Face-to-face Interactions, Tenant Resilience, and Commercial Real Estate Performance*

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Abstract

The COVID-19 pandemic has induced an exogenous shock to the face-to-face (FTF) economy and the use of commercial real estate (CRE). By linking tenants, properties, and CRE firms, we construct three novel FTF measures that capture tenant remote working, internal communication between coworkers, and external contact with customers. We find that firms holding properties with tenants that are more resilient to social distancing perform better. These FTF effects weaken over the long term. As investors are capable of compiling valuable information regarding how tenants operate at granular levels, our findings support market efficiency and shed light on post-pandemic CRE performance.

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Keywords: Commercial Real Estate, Face-to-Face Interactions, Tenant Resilience, Social Distancing, COVID-19 Pandemic

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1 Introduction

Buildings house human activities in close physical proximity and facilitate face-to-face (FTF) interactions (O'Hara (1977); Clapp (1980)). As the value of a commercial building is driven mainly by the rents paid by its tenants, commercial properties are only as economically viable as their tenants. This suggests that the way tenants' businesses function should affect commercial real estate (CRE) performance. The empirical challenge in measuring such performance lies, however, in identifying the direction of causality because, since the seminal work by Alonso (1965), Mills (1967), and Muth (1969), numerous studies have documented that a tenant's location and leasing decisions are determined endogenously by its business operations.

The COVID-19 pandemic has introduced an exogenous shock to the FTF economy and the use of commercial space, weakening the spatial relationship between work and home. In this study, we construct a novel dataset that links tenants, commercial properties, and stakeholders in these properties (including equity real estate investment trusts — REITs — and mortgage lenders). By examining how tenant-level FTF interactions affect the impact of COVID-19 on stock returns, analyst forecasts of future earnings, and mortgage spreads of collateralized loans, our study highlights the value of observing at the granular level how tenants operate.

While providing an effective means of slowing the spread of the virus, social distancing has come at the cost of disrupting tenants' businesses as a result of severe restrictions on FTF interactions between individuals. Companies more of whose employees can work remotely are less likely to experience severe disruptions (e.g. Alon et al. (2020); Dingel and Neiman (2020); Favilukis et al. (2020); Papanikolaou and Schmidt (2020); Koren and Peto (2020)). This suggests that properties occupied by tenants who are more easily able to work remotely find it easier to collect rent during the pandemic and the subsequent lockdowns because these tenants are more likely to meet their rental-payment obligations.

In addition, FTF interactions, whether internally between co-workers or externally with customers, might vary in form at a tenant's workplace (Koren and Peto (2020)). Our data suggest that teamwork-intensive tenants are well-equipped with information and communication technologies (ICTs) that facilitate telecommuting. In contrast, tenants in industries that require close contact with customers (e.g. accommodations, food service, and drinking places) have less flexibility in their business operations and have suffered significantly more severe disruptions.[1] ICT infrastructure is the central component that enables work activities at alternative workplaces (Garrett and Danziger (2007)). As pointed out by Favilukis et al. (2020), firms in industries with high labor-force telework flexibility perform significantly better thanks to ICT-enabled telework. This suggests that rent-generating properties occupied by tenants in teamwork-intensive (customer-contact-intensive) sectors are less (more) vulnerable during the pandemic.

As social distancing policies are gradually lifted, whether investors continue to price in FTF factors depends crucially on expectations for the duration of the COVID-19 pandemic and the likelihood that such shocks will occur in the future. High uncertainties regarding these issues would suggest that, even if the spread of COVID-19 is partially contained by social-distancing policies, investors will still price in pandemic risk to some extent (e.g. Hassan et al. (2020); Alfaro et al. (2020)), thereby assessing risks differently based on the importance of FTF interactions in tenants' business operations. On the other hand, if FTF factors play a less significant role in explaining changes in long-term expectations, investors should be confident in the effectiveness of policy interventions and scientific evidence of the effectiveness of vaccines and believe that the pandemic shock will prove transient in nature (Landier and Thesmar (2020); Hong et al. (2020)).

Using a sample consisting of more than 302,410 tenants located in 32,095 properties owned by 124 REIT firms, we construct three novel measures of FTF interactions at both the property and firm levels. These three measures capture distinct aspects of FTF interactions in market dynamics during COVID. Following Dingel and Neiman (2020), we construct an FTF measure that captures whether tenants cannot work remotely. We also follow Koren and Peto (2020) and disentangle FTF interactions in tenants' business operations based on the nature of communication: internal communication with co-workers (i.e. teamwork) as opposed to external communication with customers (i.e. consumer contact). Both Dingel and Neiman (2020) and Koren and Peto (2020) utilize industry-occupation information. When constructing our property- and firm-level

[1] For example, Koren and Peto (2020) find that changes in industry employment between February and May 2020 were sharpest in customer-facing industries while there were no effects on teamwork-intensive industries.

FTF measures, we first assign the three industry-level metrics to each tenant. We then construct our property-level measures based on the types of business activities undertaken by a property's tenants, weighted by the spaces occupied by the tenants.[2] Finally, we aggregate these property-level measures to the firm level using the percentages of a firm's portfolio (based on book value) invested in each property. These FTF indices and weights are measured prior to the pandemic outbreak at the end of 2019.

An initial investigation suggests that neither a building's property type nor a REIT's property-type focus fully captures the heterogeneity of FTF interactions. First, there is considerable variation in tenant composition within buildings. For example, Apple Inc., a software company that ranked highest in terms of both remote work and teamwork indexes, is among the most profitable tenants in shopping malls.[3] Tenants in retail and services (e.g. clothing and grocery stores, food and beverage chains) not only occupy retail spaces but also rent large areas of industrial and office space to house their inventories and management. This variation in tenant bases is important because it might increase interdependence among otherwise unrelated property types. Second, as CRE landlords, modern REITs, while specializing in one or only a few property types, also strategically expand their portfolios to include other property types. For instance, in our sample, an average REIT that is classified under one property type also holds five other property types. An average industrial REIT in our sample invests about 20% of its total book value in office properties and 6% in healthcare properties. Therefore, there is substantial heterogeneity in these FTF measures that can be traced to the property level. Controlling for property-type fixed effects, we show that FTF interactions measured at the tenant level are important drivers of CRE performance.

We conduct four exercises to consider different types of market participants: stock investors, analysts, and mortgage lenders. First, we examine whether and how FTF interactions affect the negative impact of COVID-19 on stock prices in the early stage of the pandemic. We find that stock investors in CRE firms whose tenants are less resilient to social distancing react more negatively to the spread of COVID, measured by geographically weighted growth in the number of

[2]The results are similar when we use alternative weights based on the number of tenants, tenant employment, and estimated revenues.

[3]According to Costar, Apple Inc. is ranked #1 in terms of retail sales per square foot (`https://www.prnewswire.com/news-releases/retails-most-profitable-square-footage-636947493.html`, accessed on Dec 5, 2020).

cases in any county in which a firm owns property. When we decompose FTF interactions into internal communications between co-workers and external communications with customers, however, we find the opposite results: teamwork-intensive (customer-contact-intensive) workers are more (less) resilient to social distancing. This is because teamwork-intensive tenants in the CRE market operate mainly in industries such as management, professional, scientific, and consulting services, which are well-equipped with ICTs to conduct telework. As most of the customer-contact-intensive tenants in CRE operate retail sales, restaurants, lodging, or healthcare businesses, it is much harder for their employees to maintain normal business operations when working remotely.

Government restrictions have played an important role in a firm's capacity to continue operations. Specifically, tenants in industries classified as "critical" (or "essential") have been subject to less severe business disruptions than those in "non-critical" sectors, regardless of their capacity to work remotely. We therefore measure FTF interactions separately for critical and non-critical sectors. Our results suggest that the effects of FTF interactions on stock-price reactions to COVID-19 cases are less (more) pronounced among firms operating in critical (non-critical) sectors.

Our second exercise aims to further understand how social distancing affects stock investors' expectations during government interventions. We adopt a cross-sectional event-study framework by focusing on announcements of lockdowns and subsequent reopenings, taking into account asset locations. Consistent with our baseline results using daily abnormal returns, the event-study results confirm that investors in firms with tenants that rely heavily on FTF contacts react more negatively around the announcements of lockdowns. We do not, however, observe any announcement effects around reopenings.

In our third exercise, we conduct a difference-in-differences (DID) analysis using the COVID-19 pandemic as an unexpected and exogenous shock (e.g. Albuquerque et al. (2020); Acharya and Steffen (2020)). Our outcome variable is short-term or long-term analyst forecasts of earnings per share (EPS), which are advantageous for directly measuring changes in investor beliefs (Landier and Thesmar (2020); Hong et al. (2020)). Controlling for firm, analyst, and forecast-timing fixed effects, we find that, following the COVID-19 outbreak, short-term forecasted EPS growth is lower if a firm's tenant base is less able to work remotely or depends more heavily on FTF contact with customers. On the other hand, analysts are less pessimistic about REITs with tenants working in teamwork-intensive occupations. The FTF effects weaken, however, at the long horizon.

Hong et al. (2020) argue that security analysts should incorporate expected damage to firm earnings caused by macroeconomic conditions, including scientific evidence on the development of vaccines, into their estimations. Given the weakened long-run effects, we also use a simple dividend discount model to examine the dynamics of implicit discount rates (IRRs) (Landier and Thesmar (2020)). While the implicit IRRs surged after the outbreak and peaked in late March, they returned to pre-crisis levels by the beginning of May. Given the heated debates over the concern that remote work might reduce demand for commercial real estate and CRE prices might fall in the post-pandemic era, we check separately for firms with high and low FTF indices and find similar trends for both groups. Overall, these results based on analyst forecasts suggest that the pandemic-induced effects might not last over the long term.

Our final exercise operates at the property level. We examine mortgage spreads, which reflect the cost of debt for loans collateralized by commercial properties. As commercial mortgages are non-recourse loans, screening and monitoring at the asset level is of greater importance to lenders (Letdin (2017); Eichholtz et al. (2019); Agrawal et al. (2020)). We find that post-COVID mortgage spreads increased for loans collateralized with properties operated by less teamwork-intensive tenants. Remote work and costumer contact play no role, however, in explaining mortgage spreads after the COVID outbreak. These asset-level, medium- to long-term findings are generally consistent with our firm-level findings using long-term EPS forecasts.[4]

We also reproduce analyses using FTF measures constructed based on tenants' parent companies, using FTF measures estimated separately for independent and corporate tenants, and investigating firms with a higher proportion of near-expiration leases. We conclude that our baseline results are robust to these alternative FTF measures and sub-samples.

