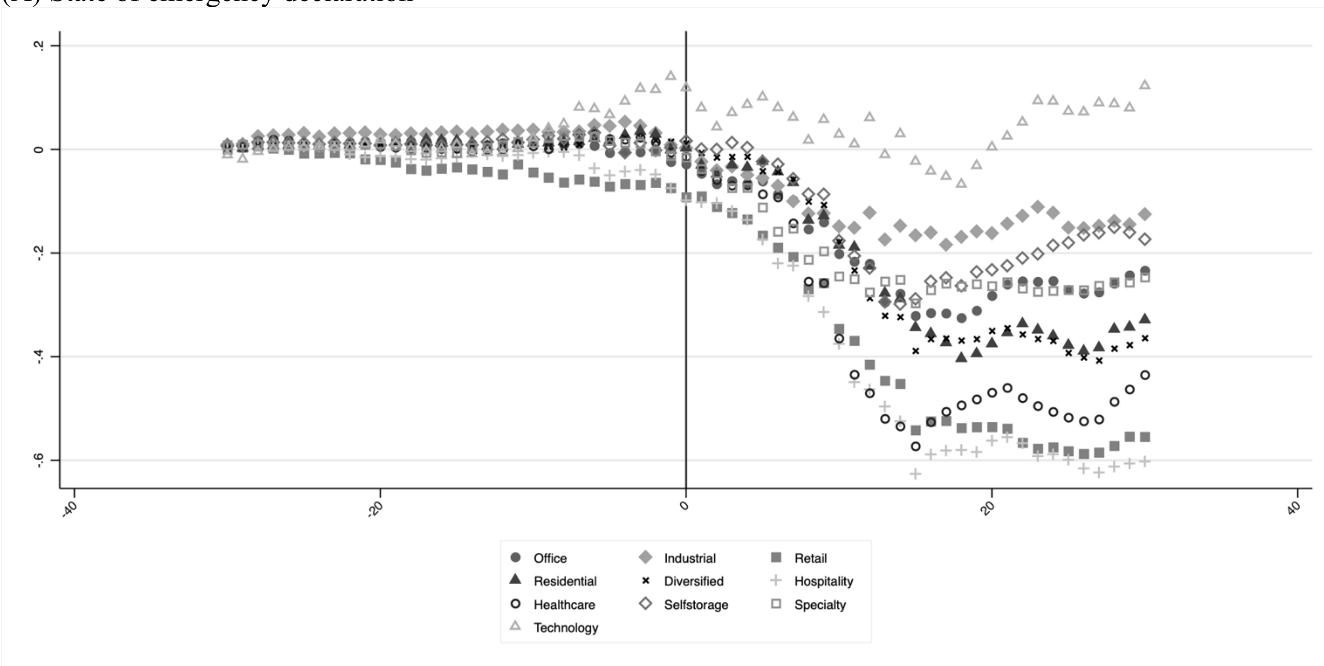


Figure 7. Market reactions to nonpharmaceutical interventions

This figure depicts the cumulative average abnormal returns (CAARs) across property types around the announcement of nonpharmaceutical interventions (vertical line at day 0). In panel A, the event date for a firm is defined as the earliest date of state of emergency declaration in any jurisdiction (city, county, or state) in the top-three states ranked by the size of its property holdings. In panel B, the event date is the earliest announcement date of shelter-in-place orders (SIPO), stay-at-home orders, or mandatory school and business closures in any jurisdiction (city, county, or state) in the top-three states ranked by the size of its property holdings. Abnormal returns (AR) for each firm are estimated using daily excess returns and a market model. The estimation window includes 250 days of stock returns and ends 50 days before the event window. The event window is from day -30 to day +30 relative to day 0. Next, the abnormal returns are averaged across firms that focus on the same property type to obtain average abnormal returns (AARs) on day t. Finally, the AARs are chain-linked over T days in the event window to obtain the buy-and-hold cumulative average abnormal return (CAAR). See Table A2 in the appendix for descriptions of property types.