Our results provide support for market efficiency, as market participants (including investors and analysts) are able to observe the complex tenant-property-firm linkages and incorporate

[4] One caveat is that, given that most CRE loans are fixed at the medium term, we need to make a strong assumption that the outcome variable at the asset level quickly adapts to changes in lenders' beliefs.

granular tenant information to evaluate the resilience of CRE firms to social distancing. In addition to observing detailed information at the tenant level, investors also need to aggregate information from multiple layers by considering various property types as well as the geography of properties.

Our findings also shed light on the ongoing debate over the demand for commercial spaces in the post-COVID era. Several studies suggest that CRE prices might fall in the long run because 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 (e.g. Delventhal et al. (2020); Davis et al. (2021); Delventhal and Parkhomenko (2021)). Rosenthal et al. (2021) estimate spatial patterns of commercial rent before and after COVID-19. They conclude that, although the pandemic reduces the value of density, the effects are heterogeneous across cities. Specifically, city centers remain attractive; the negative impact only exists in the largest and most dense cities. On the other hand, supporters of the value of agglomeration advocate that cities are resilient.[5] Francke and Korevaar (2021) study historical outbreaks of epidemic in Europe. They find that the decline in real estate prices were only transitory, and cities were resilient to pandemic shocks. A similar conclusion is made in Wong (2008) who study the SARS outbreak in Hong Kong in 2003.

Consistent with the latter view, our findings suggest that FTF factors have a muted effect on investors' reactions to reopenings and on long-term analyst forecasts. Also, in our investigation of the evolution of implicit discount rates, we do not find a pattern of divergence between firms with high and firms with low FTF measures. These results are consistent with studies that confirm the intrinsically short-term nature of the crisis (e.g. Landier and Thesmar (2020); Hong et al. (2020)). In addition, telecommunication can complement rather than substitute for FTF contacts, largely because the latter facilitate the exchange of complex and tacit knowledge (e.g. Mack and Rey (2014)), particularly in high-tech firms.[6] To predict urban growth following COVID-19, Magrini

[5] Edward Glaeser writes that these "dense agglomerations that dot the globe have been engines of innovation since Plato and Socrates bickered in an Athenian marketplace Glaeser (2011)." In a recent American Enterprise Institute (AEI) event, Glaeser said that "There are many assets that come with urban proximity: the ability to work collaboratively, the ability to learn from one another, the ability to innovate and to be entrepreneurs. But there are also demons that come with density, and the worst of these demons is plague and pandemic." (`https://www.aei.org/events/webinar-unlocking-the-potential-of-americas-cities/` Accessed: Feburary 4, 2021.)

[6] In an extensive stream of literature spawned by Romer (1990), knowledge can be abstract or tacit. Abstract knowledge is codifiable, can be spread freely to every user, and is independent of a user's location. On the other hand, tacit knowledge cannot be codified and spreads only through direct, face-to-face contact. This knowledge spillover

et al. (2020) find that, although internet communication and videoconferencing reduce frictions caused by geographic distance, social distancing impacts productivity negatively in the R&D sector. Our finding of positive effects of FTF interactions through internal teamwork is in line with this story. If FTF interactions in close physical proximity are essential to localized productivity and knowledge spillovers, CRE occupied by teamwork-intensive tenants, mainly in high-tech and R&D industries, is expected to perform well even after the pandemic passes.

Our study is related to studies that examine resilience to and performance during pandemics. For example, Pagano et al. (2020) and Papanikolaou and Schmidt (2020) also borrow metrics from Dingel and Neiman (2020) and Koren and Peto (2020). They find that a firm is more resilient to a pandemic if the industry in which the firm operates has a higher fraction of jobs that can be performed from home and relies to a lesser extent on human interaction in physical proximity. Our paper differs from these insofar as, instead of analyzing the industry in which a firm operates, we focus on the diverse pool of sources from which a firm derives its cash flow and build our FTF proxies based on the tenants located at each property owned by the firm. Furthermore, Pagano et al. (2020) find a positive relationship between firm performance and remote working while we find that FTF interactions affect firm performance differently depending on the nature of the communication involved (i.e., internal or external).

Finally, our study contributes to a growing body of literature that studies the impact of COVID-19 on real estate markets, including Ling et al. (2020), Agrawal et al. (2020), van Dijk et al. (2020), Milcheva (2020), Liu and Su (2020), Gupta et al. (2021), and D'Lima et al. (2020). Ling et al. (2020) show that the COVID-19 shock transmits to financial markets from a firm's asset base. Our study is the first to disaggregate this transmission channel into three layers: the firm level, the asset level, and the tenant level. More broadly, our paper is related to studies of tenant mix (e.g. Liu and Liu (2013); Liu et al. (2019); Lu-Andrews (2017)) and urban spatial structure (e.g. Drennan and Kelly (2011); Koster et al. (2014); Liu et al. (2018, 2020)).

could explain why the clustering of R&D labs in the U.S. is more prominent than the clustering of manufacturing facilities (Buzard et al. (2017)), and why 97% of venture capital investments, a key driver of both innovation and high-tech start-ups, is concentrated in the top 50 US metropolitan areas (Florida and King (2016)). As Moretti (2013) estimated, for each new high-tech job in a metropolitan area, five new local jobs are created in other industries over the long run. Employment in these high-paying industries are important drivers of CRE demand for all property types.

2 Sample Construction

2.1 Matching Tenants, Properties, and Landlords

We build a sample that links tenants, commercial properties, and the REITs which own these properties as of 2019Q4. Tenant information is collected using business listings from the S&P Global Marketing List: Businesses (U.S.) Database. The business listing data include establishment-level information such as company name, number of employees, estimated annual sales, leased area (sq. ft.), latitude and longitude, and the North American Industry Classification System (NAICS) code.[7] Property information is obtained from the S&P Global Real Estate Properties (formerly SNL Real Estate) database. We collect the following data for each property held by a REIT at the end of 2019Q4: institution (owner) name, property type, address, net book value, initial cost, and historic cost.

We then match these business listings to properties using street addresses, latitude and longitude, and manual searches. Appendix 1 includes detailed descriptions of our matching algorithm. As business listings include only commercial tenants, residential properties and some special-purpose properties are dropped from our sample.[8] Our initial sample includes 310,609 tenants located in 33,023 properties owned by 132 unique equity REITs traded on the NYSE, the AMEX, and Nasdaq as of 2019.

Property-level data are then matched with firm-level data using firm identifiers (SNL Institution Keys). Our initial sample contains 132 unique equity REITs operating in 2019Q4. For our firm-level analysis, we obtain quarterly accounting data and daily returns on individual REITs and on our broad-based market indices from the S&P Global Companies database. We require non-missing values for the following items for each REIT at the end of each day in the period running from January 1, 2019 through April 15, 2020: total return, stock price, property type, and stock-market capitalization. We delete REIT firms with missing financial information after

[7] We delete listings that lack information on business street address, primary NAICS 6-digit code, or leased area.

[8] Specifically, properties that are classified by S&P Global as "Advertising", "Agriculture", "Land", "Manufactured Home", "Multifamily", "Prison", "Recreation", "Single Family", "Student Housing", or "Timber" are dropped from our sample.

merging with our data with CRSP-Compustat data. These mergers reduce our final sample to 302,410 tenants in 32,095 properties owned by 124 REIT firms.

2.2 Critical versus Non-critical Industries

We classify each tenant into a critical or non-critical sector, following Papanikolaou and Schmidt (2020), or PS.[9] While the Cybersecurity and Infrastructure Security Agency (CISA) provided guidance to states regarding the types of essential businesses that should remain open during lockdowns, PS argue that the CISA classification of essential industries seems too coarse and imprecisely captures operational restrictions. PS thus revise the CISA list, providing a more conservative list of critical industries related to the production and sale of food and beverages, utilities, pharmacies, transportation, waste collection and disposal, and some healthcare and financial services. They also validate their classification using changes in foot traffic.

3 Measures of Face-to-face (FTF) Interactions

Dingel and Neiman (2020), or DN, classify the feasibility of working remotely for all occupations based on 17 questions from two surveys administered by the Occupation Information Network (O*NET).[10] DN code an occupation as unable to be performed at home if any of the 17 questions is true. By merging the number and wages of workers in each standard occupational classification (SOC) code with the information from the US Bureau of Labor Statistics (BLS), they calculate for each occupation the share of jobs in that industry that can be performed at home. We follow DN and construct *Nonremote*, which equals one minus the percentage of jobs that can be performed at home.

We also follow, Koren and Peto (2020), or KP, who measure two dimensions of communi-

[9] The list of critical industries is available in their Appendix Table A.1.

[10] The first survey, the Work Context Questionnaire, captures "the physical and social factors that influence the nature of work", such as email usage, interaction with others, and outdoor activities. The second survey, the Generalized Work Activities Questionnaire, captures "the general types of job behaviors occurring on multiple jobs" such as the importance of physical activities, handling of moving objects, and controlling machines. GitHub link: `https://github.com/jdingel/DingelNeiman-workathome`.

cation: internal communication between co-workers (teamwork) and direct external communication with customers (customer contact).[11] The *Teamwork* index is based on work by groups or teams, including providing consultation and advice to others, coordinating the work and activities of others, developing and building teams, etc. The *Customer* index is based on communication with external customers, including assisting, providing consultation and advice, and maintaining interpersonal relationships. DN and KP map their indices from the occupation level to the industry level using NAICS codes.

Although both DN and KP utilize O*NET data to measure FTF interactions, their measures differ in nature. KP emphasize interaction and physical proximity between people, while DN capture whether a certain type of job can be performed at home, regardless of how people interact in brick-and-mortar facilities. In our study, the distinction between internal communication (through teamwork) and external communication (with customers) is important in CRE.

We first match commercial tenants to the DN and KP indices using 4-digit NAICS industry classification. We then aggregate these tenant-level indices to the property level. Our property-level FTF interaction index is calculated as:

$$FTF_p = \sum_{i}^{N} FTF_{p,i} \times weights_{p,i} \tag{1}$$

where $FTF_{p,i}$ is one of the three FTF interaction indices ($Nonremote$, $Teamwork$, or $Customer$) for tenant i in property p. We construct four different weights: (1) a simple average among all tenants, (2) the square footage occupied by a tenant, (3) the range of the number of workers employed by a tenant, or (4) a tenant's projected sales revenues. Our preferred weight is the share of square footage occupied by a tenant because it captures the importance of the tenant within a specific building.[12]

[11] Koren and Peto (2020) also construct a third indicator, physical presence, to capture the possibility that workers may need to be in physical proximity to one another even if they do not communicate. This indicator covers jobs involving handling and moving objects, operating vehicles, and repairing and maintaining equipment. As only a small proportion of tenants fall into this category in our CRE sample, we do not use this indicator.

[12] The results are qualitatively similar when using alternative weights, including the number of tenants, tenant employment, and estimated revenues.

Our firm-level FTF index is calculated as:

$$FTF_f = \sum_{f,p}^{f,P} FTF_{f,p} \times weights_{f,p} \tag{2}$$

where $FTF_{f,p}$ is the property-level FTF index in equation (1) for property p owned by firm f and $weights_{f,p}$ is the share of book value of property p in firm f's portfolio.

We construct our FTF indices for critical and non-critical industries separately. For instance, the property-level FTF index of tenants operate in critical industries is calculated as:

$$FTF\_C_p = \sum_{i}^{N} FTF_{p,i} \times 1_{p,i=critical} \times weights_{p,i} \tag{3}$$

where $1_{p,i=critical}$ indicates whether tenant i operates in a critical industry.

Resembling equation (2), the firm-level non-critical index is:

$$FTF\_C_f = \sum_{f,p}^{f,P} FTF\_C_p \times weights_{f,p} \tag{4}$$

We calculate the non-critical counterparts, FTF_NC_p and FTF_NC_f, in a similar way.

To show the relationship between tenants' FTF measures and their demand for CRE spaces, in Figure 1 we plot the average percentage share of spaces occupied within buildings against each of the FTF measures. For ease of presentation, we aggregate 4-digit NAICS industries to 2-digit industries. The horizontal axis is one of our FTF proxies. As expected, workers in accommodation and food services (NAICS=72), agriculture (11), and transportation (48) are unable to work remotely. In contrast, sectors such as finance and insurance (52), professional, scientific, and technical services (54), and management of companies and enterprises (55) rank the lowest in *Nonremote %*. Unsurprisingly, retail trade (44-45) and healthcare (62) workers must engage in a great deal of FTF contact with their customers but rank low in the other two indices.

The vertical axis corresponds to the average share of space occupied by each industry within a building. Although certain industries such as manufacturing (33) and accommodation

(72) are more likely to be located in single-tenant properties (therefore ranking high along the y-axis), we do not observe a clear pattern between these FTF measures and space share. This is important because our property-level FTF indices are calculated by multiplying the tenant-level FTF measure by the corresponding space share in a given property. Finding no clear correlation between these two inputs suggests that our FTF measures are not driven by tenants in (a few) particular industries.

We replot Figure 1 by property type. Again, as seen in Figure 2, we do not observe a clear correlation between FTF measures and space share, suggesting that the variations of our FTF measures cannot be fully explained by property type. In fact, many REITs that focus on one property type often have top tenants that typically also rent properties of another type. For example, Macy's, a department store chain, is among the top tenants of office spaces for Vornado Realty Trust (Ticker: VNO). On the other hand, JPMorgan Chase & Co, a typical tenant in office buildings, also rents substantial retail spaces from Retail Opportunity Investments Corp. (Ticker: ROIC) and technology spaces from Digital Realty Trust, Inc. (Ticker: DLR).[13]

In Figure 3 we plot the tenant-level correlation between *Teamwork* and *Nonremote* as well as that between *Teamwork* and *Customer*. Specifically, we aggregate the total square footage (represented by circle size) occupied by individual tenants in a 2-digit NAICS code. In Panel A, we show a strong negative correlation between *Teamwork* and *Nonremote*. This negative relationship is driven mainly by industries with high ranking in *Teamwork* but low ranking in *Nonremote*, such as information, finance and insurance, professional, scientific, and technical services, and management (e.g. 51, 52, 54, 55) and those ranked low in *Teamwork* but high in *Nonremote*, such as retail trade, and accommodation and food services (e.g. 44, 45, 72).

As seen in Panel B, when we switch the horizontal axis to *Customer*, we find a negative relationship between *Teamwork* and *Customer*. This is because demand for CRE spaces is driven by commercial tenants whose business operations tilt toward either internal cooperation or external customer service. Industries that rank low (e.g. farming) or high (e.g. hospitals) along both dimensions require relatively less CRE space. This finding is likely explained by clustering and

[13]The median space share is 3.74% and 1.96% for an average office and retail REIT, respectively. Macy's occupies 6.7% of spaces of VNO. JPMorgan Chase & Co occupies 3.43% and 3.31% of spaces of ROIC and DLR, respectively.

tenant sorting within building due to the benefit of agglomeration (Liu et al. (2020)). This negative pattern among individual tenants is the opposite of that documented in KP, where they show *Teamwork* and *Customer* aggregated at the industry level are positively correlated. In fact, when we plot *Teamwork* and *Customer* using simple industry averages, we find a positive relationship that is consistent with that reported in KP (results unreported). The pattern is reversed, though, when we use spaces occupied by all tenants within each NAICS code as the weighting scheme. The opposite pattern observed using individual tenants highlights the importance of looking at business operations at a granular level within a firm.

Figures 4 and 5 plot property-level and firm-level *Teamwork* against *Nonremote* (*Customer*) in Panels A and B, respectively. Consistent with our tenant-level results, we observe a negative relationship between Teamwork and *Nonremote* (*Customer*). Although office properties show on average higher *Teamwork* % while retail properties show higher *Nonremote* % and higher *Customer* %, there is still significant variation along each of the three dimensions within property types. In addition, as these measures are conceptually different, one single metric cannot fully capture the heterogeneity of the other metrics. For example, although *Teamwork* and *Nonremote* are negatively correlated, several firms (e.g. MPW and GMRE) rank highly along both dimensions, as shown in Figure 5. The negative correlations reported in both Panels A and B would suggest that *Nonremote* and *Customer* should be positively correlated. However, several firms (e.g. COLD) are high on the *Nonremote* index but low on the *Customer* index.

Together, these visual presentations of the relationships between the three FTF measures at varying levels and by property types suggest negative correlations between *Teamwork* and *Nonremote* and between *Teamwork* and *Customer*. Importantly, neither a building's property type nor a REIT's property-type focus fully captures the heterogeneity of FTF interactions between CRE tenants.

4 Results

4.1 FTF Interactions and Stock Market Reactions

We begin our analysis by investigating whether and how FTF interactions affect the impact of COVID-19 lockdowns on abnormal returns. The first reported case in the U.S. occurred on January 21, 2020. From end-February to mid-April, we observe a rapid-and-then-decelerating rise in COVID-19 cases.[14] As social distancing became less restrictive after reopenings, we therefore follow Ling et al. (2020) and focus on the early stage of the pandemic, from January 21 through April 15, prior to when the first state (i.e. South Carolina) adopted a reopening policy, on April 20. We regress daily abnormal returns on firm-level FTF indices, COVID case growth, and the interaction between the two, as follows:

$$Ret_{f,t} = \beta\, FTF_{f,preCovid}\, GeoCOVID_{f,t-1} + \boldsymbol{\gamma}\, \boldsymbol{X_{f,t}} + \boldsymbol{\delta}\, \boldsymbol{Z_{f,preCovid}} + \theta_j + \epsilon_{f,t} \tag{5}$$

In the above equation, $Ret_{f,t}$ is the one-day abnormal return on firm f on day t. It is calculated by first regressing a firm's daily stock return in excess of the 30-day U.S. Treasury bill rate on the contemporaneous total return on the market benchmark. Specifically, we estimate return sensitivities for each firm using a simple market model and data from January 1, 2019 through January 20, 2020. We use the S&P 500 Index as our benchmark.[15] The estimated firm-level return sensitivities are used to compute daily abnormal returns for the baseline period that runs between January 21, 2020 and April 15, 2020. $FTF_{f,preCovid}$ is one of the firm-level FTF indices ($Nonremote$, $Teamwork$ or $Customer$) shown in equation (2). $GeoCOVID_{f,t-1}$ represents the geographically weighted COVID case-growth rate for firm f on day t-1. As pointed out by Ling et al. (2020), the pandemic shock likely transmits to stock markets from a firm's asset base and REIT stock reactions during the pandemic depend largely on the location of a firm's underlying assets. To estimate $GeoCOVID$, we calculate, for each REIT, the percentage of its property portfolio based on depreciated book values invested in each county at the end of 2019. We then

[14] See Ling et al. (2020) Figure 3 for the hump-shaped trend in COVID-19 case growth.

[15] Using abnormal returns based on the FTSE-NAREIT Equity Index generates similar results.

match these portfolio allocations with the daily growth rates of county-level confirmed COVID-19 cases.[16] These county-level growth rates are then value-weighted by the percentage of the CRE portfolio invested in each county.

$X_{f,t}$, represents firm-specific and time-varying controls, for which we include $FTF_{f,preCovid}$ and $GeoCOVID_{f,t-1}$. To account for firm-specific time trends, we include $Days\ since\ outbreak_{f,t}$, the number of days since the first COVID-19 case was reported in any county in which a firm owns property. We include $Days\ since\ outbreak^2_{f,t}$ to account for non-linearity. $Z_{f,preCovid}$ includes pre-pandemic determinants of daily stock returns (see e.g. Brennan et al. (2013); Giannini et al. (2018); Patel and Welch (2017); Wheaton and Thompson (2020)). Table A.1 summarizes the variable definitions and data sources. θ_j are property-type fixed effects.[17]

In Panel A of Table 1 we report summary statistics using a sample of 7,198 firm-day observations for the period running from January 21, 2020 through April 15, 2020. The average 1-day abnormal return is -0.7%. As a result of extreme stock market volatility during the pandemic, the standard deviation (6.5%) is more than nine times its mean. Prior to COVID, for an average firm, about 66% of its spaces were occupied by tenants that cannot work remotely, while 23% (43%) of its spaces were occupied by tenants in teamwork-intensive (customer-contact-intensive) occupations. These numbers are in line with results reported in Papanikolaou and Schmidt (2020).[18] Separating the tenants into critical and non-critical industries, we find that $Nonremote$ is higher for non-critical industries while $Teamwork$ and $Customer$ measures are higher for critical industries. This is consistent with Blau et al. (2020), who find that a large percentage of essential workers are, in fact, able to work remotely and that many frontline workers in essential industries take on considerable risk to do their jobs because they must provide their labor in person. Other variables are largely consistent with findings reported in Ling et al. (2020).

[16]Data are obtained from the Coronavirus COVID-19 Global Cases database at Johns Hopkins University. `https://github.com/CSSEGISandData/COVID-19`

[17]REITs are in general classified as core (including office, retail, industrial, and residential properties) or non-core (other property types). As our study includes only commercial tenants, we use four property types: office, retail, industrial, and others. Our results are robust to controlling for property types at more granular levels. For example, "others" can be further divided into hospitality, healthcare, technology, and specialty.