(A) State of emergency declaration



(B) Shelter-in-place orders

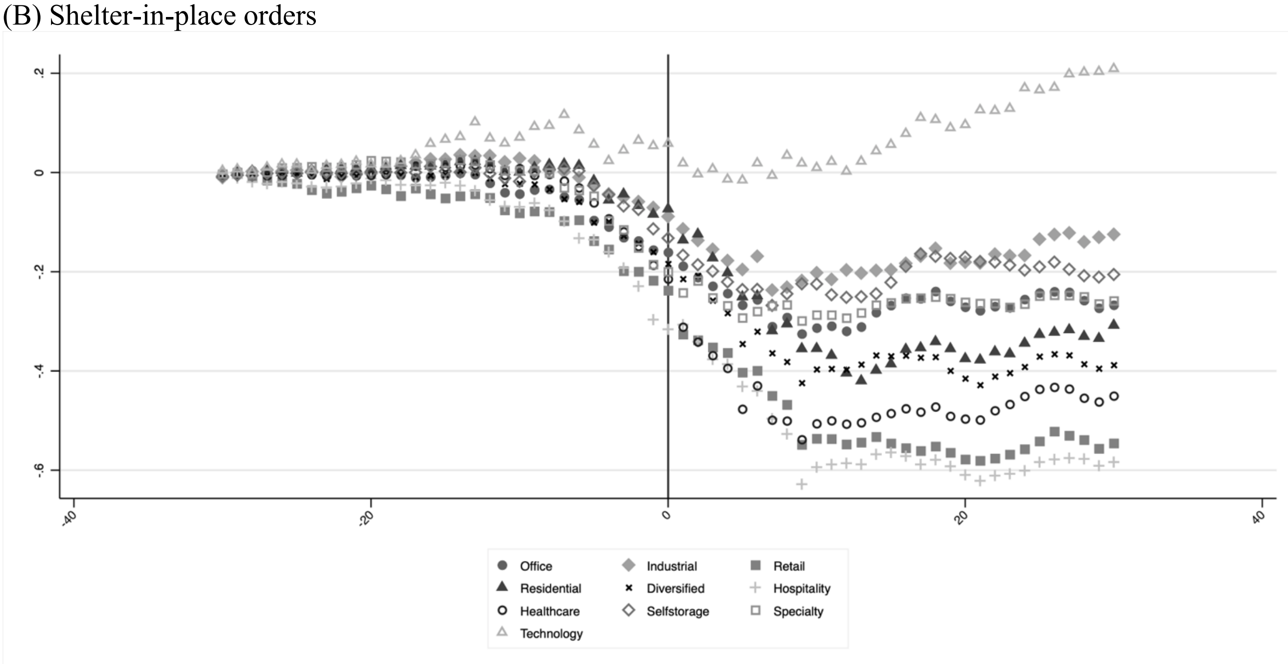


Figure 8. Market reactions to reopenings

This figure depicts the cumulative average abnormal returns (CAARs) across property types around the announcement of state reopenings (vertical line at day 0). The event date for a firm is defined as the earliest reopening announcement date in any of the top-three states ranked by the size of its property holdings. Abnormal returns (AR) for each firm are estimated using daily excess returns and a market model. The estimation window includes 250 days of stock returns and ends 50 days before the event window. The event window is from day -30 to day +30 relative to day 0. The abnormal returns are averaged across firms that focus on the same property type to obtain average abnormal returns (AARs) on day *t*. The AARs are chain-linked over *T* days in the event window to obtain the buy-and-hold cumulative average abnormal return (CAAR). See Table A2 in the appendix for descriptions of property types.

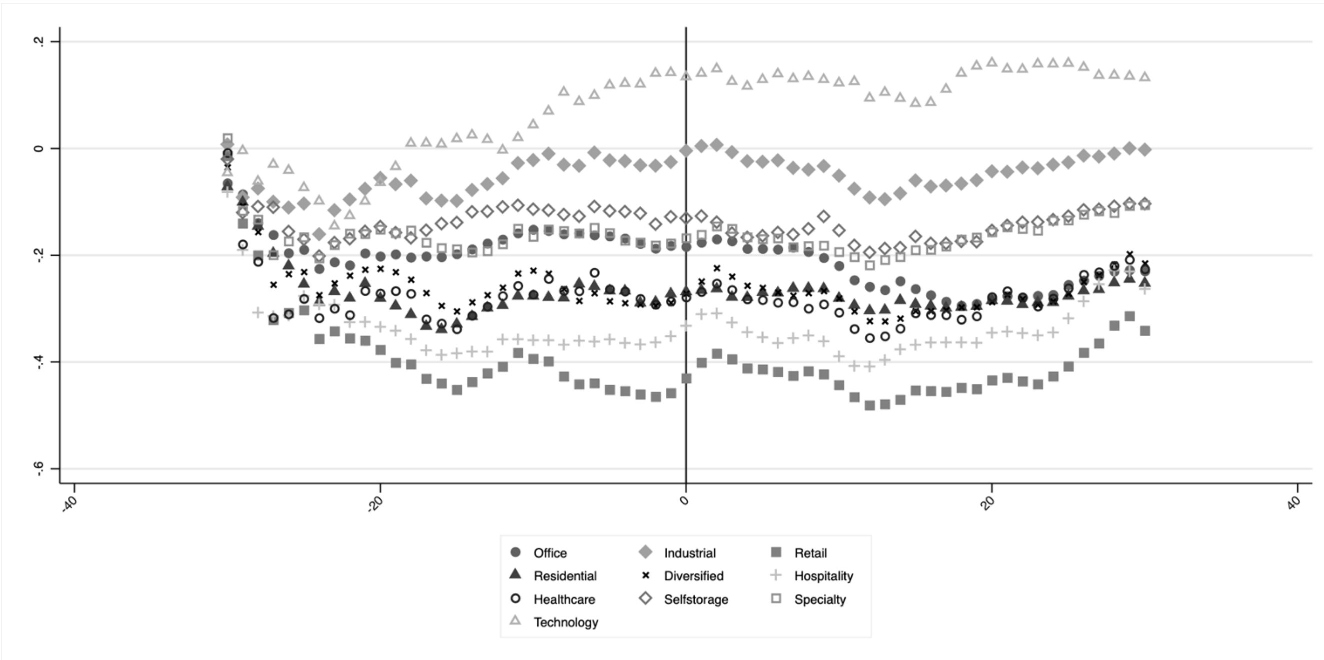


Table 1. Summary statistics

This table shows summary statistics (number of observations, mean, standard deviation (SD), and 25th, 50th, and 75th percentiles) for a sample of 11,210 firm-day observations from the period January 21, 2020, through April 15, 2020. Statistics for *GeoReopen* and *GeoNetExp* are estimated based on an extended sample that runs through June 30, 2020. Table A1 in the appendix defines all variables and lists all data sources.

Variable	N	Mean	SD	p25	p50	p75
Abnormal returns (*based on S&P 500*)						
1-day AR	11,210	-0.006	0.061	-0.022	-0.001	0.013
2-day CAR	5,510	-0.013	0.079	-0.039	-0.003	0.016
3-day CAR	3,800	-0.019	0.102	-0.054	-0.005	0.019
Abnormal returns (*based on NAREIT*)						
1-day AR	11,210	-0.008	0.070	-0.026	-0.001	0.016
2-day CAR	5,510	-0.015	0.087	-0.046	-0.004	0.017
3-day CAR	3,800	-0.022	0.112	-0.061	-0.006	0.020
COVID-19 exposure variables						
GeoCOVID	11,210	0.066	0.094	0	0.005	0.117
Days since outbreak	11,210	33	29	11	33	56
GeoNPI	11,210	0.236	0.320	0	0	0.540
GeoReopen	21,404	0.370	0.464	0	0	1
GeoNetExp	21,404	0.289	0.408	0	0	0.734
Control variables						
GeoDensity	11,210	4887	9373	1180	1793	4165
PropHHI	11,210	0.788	0.280	0.583	0.949	0.999
GeoHHI	11,210	0.119	0.175	0.020	0.049	0.126
Leverage	11,210	0.490	0.159	0.403	0.474	0.575
Cash	11,210	0.037	0.083	0.005	0.013	0.036
Size	11,210	6641	10129	1664	3925	8297
Tobin's q	11,210	1.498	0.584	1.147	1.372	1.690
LAG3MRET	11,210	0.034	0.061	0.001	0.040	0.066
InstOwn	11,210	0.811	0.237	0.688	0.880	0.979
Investment	11,210	0.092	0.331	-0.032	0.028	0.171
EBITDA/AT	11,210	0.021	0.012	0.015	0.020	0.025
Office	11,210	0.111	0.314	0	0	0
Industrial	11,210	0.068	0.252	0	0	0
Retail	11,210	0.189	0.392	0	0	0
Residential	11,210	0.074	0.261	0	0	0
Diversified	11,210	0.147	0.354	0	0	0
Hospitality	11,210	0.142	0.349	0	0	0
Health care	11,210	0.105	0.307	0	0	0
Self-storage	11,210	0.037	0.188	0	0	0
Specialty	11,210	0.095	0.293	0	0	0
Technology	11,210	0.032	0.175	0	0	0

Table 2. Baseline results: Abnormal returns and geographically weighted COVID-19 growth

This table shows regression results on the relationship between abnormal returns and the growth rate of geographically weighted COVID-19 cases. The dependent variable *Ret* is the daily *AR*s in columns 1–3, the 2-day *CAR*s in columns 4–6, and the 3-day *CAR*s in columns 7–9. *GeoCOVID* is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of a firm's portfolio allocated to each county at the end of 2019Q4. Panel A (B) shows the results using abnormal returns based on the S&P 500 index (NAREIT Equity index) as the dependent variable. The numbers in parentheses are *t*-statistics. Standard errors are clustered at firm level. Table A1 in the appendix defines all variables and lists all data sources. *$p < .1$; **$p < .05$; ***$p < .01$.

A. Abnormal returns based on the S&P 500

	(1) *Ret (1-day)*	(2) *Ret (1-day)*	(3) *Ret (1-day)*	(4) *Ret (2-day)*	(5) *Ret (2-day)*	(6) *Ret (2-day)*	(7) *Ret (3-day)*	(8) *Ret (3-day)*	(9) *Ret (3-day)*
GeoCOVID	-0.024***	-0.026***	-0.022***	-0.070***	-0.086***	-0.080***	-0.089***	-0.099***	-0.088***
	(-4.70)	(-3.82)	(-3.01)	(-6.72)	(-5.98)	(-5.13)	(-5.91)	(-4.72)	(-3.89)
Days since outbreak		-0.000***	-0.000***		-0.000***	-0.000***		-0.001***	-0.001***
		(-7.01)	(-6.72)		(-6.39)	(-5.89)		(-6.53)	(-6.23)
Days since outbreak^2		0.000***	0.000***		0.000***	0.000***		0.000***	0.000***
		(8.73)	(8.24)		(9.00)	(8.42)		(8.51)	(8.06)
ln(GeoDensity)		0.001***			0.001***			0.002***	
		(5.17)			(6.08)			(5.73)	
PropHHI		-0.001*			-0.003**			-0.005**	
		(-1.97)			(-2.16)			(-2.22)	
GeoHHI		-0.002*			-0.003			-0.006*	
		(-1.97)			(-1.28)			(-1.86)	
Leverage		-0.003***			-0.006***			-0.009***	
		(-2.82)			(-2.99)			(-2.93)	
Cash		-0.003*			-0.006			-0.011*	
		(-1.66)			(-1.38)			(-1.74)	
ln(Size)		0.000			0.000			0.000	
		(1.42)			(1.41)			(0.92)	
Tobin's q		0.001*			0.001**			0.002**	
		(1.79)			(1.98)			(2.18)	
LAG3MRET		0.000***			0.000***			0.001***	
		(20.05)			(20.76)			(19.42)	
InstOwn		0.001			0.001			0.003	
		(0.65)			(0.57)			(1.10)	
Investment		0.000			0.000			0.000	
		(0.19)			(0.02)			(0.32)	
EBITDA/AT		0.005			0.011			0.013	
		(0.33)			(0.42)			(0.33)	
Constant	-0.005***	-0.001	-0.004***	-0.008***	-0.003	-0.008***	-0.013***	-0.002	-0.011***
	(-12.18)	(-0.70)	(-8.99)	(-10.00)	(-0.73)	(-8.46)	(-10.86)	(-0.43)	(-8.97)
FE	Prop type	Prop type	Firm	Prop type	Prop type	Firm	Prop type	Prop type	Firm
R-squared	.005	.012	.013	.016	.034	.037	.018	.041	.044
No. observations	11,210	11,210	11,210	5,510	5,510	5,510	3,800	3,800	3,800