[18]Papanikolaou and Schmidt (2020) construct Covid-19 work exposure, which is calculated as 1 - the percentage of workers who are able to work from home. For their Table 1, they break down firms into four quartiles. The medians of the industry-based measure of Covid-19 work exposure in each quartile (from low to high) are 0.45, 0.64, 0.82, and 0.98 (0.32, 0.67, 0.86, and 0.97) for all (non-critical only) industries.

In Table 2 we report our key regression results. The coefficients of control variables (suppressed in Table 2 but shown in Table A.2) are consistent with those reported in prior studies. Standard errors are clustered at the firm level. In column (1), the estimated coefficients on $Nonremote_{f,preCovid} \times GeoCOVID_{t-1}$ are negative and statistically significant, indicating that a firm with a higher *Nonremote* index responds more negatively to COVID case growth. In other words, firms with tenants whose operations are more compatible with social distancing are more resilient to the pandemic shock. This finding is consistent with Papanikolaou and Schmidt (2020) and Pagano et al. (2020), who find that sectors with a higher fraction of workers who can work remotely experienced smaller declines in stock prices. Economically, a one-standard-deviation increase in $Nonremote_{f,preCovid}$ would exacerbate negative stock-price reactions to the pandemic by 1.78 ($= 0.163 \times (-0.120 + 0.011)$) percentage points.

To capture the differences between internal and external interactions, for columns (2) and (3) we replace $Nonremote_{f,preCovid}$ with the teamwork index ($Teamwork_{f,preCovid}$) and the customer index ($Customer_{f,preCovid}$), respectively. We observe the opposite results: teamwork *mitigates* the negative stock-price reaction to the pandemic while customer contact *intensifies* the reaction. These opposite findings can be explained by the negative correlation between $Teamwork$ and $Customer$ among commercial tenants discussed in Section 3. A one-standard-deviation increase in $Teamwork_{f,preCovid}$ ($Customer_{f,preCovid}$) is associated with an increase (reduction) in the stock-price reaction of 1.46 (1.69) percentage points.

As pointed out by KP, the terms "teamwork" and "customer contact" differ conceptually. The former captures the extent to which a work routine involves group discussions and coordination while the latter captures service provision based on interpersonal relationships. The opposite results are intuitively plausible in the CRE market: demand for CRE spaces is driven by whether commercial tenants' business operations are oriented towards either internal cooperation and coordination or external customer service, which is consistent with clustering and tenant-sorting as documented in Liu et al. (2020). Top commercial tenants that rely on internal communication comprise mostly high-tech firms, which are less prone to disruptions of ICT infrastructure, the main driver of the positive relationship between labor force telework flexibility and stock returns during the pandemic (Favilukis et al. (2020)). In contrast, top tenants that rely heavily on customer contact operate mostly in the hospitality and retail sectors, which are more susceptible to business disruption when FTF interactions are restricted by social distancing. Interestingly, our findings contrast with those reported in Pagano et al. (2020), who find a positive relationship between stock performance and remote work proxies using both teamwork and customer contact as defined for the single industry in which a firm operates. Our study highlights the importance of considering granular-level business operations (across multiple industries) within a firm.

During the pandemic, government restrictions have played an important role in tenants' ability to continue operations. For example, tenants operating in "critical" industries that provide essential goods and services are subject to less severe disruptions than those operating in "non-critical" industries. We thus measure remote work in critical and non-critical industries separately. We perform this "decomposition" at the property level. Specifically, for every property we classify each of its tenants into either the critical or non-critical category and re-calculate the remote work indices using the share of a tenant's occupied space in its corresponding category (see equations (3) and (4)). The objective is to capture the importance of remote work independently of a property's business classification. If critical industries are less susceptible to disruptions, we would expect the ability to work remotely to play a more important role in non-critical industries.

As can be seen in Table 3, columns (1) and (2), by separating the remote work index into critical and non-critical categories, we find that interaction coefficients using both $Nonremote\_C$ and $Nonremote\_NC$ are negative and significant. The magnitude for non-critical businesses is, however, much larger: a one-standard deviation increase in $Nonremote\_NC$ is associated with a reduction in the magnitude of negative stock-price reactions to COVID case growth by 2.02 percentage points ($= (-0.131 + 0.012) \times 0.17$), whereas the effect of a one-standard deviation increase in $Nonremote\_C$ is only 1.22 percentage points ($= (-0.074 + 0.006) \times 0.18$).

The results reported in columns (3) and (4) using $Teamwork$ are consistent with those reported in Table 2, column (2). Prior to reopenings, firms with tenants that rely on teamwork are less severely disrupted by social distancing. Again, we observe much larger effects for non-critical industries, as seen by comparing the results shown in column (3) with those shown in column (4). The interaction coefficient for $GeoCOVID \times Teamwork\_C$ is only marginally significant, with an economic significance of about a half that of its non-critical counterpart. As can be seen in columns (5) and (6), more customer contact tends to intensify the negative stock-price reaction to COVID. Moreover, this intensification is more pronounced if a firm rents space to more tenants in non-critical industries that are not able to work remotely.

One might argue that these FTF effects simply reflect variation across property types. For example, teamwork-focused high-tech firms are more likely to rent offices while customer-focused companies are typically located in retail properties. As shown in Figures 2 and 3, we find that the variation in our FTF measures is not fully explained by tenant industry or by property type. Nevertheless, to check whether our regression results are driven by property types, for Table A.3 we re-estimate the regressions reported in Table 2 by comparing our baseline results (controlling for property-type) with the results based on no property-type fixed effects (in Panel A) by deleting one property type at a time (for Panels B through E), and by using seven property types instead of four (for Panel F).[19] We find that our baseline results are highly similar to those estimated without property-type fixed effects. Our results are not driven by a specific property type and remain robust to using alternative property-type fixed effects. This is consistent with our findings reported in Section 3, which indicate that there is significant variation in FTF proxies within a given property type.

4.2 Event Studies based on Lockdowns and Reopenings

Investors' expectations might shift depending on the status of the economy. For example, during March and April 2020, local lockdowns were announced across the U.S. These supply-side disruptions might prevent employees from going back to work (Bonadio et al. (2020); Papanikolaou and Schmidt (2020)). The associated social distancing policies were lifted in late April and early May. How does tenants' ability to work remotely, or the need to engage in FTF contact with co-workers and customers, affect REIT investors' responses to these distinct government interventions?

[19] The seven property types include retail, office, industrial, hospitality, healthcare, specialty, and technology (including data center and infrastructure). As business listings include only commercial tenants, residential and self-storage properties are dropped from our sample. We also drop diversified properties because a significant proportion of properties accommodate mixed uses, including residential.

To investigate this issue, we look at market reactions around two types of major events: lockdown announcements and subsequent reopenings. We expect that investor reactions to lockdowns will capture the extent to which a firm's rental cash flows might be adversely affected by tenants' business disruptions. Tenants in industries in which a higher fraction of workers can work remotely are more resilient to disruptions in their business operations. Therefore, REITs with higher $Nonremote$ and $Customer$ ($Teamwork$) measures should experience worse (better) performance around lockdown announcements. On the other hand, if investors believe that a pandemic shock is intrinsically transient in nature after social distancing restrictions are lifted, FTF factors should play an insignificant role in explaining investors' response to reopenings.

Identifying the announcement dates of these non-pharmaceutical interventions (NPIs) is not an easy task because jurisdictions at various levels might adopt policies at various points in time. In addition, a policy enacted by one jurisdiction might influence what happens in other jurisdictions as they consider adopting a similar policy. To reconcile the impact of the spillover effects of policy adoption, for each firm we identify state-level NPI event dates as the first dates on which major NPIs, including shelter-in-place orders, stay-at-home orders, and mandatory school and business closures, were announced at the city, county, or state level.[20] In contrast to a lockdown, a reopening is a gradual process in which certain types of businesses in certain locations open before others. In addition, cities and counties might have discretion over whether, and how, to reopen. We therefore follow the literature (Chetty et al. (2020); Nguyen et al. (2020); Raifman et al. (2020)) and define reopenings as dates on which a state government allows the first set of businesses to reopen.[21] REITs own properties in multiple locations, so we match these announcements to the states in which a REIT owns properties.

We run the following regressions using firm-state cross-section observations weighted by the share of each REIT's portfolio located in the state,

[20] We collected open-source data using 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)). The NPI data are available at `https://github.com/jataware/covid-19-data`.

[21] The list of state reopening dates is taken from Nguyen et al. (2020)

$$CAR^{\tau}_{f,s} = \beta \, FTF_{f,preCovid} + \boldsymbol{\delta} \, \boldsymbol{Z_{f,preCovid}} + \theta_j + \gamma_s + \epsilon_{f,s} \tag{6}$$

where $CAR^{\tau}_{f,s}$ is the cumulative abnormal returns (CARs) over a period of τ days around the announcements of interventions (either lockdown or reopen) in state s in which firm f owns properties. $FTF_{f,preCovid}$ is one of the firm-level FTF indices and $Z_{f,preCovid}$ is the set of control variables used for Tables 2 and 3. θ_j is property-type fixed effects. γ_s is state fixed effects. Standard errors are clustered at the firm level.

The summary statistics reported in Panel B of Table 1 suggest that returns were affected in a significantly negative way by lockdown announcements: the means of 3-day and 5-day NPI CARs are -16% and -25%, respectively. Reopening announcements, however, had weak, although positive, effects on stock returns.

Table 4 summarizes the event-study results. Each coefficient represents a separate regression in which the combination of an FTF index ($Nonremote$, $Teamwork$, or $Customer$), an event (lockdown or reopening), and an event window (3-day or 5-day) varies. For example, the coefficient of $Nonremote$ reported in Panel A, column (1) shows the effect of remote work on the 3-day CAR around the lockdown announcements. We suppress the coefficients for all the control variables.

Results in Table 4 suggest that investors react more negatively if a firm's tenant base is less resilient to lockdowns: the coefficient estimates on $Nonremote$ reported in Panel A, column (1) are positive and significant. For example, a one-standard-deviation increase in $Nonremote$ is associated with an approximately 1.5 (5.5) percentage point reduction in 3-day (5-day) CAR, or about 9% (22%) of the sample mean. $Teamwork$ is positively correlated with investor reactions, as shown in Panel A, column (2). The coefficient estimates on $Customer$ are negative, however, suggesting that investors react more negatively if a firm has more tenants who rely on direct customer contact. We measure the FTF indices separately for critical and non-critical industries. The results reported in columns (4) and (5) are consistent with our previous findings reported in Table 3. Remote work is not correlated with investor reactions to lockdowns in critical industries. The effects are driven by non-critical industries in which business disruptions are more severe than in critical industries.