B. Abnormal returns based on NAREIT

	(1) *Ret (1-day)*	(2) *Ret (1-day)*	(3) *Ret (1-day)*	(4) *Ret (2-day)*	(5) *Ret (2-day)*	(6) *Ret (2-day)*	(7) *Ret (3-day)*	(8) *Ret (3-day)*	(9) *Ret (3-day)*
GeoCOVID	-0.021***	-0.031***	-0.028***	-0.069***	-0.108***	-0.105***	-0.070***	-0.103***	-0.094***
	(-3.92)	(-4.32)	(-3.61)	(-6.44)	(-7.15)	(-6.53)	(-4.42)	(-4.53)	(-3.80)
Days since outbreak		-0.000***	-0.000***		-0.000***	-0.001***		-0.001***	-0.001***
		(-6.99)	(-6.30)		(-6.24)	(-5.34)		(-6.66)	(-5.98)
Days since outbreak^2		0.000***	0.000***		0.000***	0.000***		0.000***	0.000***
		(10.55)	(9.57)		(10.79)	(9.79)		(10.24)	(9.37)
ln(GeoDensity)		0.001***			0.002***			0.002***	
		(6.58)			(7.35)			(6.80)	
PropHHI		-0.002**			-0.003**			-0.005**	
		(-2.31)			(-2.50)			(-2.52)	
GeoHHI		-0.003**			-0.003			-0.008**	
		(-2.15)			(-1.12)			(-2.09)	
Leverage		-0.003***			-0.007***			-0.010***	
		(-3.48)			(-3.75)			(-3.62)	
Cash		-0.004**			-0.008*			-0.014**	
		(-2.41)			(-1.88)			(-2.54)	
ln(Size)		0.000			-0.000			-0.000	
		(0.16)			(-0.06)			(-0.34)	
Tobin's q		0.001***			0.001***			0.002***	
		(2.61)			(3.22)			(3.04)	
LAG3MRET		0.000***			0.000***			0.001***	
		(22.85)			(24.27)			(22.43)	
InstOwn		0.001			0.001			0.004	
		(1.14)			(1.03)			(1.62)	
Investment		-0.000			-0.001			-0.001	
		(-0.92)			(-1.33)			(-0.85)	
EBITDA/AT		-0.001			0.004			-0.004	
		(-0.07)			(0.18)			(-0.12)	
Constant	-0.006***	-0.002	-0.006***	-0.011***	-0.004	-0.013***	-0.018***	-0.005	-0.018***
	(-14.70)	(-1.05)	(-10.98)	(-12.04)	(-0.99)	(-11.04)	(-13.66)	(-0.80)	(-11.60)
FE	Prop type	Prop type	Firm	Prop type	Prop type	Firm	Prop type	Prop type	Firm
R-squared	.004	.013	.014	.014	.041	.043	.014	.045	.048
No. observations	11,210	11,210	11,210	5,510	5,510	5,510	3,800	3,800	3,800

Table 3. Abnormal returns and geographically weighted COVID-19 growth by property type

This table shows regression results on the relationship between daily abnormal returns and the growth rate of geographically weighted COVID-19 cases interacted with property type dummies. Columns 1–3 (4–6) present the results using abnormal returns based on the S&P 500 index (NAREIT Equity index) as the dependent variable. *GeoCOVID* is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of a firm's portfolio allocated to each county at the end of 2019Q4. Control variables are the same as those used in column 2 in Table 2 and are suppressed. See Tables A1 and A2 in the appendix for variable descriptions and descriptions of property types, respectively. The numbers in parentheses are *t*-statistics. Standard errors are clustered at firm level. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Abnormal returns using S&P 500			*Abnormal returns using NAREIT*		
	Ret (1-day)	*Ret (2-day)*	*Ret (3-day)*	*Ret (1-day)*	*Ret (2-day)*	*Ret (3-day)*
Office × GeoCOVID	-0.026***	-0.073***	-0.089***	-0.030***	-0.100***	-0.112***
	(-4.67)	(-5.24)	(-3.69)	(-4.59)	(-6.13)	(-3.75)
Industrial × GeoCOVID	0.002	-0.060**	0.004	-0.006	-0.081***	0.012
	(0.13)	(-2.02)	(0.13)	(-0.34)	(-2.67)	(0.36)
Retail × GeoCOVID	-0.073***	-0.183***	-0.229***	-0.074***	-0.192***	-0.210***
	(-4.80)	(-6.62)	(-5.23)	(-4.79)	(-6.95)	(-4.89)
Residential × GeoCOVID	-0.066***	-0.167***	-0.138***	-0.069***	-0.180***	-0.143***
	(-5.15)	(-5.67)	(-3.78)	(-4.88)	(-5.66)	(-3.68)
Diversified × GeoCOVID	-0.037**	-0.099***	-0.085*	-0.044**	-0.122***	-0.084
	(-2.34)	(-3.38)	(-1.92)	(-2.58)	(-3.93)	(-1.64)
Hospitality × GeoCOVID	-0.026**	-0.045	-0.199***	-0.031**	-0.078**	-0.208***
	(-2.00)	(-1.30)	(-4.38)	(-2.25)	(-2.19)	(-4.47)
Health Care × GeoCOVID	0.039**	0.017	0.076	0.038**	0.013	0.098*
	(2.41)	(0.52)	(1.43)	(2.20)	(0.35)	(1.69)
Self-storage × GeoCOVID	-0.016**	-0.073***	-0.039	-0.021***	-0.089***	-0.041
	(-2.20)	(-2.93)	(-0.70)	(-2.77)	(-3.69)	(-0.78)
Specialty × GeoCOVID	0.016	-0.020	-0.013	0.011	-0.026	-0.003
	(0.92)	(-0.62)	(-0.17)	(0.66)	(-0.71)	(-0.04)
Technology × GeoCOVID	0.038**	0.039	0.104***	0.030	0.016	0.105***
	(2.33)	(1.14)	(3.27)	(1.50)	(0.39)	(2.66)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type
R-squared	.023	.058	.071	.022	.061	.071
Observations	11,210	5,510	3,800	11,210	5,510	3,800

Table 4. Asset allocation and COVID-19 growth

This table shows regression results on the relationship between abnormal returns and alternative measures of COVID-19 exposure. The dependent variable *Ret* is the 1-, 2-, or 3-day abnormal returns based on the S&P 500. *USCOVID* is the U.S. daily growth rate of COVID-19 cases. *GeoCOVID* is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of a firm's portfolio allocated to each county at the end of 2019Q4. The numbers in parentheses are *t*-statistics. Standard errors are clustered at firm level. Table A1 in the appendix defines all variables and lists all data sources. *$p < .1$; **$p < .05$; ***$p < .01$.

	(1) *Ret (1-day)*	(2) *Ret (2-day)*	(3) *Ret (3-day)*	(4) *Ret (1-day)*	(5) *Ret (2-day)*	(6) *Ret (3-day)*
USCOVID	-0.023***	-0.086***	-0.089***	-0.020***	-0.076***	-0.080***
	(-8.86)	(-14.39)	(-14.84)	(-7.06)	(-12.00)	(-12.87)
GeoCOVID				-0.016**	-0.044***	-0.056***
				(-2.15)	(-2.91)	(-2.73)
Days since outbreak	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-6.85)	(-5.85)	(-6.86)	(-6.22)	(-4.87)	(-5.80)
Days since outbreak^2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(7.55)	(6.70)	(6.90)	(7.83)	(7.15)	(7.21)
ln(GeoDensity)	0.000***	0.000**	0.001***	0.000***	0.001***	0.001***
	(3.19)	(2.58)	(3.62)	(3.77)	(3.41)	(4.33)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type
R-squared	.013	.045	.050	.014	.046	.052
Observations	11,210	5,510	3,800	11,210	5,510	3,800

Table 5. Abnormal returns and geographically weighted COVID-19 growth during different periods

This table shows regression results on the relationship between daily abnormal returns and the growth rate of geographically weighted COVID-19 cases during different sample periods. Columns 1–3 present the results based on 1-, 2-, and 3-day abnormal returns during the hump-shaped period of case growth from trading days 27 to 58 (i.e., February 27 to April 13, 2020) depicted in Figure 3. Columns 4–6 present the results using the extended sample period from January 21 through June 30, 2020. *GeoCOVID* is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of a firm's portfolio allocated to each county at the end of 2019Q4. Control variables are the same as those used in column 2 in Table 2 and are suppressed. See Tables A1 and A2 in the appendix for variable descriptions and descriptions of property types, respectively. The numbers in parentheses are *t*-statistics. Standard errors are clustered at firm level. *$p < .1$; **$p < .05$; ***$p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Hump-shaped period, February 27 to April 13, 2020			Extended period, January 21 to June 30, 2020		
Abnormal returns (S&P 500)	*Ret (1-day)*	*Ret (2-day)*	*Ret (3-day)*	*Ret (1-day)*	*Ret (2-day)*	*Ret (3-day)*
GeoCOVID	-0.020**	-0.057***	-0.073***	-0.032***	-0.083***	-0.111***
	(-2.21)	(-3.01)	(-2.66)	(-5.68)	(-7.33)	(-6.58)
Days since outbreak	-0.001***	-0.001***	-0.003***	0.000*	0.000***	0.000**
	(-5.24)	(-4.23)	(-5.17)	(1.79)	(2.75)	(2.58)
Days since outbreak^2	0.000***	0.000***	0.000***	0.000**	0.000	0.000
	(8.66)	(7.70)	(8.56)	(2.52)	(1.54)	(0.66)
ln(GeoDensity)	-0.000	-0.001	-0.001	-0.000	-0.000	-0.000
	(-1.03)	(-1.09)	(-0.96)	(-1.16)	(-0.46)	(-0.83)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type
R-squared	.035	.064	.117	.007	.018	.023
Observations	5,890	3,040	1,900	21,404	10,411	6,936