Panel B summarizes the results based on reopening announcements. Differing from the results reported in Panel A, here we find that FTF indices have no effect on investor reactions to reopening, unlike reactions to lockdowns. These results suggest that FTF interactions play little role after social distancing restrictions are lifted. Another possible explanation is that, as mentioned earlier, in contrast to mandatory lockdowns, reopening is a gradual and voluntary process. This null effect is consistent with findings in prior studies indicating that reopenings have little impact on local employment or business activities (e.g., Balla-Elliott et al. (2020); Chetty et al. (2020)). We will discuss Post-COVID implications further in the next section when we examine long-term analyst forecast.

4.3 FTF Interactions and Earnings Expectations

We next examine analyst forecasts of earnings per share (EPS) as a forward-looking variable in a difference-in-differences (DID) setting. Our setting is similar to that used in Albuquerque et al. (2020), who argue that COVID-19 and subsequent lockdowns hit the stock market with an exogenous shock. Similar studies using COVID-19 as an unexpected shock include Barrios et al. (2021), Egorov et al. (2021), and Gupta et al. (2020).[22]

We retrieve historical IBES forecasts from WRDS. As analyst forecasts are sparsely populated at medium horizons such as three years, we focus on forecast periods of "1 year" (forecast period indicator (FPI) = 1) and "Long Term" (forecast period indicator (FPI) = O). The long-term forecasts are not as populated as their short-term counterparts, but they augment short-term projections by incorporating an analyst's view of the persistence of the COVID shock, which helps us compare short-term with long-term expectations. Our sample period starts in 2017 to cover pre-pandemic periods. The results are qualitatively similar when we use a sample period that starts in 2018.

[22] Albuquerque et al. (2020) use a DID design to study how firms' environmental and social policies (measured prior to COVID) affect stock returns and return volatility during the market crash. Barrios et al. (2021) examine the impact of civic capital, measured prior to COVID, on social distancing behavior. Egorov et al. (2021) examine how ethnicity affects mobility after the first reported case in a region. Gupta et al. (2020) examine the effects of social distancing policy on labor market outcomes.

We run the following DID specification:

$$EPS^{\tau}_{j,f,t} = \beta \, FTF_{f,preCovid} \, Post_t + \alpha_j + \delta_f + \gamma_t + \epsilon_{i,f,t} \tag{7}$$

where $EPS^{\tau}_{j,f,t}$ is the log of forecasted EPS by analyst j at time t for firm f over forecast period τ. $FTF_{f,preCovid}$ is one of the firm-level remote work indices, aggregated from the property level and weighted by the square footage occupied in a property as of the end-2019. $Post_t$ represents the post-COVID indicator constructed based on the analyst forecast date.

As analysts' expectations might shift depending on the status of the economy, we construct three post dummies using (1) January 21 (the first reported case in the U.S.), (2) the earliest date on which a non-pharmaceutical intervention (NPI) was announced in a specific locality (either a city, a county, or a state) in which a firm owns properties, or (3) the earliest date of reopening in any state in which a firm owns properties. As is the case with our event studies, here the latter two post dummies vary by firm, depending on a firm's geographic footprint. α_j is analyst fixed effects, δ_f is firm-fixed effects, and γ_t is analysts' forecast week fixed effects. Standard errors are clustered at the firm level.

In our DID model, the FTF proxies, measured prior to the pandemic, act as a (continuous) treatment. Our coefficient of interest is β, which captures how FTF interactions affect analyst forecasts (for a given firm at a given horizon) before and after the pandemic. Our identification assumption is that, after controlling for heterogeneity across individual firms, individual analysts, and forecast timing, there is no correlation between pre-pandemic FTF proxies and the COVID-induced expectation shocks.

The summary statistics reported in Panel C of Table 1 suggest that long-term forecasts are lower than short-term forecasts, consistent with Landier and Thesmar (2020). The number of observations with "Long-term" forecast periods are lower than those for "1-year" periods, as long-term forecasts are not as populated as their short-term counterparts. The pandemic caused a sharp drop in earnings expectations: unreported results show that the mean of "1-year" ("Long-term") EPS drops from 1.74 to 1.08 (0.44 to 0.42) between the pre-COVID and the post-COVID period.

The regression results are summarized in Table 5. Each coefficient represents a separate regression in which the combination of the FTF index, a post indicator, and the forecast period varies. For example, the coefficient on $Nonremote$ reported in column (1) is $\hat{\beta}$ for $Nonremote_{f,preCovid} \times Post_t$ using the outcome variable of 1-year-ahead EPS forecasts and $Post_t$ for the post-January 21 period.

In Panel A, the dependent variable is 1-year-ahead EPS forecasts. The results reported in the "Nonremote" row suggest that after the COVID outbreak the short-term analysts' earnings forecasts are lower for firms with more tenants that are less capable of working remotely. Relative to the baseline scenario, a one-standard-deviation increase in $Nonremote_{f,preCovid}$ reduces 1-year-ahead EPS forecasts by an additional 15%-21%, depending on the definition of the post indicator.[23] All the coefficient estimates for $Customer_{f,preCovid}$ are negative; earnings forecasts drop by 6%-8% for a one-standard-deviation increase in $Customer_{f,preCovid}$. This reduction in firms that rely to a greater extent on internal teamwork is much smaller. The effects of teamwork are positive and economically large: a one-standard-deviation increase in $Teamwork_{f,preCovid}$ correlates with an increase in 1-year EPS forecasts of 12%-17%. Consistent with our previous results using abnormal returns, these FTF effects are driven by non-critical industries, as shown in columns (4) and (5).

As can be seen in Panel B, the FTF effects on long-term forecasts are much smaller. This is consistent with findings reported in Landier and Thesmar (2020), who study revisions of analyst forecasts and find that long-term forecasts reacted much less to the COVID-19 outbreak than short-run forecasts. Similarly, we find that the FTF effects on long-term forecasts are mostly statistically insignificant, as seen in columns (1)-(3). Although $Nonremote$ coefficients are still statistically significant, the economic magnitudes are modest: a one-standard-deviation increase in $Nonremote$ leads to 5%-7% increase in long-term EPS forecasts, about a third the size of the short-term effects.

Our results so far imply a weakening of the long-run effects. In the context of heated debates over the concern that remote work might reduce future demand for real estate and that real estate prices might fall in the post-pandemic era, we check the dynamics of the implicit discount

[23]For example, using January 21 as our post-pandemic dummy (i.e. Outbreak) a one-standard-deviation increase in $Nonremote_{f,preCovid}$ reduces 1-year-ahead EPS forecasts by 15% (=0.924*0.163)

rate using a simple dividend discount model following Landier and Thesmar (2020). For each firm f on date t, we compute the internal rate of return (IRR), $r_{f,t}$, by solving the following equation,

$$P_{f,t} = \frac{payout_f \times EPS^{2020}_{f,t}}{1+r_{f,t}} + \frac{payout_f \times EPS^{2021}_{f,t}}{(1+r_{f,t})^2} + \frac{payout_f \times EPS^{2021}_{f,t}}{(1+r_{f,t})^2} + \frac{(1+g_f) \times payout_f \times EPS^{2021}_{f,t}}{(r_{f,t}+g_f) \times (1+r_{f,t})^3}, \tag{8}$$

where $P_{f,t}$ is the stock price for firm f on date t and $payout_f$ is the average payout ratio for 2010-2019, calculated as the sum of dividends and common stock repurchases normalized by net income. We winsorize $payout_f$ at zero and one. g_f is the long-term growth rate for firm i's property type for 2010-2019. For a given property type, we calculate the average firm sales growth over 2010-2019, weighted by 2010 sales. $EPS^{2020}_{f,t}$ ($EPS^{2021}_{f,t}$)) represents the average forecast at date t of annual earnings per share for firm i at horizon 2020 (2021). By solving Equation (8) for each observation for firm f on date t, we obtain a panel of implicit discount rates.

In Figure 6, we plot the mean of these implicit IRRs from January 1 to July 1, 2020. Panel A shows results obtained using the full sample. The implicit IRRs increased sharply from less than 9% in the pre-pandemic period to a peak of above 11% in late March. However, this percentage dropped to about 9% in April, very close to it pre-pandemic level. This is consistent with the conjecture that pandemic-induced effects might not last over the long term (Landier and Thesmar (2020) and Hong et al. (2020)). We further compare the implicit IRRs of firms with above and below median FTF. If investors anticipate reduced demand for CRE spaces in the long run, the implicit IRR for those firms with higher FTF might rise above its pre-crisis level. As shown in Panels B-D, the average discount rates are higher for firms with a higher (lower) than median non-remote and customer (teamwork) measure. The discount rates, however, have returned to their pre-crisis levels for both the above- and below-median FTF groups.

4.4 Property-level Evidence: FTF Interactions and Loan Performance

In our last exercise, we further granulate our analysis to the property level. There are merits to conducting analyses at both the firm and asset levels. The former allows us to examine, in a timely manner, investors' short-run and long-run expectations on future cash flows through changes in the prices of liquid stocks and analyst forecasts. As our FTF proxies are originally constructed at the building level, asset-level analysis helps us mitigate the loss of information caused by aggregation and allows us to leverage our granular sample at the individual asset level. Mortgage lenders are presumably better informed about the commercial properties they pledge as collateral. As the terms of commercial mortgages typically range from five to twenty years, changes in mortgage spreads presumably reflect lenders' risk perceptions in the medium to long term.

We download quarterly encumbrance data on commercial properties from S&P Global for the period running from 2017Q1 through 2020Q2.[24] Specifically, S&P Global provides information for each property on the unpaid principal balance of the encumbrance collateralized by the property, the interest rate on the encumbrance, the maturity date, whether it is a mortgage or line of credit, whether it is a fixed-rate debt contract, and whether it is cross-collateralized by multiple properties. Mortgage spreads are calculated as differences between mortgage rates and Treasury rates with the same or closest maturity.[25] For instance, if the maturity of a mortgage is 10 years, we subtract the 10-year Treasury rate from the interest rate on the mortgage to obtain the mortgage spread. Because encumbrance data have been updated every year since 1995, we follow Eichholtz et al. (2019) and derive the year of origination based on the first appearance of the encumbrance in the database.