Table 6. Abnormal returns and nonpharmaceutical interventions

This table shows regression results on the relationship between daily abnormal returns and the growth rate of geographically weighted COVID-19 cases interacted with measures of nonpharmaceutical interventions (NPIs). The dependent variable *Ret* is the 1-, 2-, or 3-day abnormal returns based on the S&P 500. *GeoNPI* is the percentage share of a firm's portfolio (based on total adjusted cost) exposed to NPIs at the county level. *Post-NPI* indicates that *GeoNPI* is greater than zero. *GeoCOVID* is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of a firm's portfolio allocated to each county at the end of 2019Q4. Control variables are the same as those used in column 2 in Table 2 and are suppressed. See See Tables A1 and A2 in the appendix for variable descriptions and descriptions of property types, respectively. The numbers in parentheses are *t*-statistics. Standard errors are clustered at firm level. *$p < .1$; **$p < .05$; ***$p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
Abnormal returns (S&P 500)	*Ret (1-day)*	*Ret (2-day)*	*Ret (3-day)*	*Ret (1-day)*	*Ret (2-day)*	*Ret (3-day)*
Post-NPI	0.011***	0.031***	0.043***			
	(3.27)	(5.04)	(4.80)			
Post-NPI × GeoCOVID	0.067***	0.058**	0.078			
	(3.85)	(2.00)	(1.41)			
GeoNPI				0.029***	0.045***	0.048***
				(5.84)	(4.20)	(2.98)
GeoNPI × GeoCOVID				0.150***	0.420***	0.663***
				(4.29)	(4.75)	(4.56)
GeoCOVID	-0.078***	-0.169***	-0.239***	-0.035***	-0.116***	-0.137***
	(-9.49)	(-12.13)	(-8.50)	(-4.30)	(-6.16)	(-4.90)
Days since outbreak	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***
	(-6.19)	(-4.32)	(-4.36)	(-7.95)	(-7.05)	(-8.08)
Days since outbreak^2	-0.000	-0.000	-0.000	-0.000**	-0.000**	-0.000
	(-0.58)	(-1.48)	(-1.10)	(-2.40)	(-2.01)	(-1.31)
ln(GeoDensity)	0.001***	0.001***	0.002***	0.001***	0.002***	0.002***
	(3.84)	(4.27)	(4.92)	(3.40)	(4.05)	(4.08)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type
R-squared	.033	.083	.116	.032	.085	.099
Observations	11,210	5,510	3,800	11,210	5,510	3,800

Table 7. Abnormal returns and reopenings

This table shows the results of estimating the relation between daily abnormal returns and the growth rate of geographically weighted COVID-19 cases interacted with measures of reopenings. The dependent variable is the 1-day abnormal return based on the S&P 500. *GeoReopen* is the percentage share of a firm's portfolio exposed to an announced reopening plan. *Post-Reopen* indicates that *GeoReopen* is greater than zero. *Severity (April 15)* is the percentage of the county population that has tested positive, weighted by the percentage of each REIT's portfolio located in the county, measured as of April 15th. *GeoNPI (April 15)* is the firm's exposure to NPIs (*GeoNPI*) as of April 15th. *GeoNetExp* is the proportion of a firm's portfolio exposed to NPIs net of its exposure to reopenings. *GeoCOVID* is the average of state-level daily growth rates of COVID-19 cases, weighted by the percentage of a firm's portfolio allocated to each state at the end of 2019Q4. Control variables are the same as those used column 2 in Table 2 and are suppressed. See Tables A1 and A2 in the appendix for variable descriptions and descriptions of property types, respectively. Columns 1 and 6 are based on a sample runs from January 21 to June 30, 2020. Columns 2, 3, and 5 are based on a sample runs from April 16 to June 30. Column 4 is based on a sample runs from January 21 to April 16. The numbers in parentheses are *t*-statistics. Standard errors are clustered at firm level. *$p < .1$; **$p < .05$; ***$p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
Ret (1-day)	*Full sample*	*After Apr. 15*	*After Apr. 15*	*Before Apr. 15*	*After Apr. 15*	*Full sample*
Post-Reopen	0.007***					
	(5.64)					
Post-Reopen × *GeoCOVID*	-0.014					
	(-0.55)					
GeoReopen		-0.001	0.004			
		(-0.29)	(1.47)			
GeoReopen × *GeoCOVID*		-0.050				
		(-0.67)				
Severity (Apr 15)			-0.045			
			(-0.78)			
GeoReopen × *Severity*			-0.026			
			(-0.34)			
GeoNPI (Apr 15)			-0.005			
			(-1.33)			
GeoReopen × *GeoNPI*			0.004			
			(1.09)			
GeoNetExp				0.116***	0.043	0.138***
				(5.53)	(0.63)	(8.04)
GeoNetExp × *GeoCOVID*				0.009***	-0.003	0.003**
				(3.10)	(-1.37)	(2.55)
GeoCOVID	-0.022***	-0.186***	-0.035	-0.080***	-0.171***	-0.096***
	(-3.56)	(-3.20)	(-1.00)	(-9.69)	(-3.87)	(-10.84)
Days since outbreak	-0.000	0.000***	0.000***	-0.000***	0.000**	-0.000
	(-1.57)	(2.99)	(3.37)	(-7.66)	(2.50)	(-0.82)
Days since outbreak^2	0.000	-0.000***	-0.000***	-0.000	-0.000***	0.000***
	(1.27)	(-3.80)	(-3.95)	(-0.46)	(-3.76)	(3.14)
ln(GeoDensity)	-0.000**	0.000	-0.000	0.001***	0.000	0.000
	(-2.13)	(0.03)	(-0.96)	(5.23)	(0.64)	(1.29)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type
R-squared	.008	.004	.002	.032	.004	.021
Observations	21,404	10,194	10,194	11,210	10,194	21,404