We examine mortgage spreads using a DID setting similar to that used in the previous section using the following regression:

$$Spread_{l,p,f,t} = \beta\, FTF_{p,f,preCovid}\, Post_t + \boldsymbol{\gamma}\, \boldsymbol{X_{l,t}} + \boldsymbol{\delta}\, \boldsymbol{Z_{p,t}} + \alpha_p + \delta_f + \gamma_t + \epsilon_{p,f,t} \tag{9}$$

where $Spread_{l,p,f,t}$ is the mortgage spread for loan l on property p held by firm f in quarter t, which is calculated by subtracting the Treasury rate with the same or closet maturity from the mortgage rate. $FTF_{p,f,preCovid}$ is one of the property-level FTF indices as of the end of 2019. represents the post-COVID indicator, which takes the value of one for 2020Q1 and 2020Q2.

[24]While encumbrance can be either a line of credit or a mortgage, the former typically has a shorter term and is more likely to be used to manage liquidity.

[25]The 30-day, 1-year, 2-year, 3-year, 5-year, 7-year, 10-year, 20-year, and 30-year U.S. Treasury rates are downloaded from the Federal Reserve System website: `https://www.federalreserve.gov/releases/h15/`.

In the above equation, $X_{l,t}$ represents loan-level controls, including the loan-to-value (LTV) ratio, time-to-maturity, a fixed-rate mortgage dummy, and a cross-collateralization dummy, following Titman et al. (2005), An et al. (2011), and Eichholtz et al. (2019). Specifically, the LTV ratio equals the unpaid principal balance divided by the depreciated book value of a property pledged as collateral, both gauged in the year of origination. Time-to-maturity is defined as the difference between the year of maturity and the year of origination of the mortgage. $Z_{p,t}$ includes property-level controls. This includes building size (depreciated book value), building vintage (whether the building is less than 10 years old), building quality (whether the building is Class A), whether the building has been renovated, and location (using state fixed effects). The Class-A dummy partially controls for tenant mix as the presence of quality tenants is an important concern to mortgage lenders. α_p are building-level property-type fixed effects, δ_f are the firm-fixed effects, and γ_t are the year-quarter fixed effects. Standard errors are clustered at the firm level.

As can be seen in Panel D of Table 1, the mean and median of property-level FTF indices are similar to those measured at the firm level (and reported in in Panel A). There is, however, a wider variation in these indices measured at the building level. In unreported summary statistics, we find that the mean (median) of mortgage spreads increased from 2.4 in the pre-COVID period to 3.19 in the post-COVID period (2.16 to 3.16), suggesting increased concern among lenders about default risk.

Because the terms of commercial mortgages typically range from five to twenty years, changes in mortgage spreads reflect lender risk perceptions over a medium-to-long horizon. The results reported in Table 6 suggest that, although mortgage spreads increased following the COVID-19 outbreak, mortgage spreads increased to a lesser extent for properties with higher proportions of tenants in teamwork-intensive occupations. This is consistent with our previous findings that investors perceive that properties occupied by teamwork-focused tenants are more resilient. $Nonremote$ and $Customer$ do not, however, explain changes in mortgage spreads, possibly because of a wide variance in these FTF indices measured at the property level. It is possible that, although this asset-level exercise allows us to control for significant heterogeneity across individual properties, mortgage rates might not instantaneously reflect investors' expectations because mortgage contracts take time to negotiate and our data include only two quarters in the post-COVID period. It would be worth extending this test using a longer sample period when more data become available.

Our control variables are in line with those used in prior studies, Eichholtz et al. (2019). For example, mortgage spreads are negatively correlated with time-to-maturity, supporting the credit-quality hypothesis. Spreads are lower if a collateralized asset is larger, newer, or higher in quality.

5 Robustness Checks

We conduct additional tests using alternative FTF indices. Key results are summarize in Table 7, in which we reproduce the analyses summarized in Tables 3, 4, and 5 in Panels A, B, and C, respectively. For columns (1)-(3), we construct FTF measures based on a tenant's parent company because remote work decisions might assume a "top-down" nature.[26] The results using parent companies' FTF measures are highly consistent with our findings using tenant level.

Insofar as independent businesses are more vulnerable to the pandemic (e.g. Bartik et al. (2020)), we classify each tenant as either a single-unit (i.e. independent) or multi-location establishment (i.e. corporate) following Foster et al. (2006, 2008), Dinlersoz (2004), and Kim and Zhou (2020). Again, the results reported in columns (4)-(9) are largely consistent with our previous findings. Firms with tenants whose operations are more resilient to social distancing earned less negative abnormal returns during the early stage of the pandemic (as shown in Panel A), experienced less negative CAR surrounding lockdown interventions (Panel B, for *NPI*), and received better short-term earnings forecasts (Panel C, for *1-Year*). FTF has little effect, however, on investor reactions to reopenings (Panel B, for *Reopen*) or analysts' long-term expectations (Panel C, for *Long-term*). Importantly, investors seem to believe that small businesses are more adversely affected during the crisis: the documented FTF effects are more pronounced for independent tenants.

Lastly, we check whether lease-term structure affects our results. Although we do not observe individual leases for each tenant in each property, S&P Global reports firm-level proportions

[26] We thank Jack Favilukis for this helpful comment.

of leases that expire in one year, two years, etc. We therefore check whether the FTF effects are larger for firms holding more leases that expire within the next 12 months. In untabulated results, we do not find that lease terms play a significant role in explaining the FTF results.[27]

6 Conclusion and Discussions

We use the COVID-19 pandemic as an exogenous shock to study how FTF interactions affect CRE performance. We build a new dataset linking stakeholders, including equity REITs and mortgage lenders, to their underlying properties, and the tenants that operate within these commercial buildings. We construct three FTF measures to capture distinct dimensions of tenants' business operations: the ability to work remotely and the demand (or need) to interact FTF with co-workers or customers in business operations. These FTF proxies are measured prior to the pandemic at both the property and firm levels.

We first analyze daily abnormal returns during the early stage of the pandemic. We show that stock prices for firms with tenants that are unable to work remotely perform significantly worse. In addition, firms with tenants working in teamwork-intensive (customer-contact-intensive) occupations are more (less) resilient to business disruptions, therefore experiencing stronger (weaker) performance. These FTF effects are especially prominent among tenants in non-critical sectors during lockdowns prior to reopenings. We next examine market reactions around lockdown and reopening announcements. The impacts of FTF interactions on CARs around lockdowns are highly consistent with findings obtained using daily abnormal returns. However, the announcement effects around reopenings are muted.

Using analyst forecasts, we are able to separately examine how FTF interactions affect investors' expectations of short-term and long-term performance. Using short-term forecasts, we find that analysts are more optimistic (pessimistic) about firms with higher $Teamwork$ ($Nonremote$ and $Customer$) measures. The FTF effects on long-term forecasts are, however, much weaker. Lastly, using property-level mortgage spreads, we find that the cost of debt for loans collateral-

[27] One possible explanation is that, due to data availability, we are unable to link lease terms directly to the FTF measures for each individual tenant.

ized with properties operated by teamwork-intensive tenants increases to a lesser extent after the outbreak of COVID-19.

Overall, our results provide strong evidence of market efficiency as CRE investors are able to observe and aggregate detailed information from tenants' business operations. During the pandemic, properties and CRE firms performed better if they have had more tenants operating businesses that are resilient to social distancing, primarily because they can adapt to ICT and maintain productivity. As the economy reopens, FTF interactions should gradually resume and the effects of remote work on firms' long-term performance might weaken. Our results hence highlight the importance of understanding how tenants operate at granular levels.

As tenant demand for CRE space underlies CRE performance over the long haul, our findings provide implications that pertain to real estate market performance in the post-COVID era. On the one hand, the temporary benefits of remote working might be replaced by reduced demand for CRE spaces and thus more vacancies in the long run. On the other hand, agglomeration and productivity gain through FTF interactions have been a major driver of demand for brick-and-mortar space. If FTF factors play a less significant role in explaining changes in long-term expectations, investors should be confident that the pandemic shock will prove intrinsically transient in nature. Our finding that FTF measures have weakened effects on long-term outcomes is consistent with the latter view.

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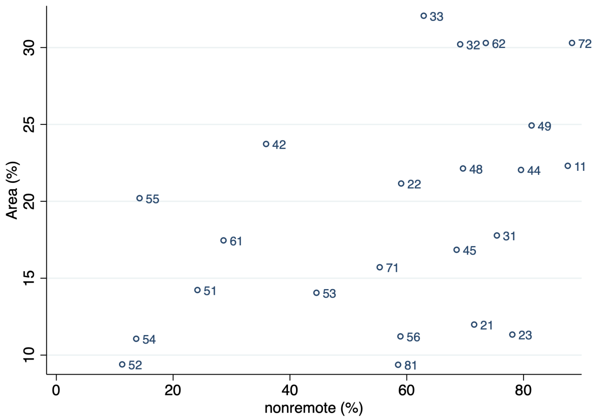
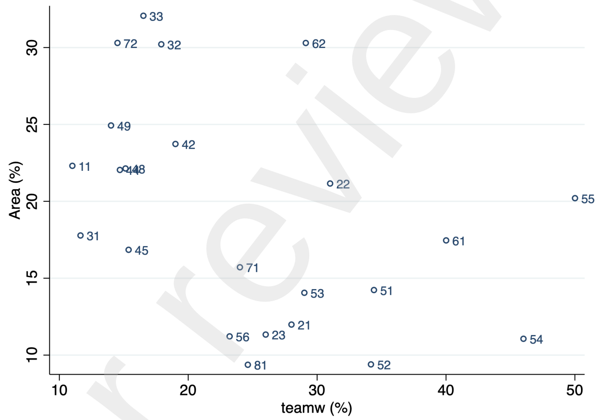
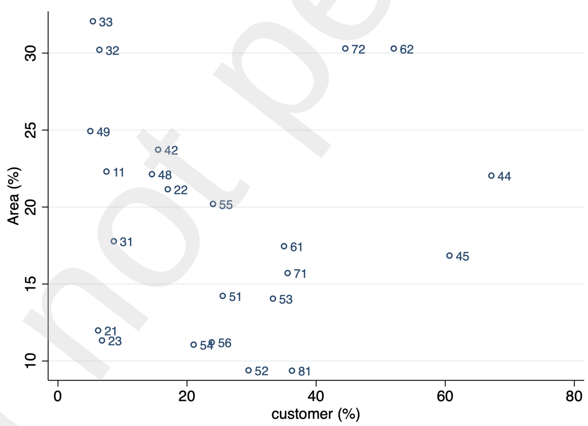