Appendix

Table A1. Variable definitions

Variable	Source	Definition
Daily abnormal returns		
1-day AR	S&P Global, NAREIT	Daily abnormal returns are calculated as $R_{i,t} - \beta_i M_t$. β_i is estimated from the market model for firm *i* from the beginning of 2019 to January 20, 2020. $R_{i,t}$ denotes stock returns for firm *i* on day *t*. M_d denotes daily returns on either the S&P 500 index or the NAREIT All Equity index
2-day CAR	S&P Global, NAREIT	Nonoverlapping cumulative abnormal returns from day *t* to *t*+1
3-day CAR	S&P Global, NAREIT	Nonoverlapping cumulative abnormal returns from day *t*-1 to *t*+1
COVID-19 exposure variables		
GeoCOVID	JHU COVID-19 Global Cases, S&P Global	The COVID-19 geographic exposure of a firm, calculated as the average county-level daily growth rates of COVID-19 cases, weighted by the percentage of the firm's portfolio allocated to each county at the end of 2019Q4. The county-level daily growth rate of confirmed COVID-19 cases in county *l* on day *t* is calculated as $ln(1 + \#CASES_{l,t}) - ln(1 + \#CASES_{l,t-1})$
HighGeoCOVID	JHU COVID-19 Global Cases, S&P Global	An indicator variable that equals one if *GeoCOVID* for firm *i* on day *t* is in the upper quartile of the growth rates across all counties in which the firm owns any property on day *t*
USCOVID	JHU COVID-19 Global Cases, S&P Global	The daily growth rates of COVID-19 confirmed cases across the United States
GeoNPI	S&P Global	The percentage share of properties (based on total adjusted cost) of a firm's portfolio exposed to county-level NPIs
GeoReopen	S&P Global	The percentage share of properties (based on total adjusted cost) of a firm's portfolio exposed to state reopenings
GeoNetExp	S&P Global	The daily proportion of a firm's portfolio exposed to state-level NPIs net of its exposure to reopenings
Days since outbreak	JHU COVID-19 Global Cases, S&P Global	The number of days since the outbreak of the COVID-19 pandemic in counties where a firm owns any property at the end of 2019Q4
Days since outbreak^2	JHU COVID-19 Global Cases, S&P Global	The quadratic term of *Days since outbreak*
Control variables		
GeoDensity	S&P Global	The average of county-level population density weighted by the percentage of the CRE portfolio allocated to each county at the end of 2019Q4. Population density is defined as the number of people per square miles
GeoHHI	S&P Global	The Herfindahl-Hirschman indexes of each firm's property weights across the U.S. counties at the end of 2019Q4
PropHHI	S&P Global	The Herfindahl-Hirschman indexes of each firm's property weights in each of the 10 property categories, including office, industrial, retail, residential, diversified, hospitality, health care, self-storage, specialty, and technology at the end of 2019Q4
Leverage	S&P Global	Sum of total long-term debt and debt in current liabilities divided by book value of assets at the end of 2019Q4
Cash	S&P Global	The ratio of cash and cash equivalents to book value of assets at the end of 2019Q4
Size	S&P Global	The book value of assets at the end of 2019Q4
Tobin's q	S&P Global	The ratio of the market value of equity plus the book value of debt to the book value of assets

Table A1. continued

LAG3MRET	S&P Global	Cumulative stock returns over 2019Q4 (in percentage)
InstOwn	S&P Global	The ratio of the number of shares held by institutional investors to the total number of shares outstanding at the end of 2019Q4
Investment	S&P Global	The percentage growth rate in noncash assets during 2019Q4

Table A2. Property type descriptions

This table summarizes REITs by property types. The classification is based on those used by S&P Global and NAREIT.

Property type	# stocks	Description
Office	22	Office REITs own and manage office real estate and rent space in those properties to tenants. Those properties can range from skyscrapers to office parks. Some office REITs focus on specific types of markets, such as central business districts or suburban areas. Some emphasize specific classes of tenants, such as government agencies or biotech firms.
Industrial	14	Industrial REITs own and manage industrial facilities and rent space in those properties to tenants. Some industrial REITs focus on specific types of properties, such as warehouses and distribution centers. Industrial REITs play an important part in e-commerce and are helping to meet the rapid delivery demand.
Retail	37	Retail REITs own and manage retail real estate and rent space in those properties to tenants. Retail REITs include REITs that focus on large regional malls, outlet centers, grocery-anchored shopping centers and power centers that feature big box retailers. Net lease REITs own freestanding properties and structure their leases so that tenants pay both rent and the majority of operating expenses for a property.
Residential	15	Residential REITs own and manage various forms of residences and rent space in those properties to tenants. Residential REITs include REITs that specialize in apartment buildings, student housing, manufactured homes and single-family homes. Within those market segments, some residential REITs further zero in on specific geographical markets or classes of properties.
Diversified	32	Diversified REITs own and manage a mix of property types and collect rent from tenants. For example, diversified REITs might own portfolios comprising both office and industrial properties.
Hospitality	27	Hospitality REITs own and manage hotels and resorts and rent space in those properties to guests. Hospitality REITs own different classes of hotels based on features such as the hotels' level of service and amenities. Hospitality REITs' properties service a wide spectrum of customers, from business travelers to vacationers.
Health care	20	Health care REITs own and manage a variety of health-care-related real estate and collect rent from tenants. Health care REITs' property types include senior living facilities, hospitals, medical office buildings, and skilled nursing facilities.
Self-storage	7	Self-storage REITs own and manage storage facilities and collect rent from customers. Self-storage REITs rent space to both individuals and businesses.
Specialty	18	Specialty REITs own and manage a unique mix of property types and collect rent from tenants. Specialty REITs own properties that do not fit within the other REIT types. Examples of properties owned by specialty REITs include movie theaters, casinos, farmland, and outdoor advertising sites. This category also includes four timber REITs that specialize in harvesting and selling timber.
Technology	6	This category includes Data Center and Infrastructure REITs. Data center REITs own and manage facilities that customers use to safely store data. Data center REITs offer a range of products and services to help keep servers and data safe, including providing uninterruptable power supplies, air-cooled chillers, and physical security. Infrastructure REITs' property types include fiber cables, wireless infrastructure, telecommunications towers, and energy pipelines.
Total	198	

Table A3. Market reactions to nonpharmaceutical interventions and reopenings

This table presents summary statistics on cumulative abnormal returns (CARs). In columns 1 and 2 (3 and 4), the announcement date for a firm is defined as the earliest date of a state of emergency declaration (shelter-in-place orders) in any jurisdiction (city or county) in the top-three states ranked by the size of the firm's property holdings. In columns 5 and 6, the announcement date is defined as the earliest date of re-sub-opening in any of the top-three states ranked by the size of the firm's property holdings. CARs are constructed based on two event windows, including (-1,1) and (-5,5), which represent, respectively, 3- and 11-day windows. Test statistics are reported within parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Top-3 SOE		Top-3 SIPO		Top-3 reopenings	
Property type	CAR(-1,1)	CAR(-5,5)	CAR(-1,1)	CAR(-5,5)	CAR(-1,1)	CAR(-5,5)
Overall	-0.04***	-0.09***	-0.11***	-0.35***	0.06***	0.00
	(-9.22)	(-8.97)	(-7.82)	(-16.93)	(9.69)	(0.46)
Office	-0.04***	-0.07***	-0.06**	-0.25***	0.01	-0.03*
	(-4.25)	(-3.99)	(-2.61)	(-8.19)	(1.04)	(-1.74)
Industrial	-0.05***	-0.10***	-0.06**	-0.20***	0.04**	-0.01
	(-3.73)	(-2.81)	(-2.45)	(-5.43)	(2.63)	(-0.85)
Retail	-0.03***	-0.11***	-0.16***	-0.40***	0.12***	0.06***
	(-2.70)	(-3.28)	(-3.72)	(-8.52)	(8.28)	(4.44)
Residential	-0.06***	-0.04***	-0.07*	-0.29***	0.03***	-0.01
	(-3.98)	(-2.75)	(-1.81)	(-5.19)	(3.40)	(-0.70)
Diversified	-0.02**	-0.06***	-0.09***	-0.35***	0.06***	0.02**
	(-2.30)	(-3.17)	(-2.99)	(-6.66)	(4.58)	(1.91)
Hospitality	-0.06***	-0.15***	-0.10**	-0.41***	0.08***	0.01
	(-5.58)	(-6.84)	(-2.30)	(-6.18)	(4.05)	(0.63)
Health care	-0.06***	-0.11***	-0.20***	-0.59***	0.03**	-0.05**
	(-4.29)	(-3.16)	(-3.61)	(-7.35)	(2.58)	(-2.64)
Self-storage	0.00	-0.05**	-0.10***	-0.26***	0.02**	-0.06***
	0.23	(-2.02)	(-2.81)	(-3.84)	(2.45)	(-4.08)
Specialty	-0.03	-0.14***	-0.11***	-0.30***	0.02	-0.02
	-1.60	(-2.70)	(-2.67)	(-4.68)	(1.39)	(-1.02)
Technology	-0.03***	0.03***	-0.04	-0.10	0.00	0.03*
	(-3.90)	(3.46)	(-1.44)	(-1.43)	(0.03)	(1.88)