(a) Nonremote



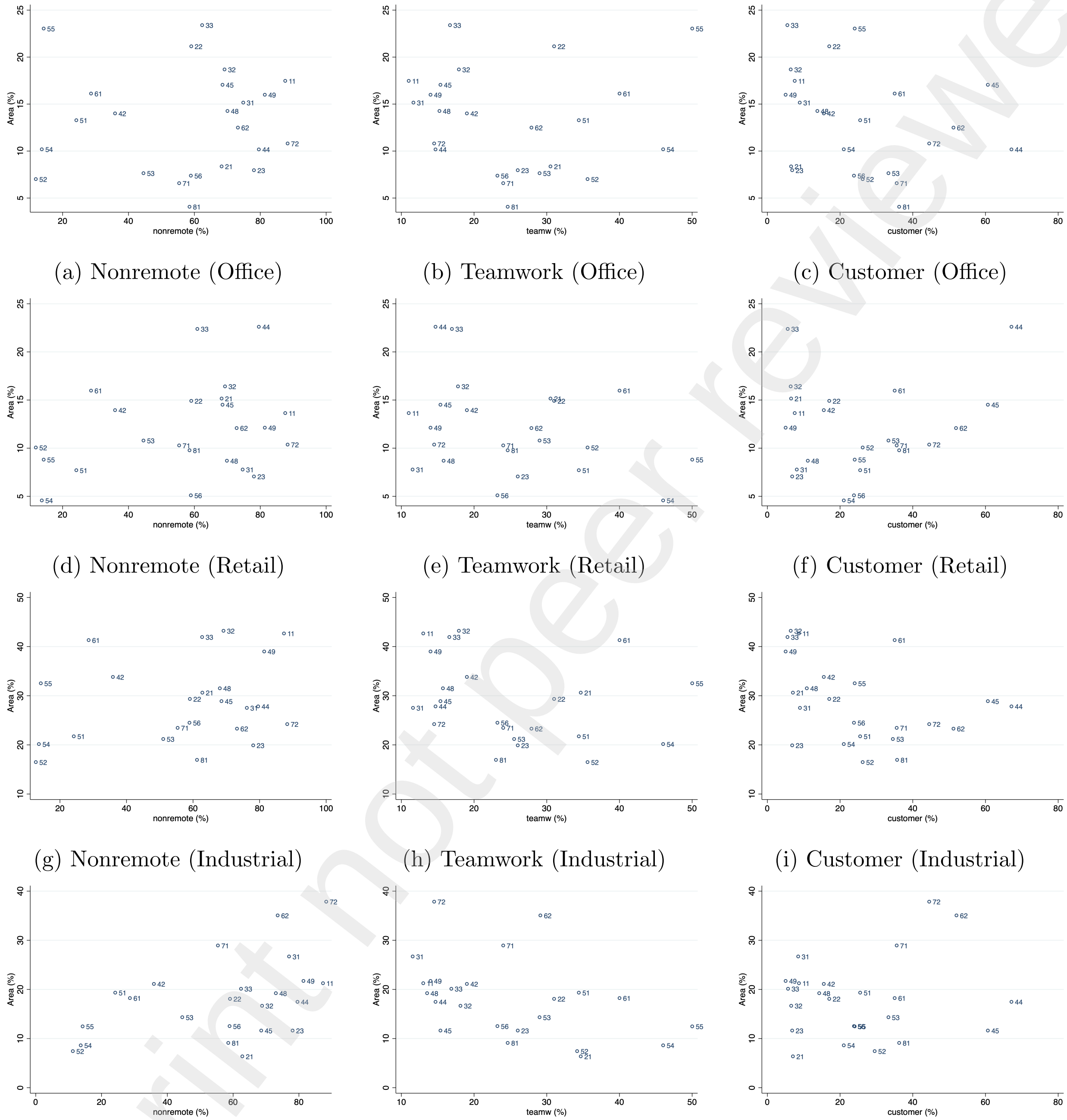
(b) Teamwork



(c) Customer

This figure shows property-level correlations between face-to-face (FTF) interactions and the average percentage space occupied at the building level. The FTF interaction index is *Nonremote*, *Teamwork*, and *Customer* for Panels (a), (b), and (c), respectively. Each point corresponds to a 2-digit NAICS. See Table A.1 for variable descriptions.

Figure 1: Property-Level Face-to-Face (FTF) Indices



(a) Nonremote (Office) (b) Teamwork (Office) (c) Customer (Office)

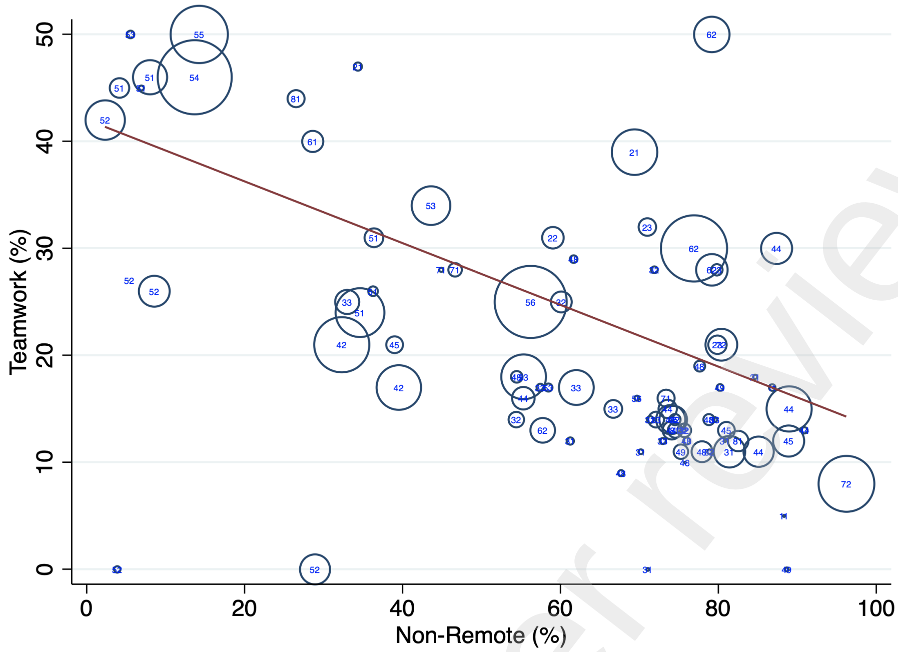
(d) Nonremote (Retail) (e) Teamwork (Retail) (f) Customer (Retail)

(g) Nonremote (Industrial) (h) Teamwork (Industrial) (i) Customer (Industrial)

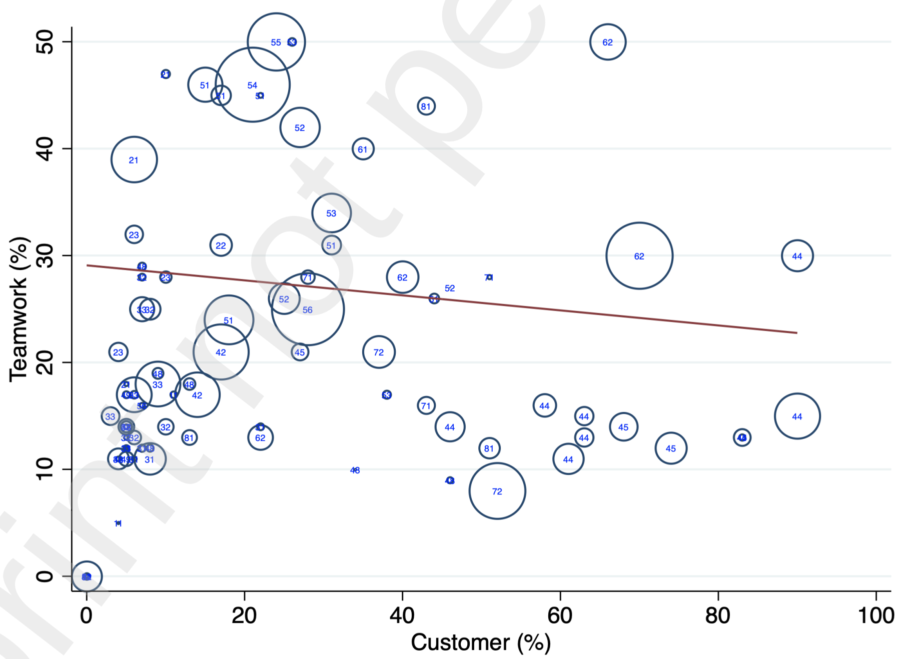
(j) Nonremote (Other) (k) Teamwork (Other) (l) Customer (Other)

This figure shows property-level correlations between face-to-face (FTF) interactions and the average percentage space occupied at the building level, by property type. The FTF interaction indices include *Nonremote*, *Teamwork*, and *Customer*. Each point corresponds to a 2-digit NAICS. See Table A.1 for variable descriptions.

Figure 2: Property-Level Face-to-Face (FTF) Indices by Property Types



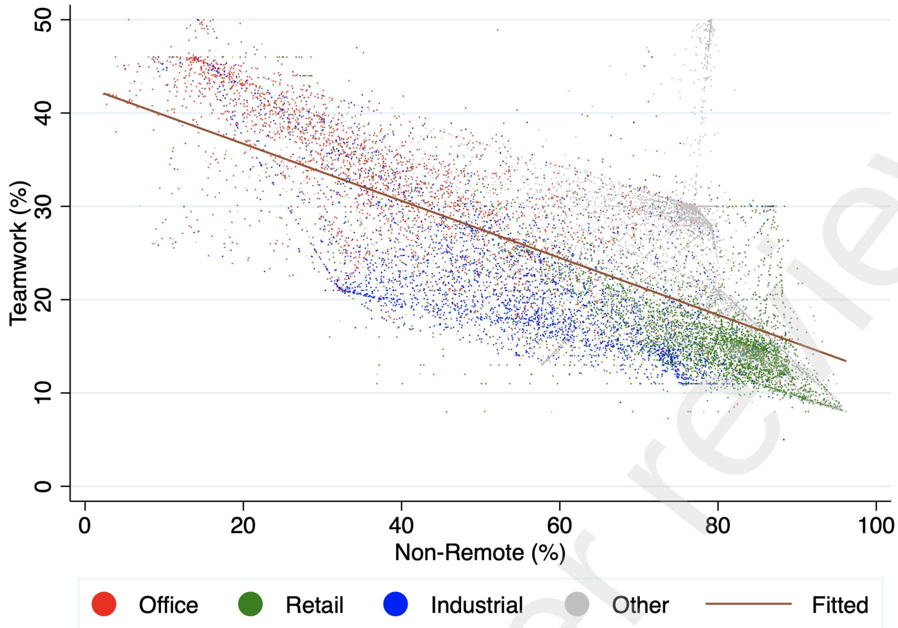
(a) Teamwork & Nonremote



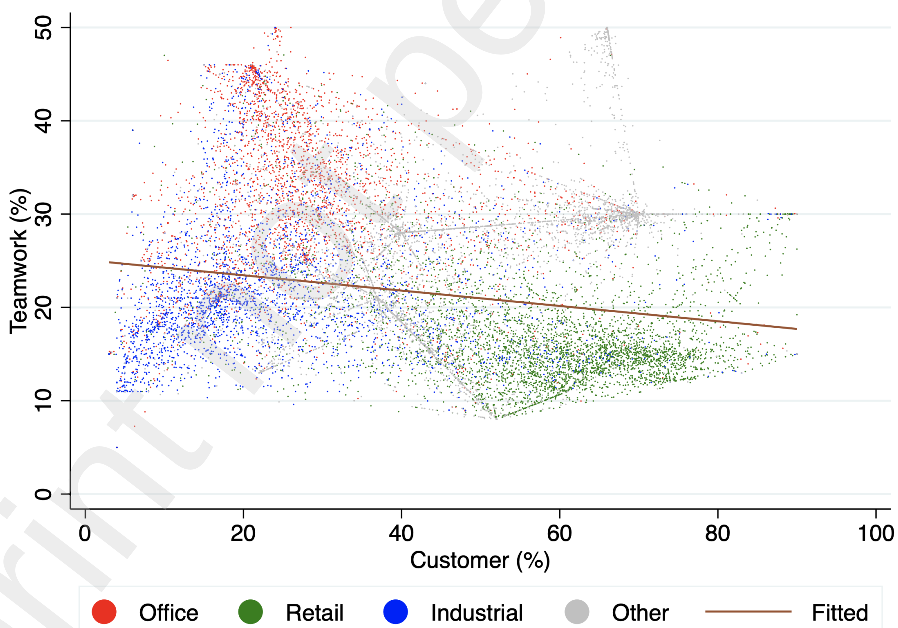
(b) Teamwork & Customer

This figure shows tenant-level correlations between *Teamwork* and *Nonremote* (*Customer*) in Panel (a) (Panel (b)). Each circle corresponds to a 3-digit NAICS. Circle size captures the total square footage occupied by all tenants of the NAICS. See Table A.1 for variable descriptions.

Figure 3: Tenant-Level Face-to-Face (FTF) Indices



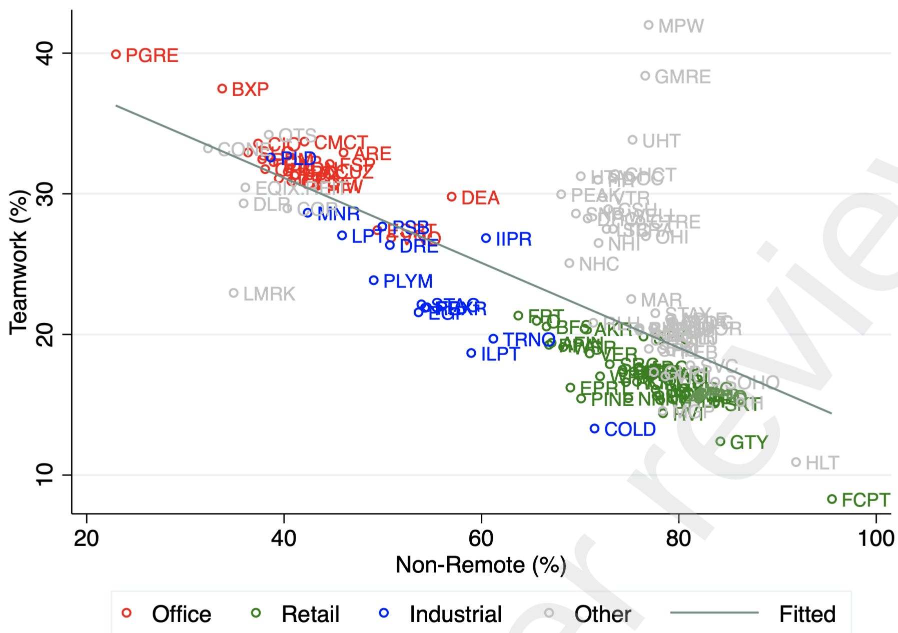
(a) Teamwork & Nonremote



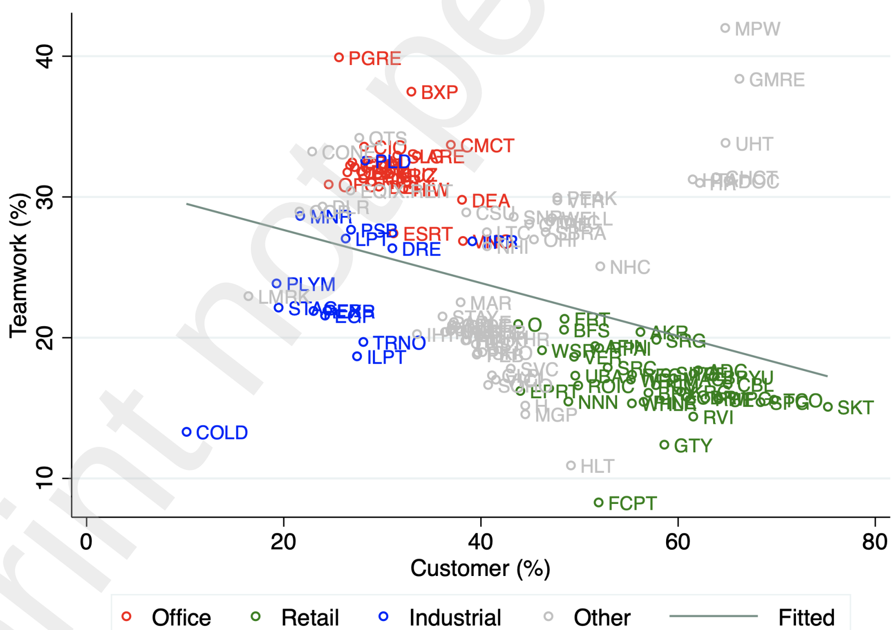
(b) Teamwork & Customer

This figure shows property-level correlations between *Teamwork* and *Nonremote* (*Customer*) in Panel (a) (Panel (b)). Each point corresponds to a firm ticker. The points in blue, red, green, and orange correspond to firms classified as Office, Retail, Industrial, and Others, respectively. See Table A.1 for variable descriptions.

Figure 4: Property-Level Face-to-Face (FTF) Indices



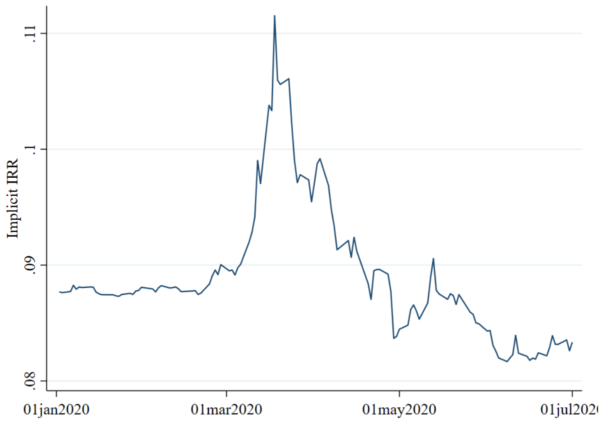
(a) Teamwork & Nonremote



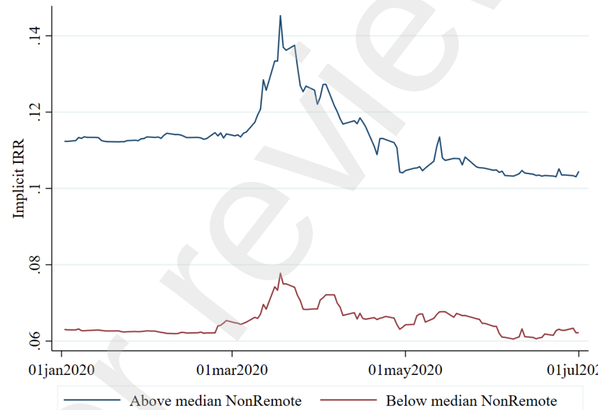
(b) Teamwork & Customer

This figure shows firm-level correlations between *Teamwork* and *Nonremote* (*Customer*) in Panel (a) (Panel (b)). Each point corresponds to a firm ticker. The points in blue, red, green, and orange correspond to firms classified as Office, Retail, Industrial, and Others, respectively. See Table A.1 for variable descriptions.

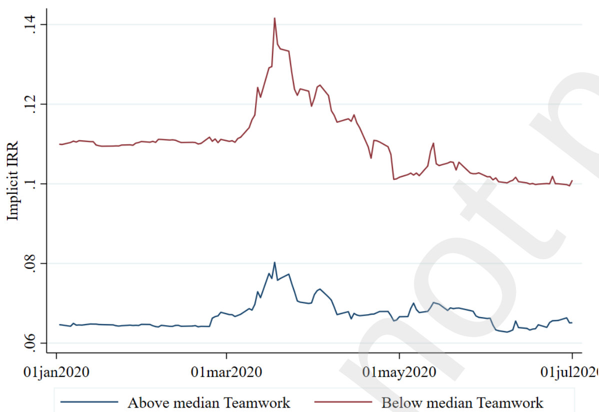
Figure 5: Firm-Level Face-to-Face (FTF) Indices



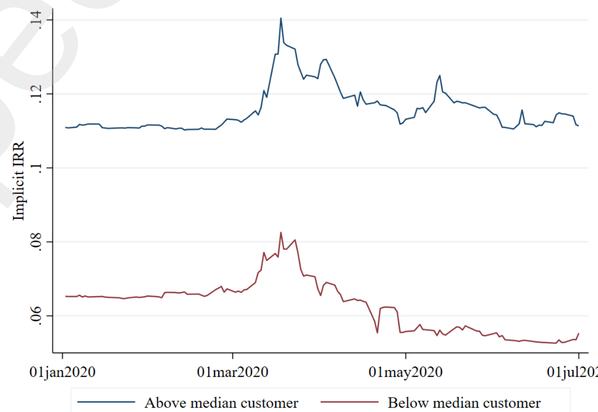
(a) All



(b) Nonremote



(c) Teamwork



(d) Customer

This figure shows the dynamics of the implicit internal rate of returns (IRRs) calculated using equation (8). Panel (a) shows average implicit IRRs using the full sample. Panel (b) compares firms with above- and below-median *Nonremote* index. Panel (c) compares firms with above- and below-median *Teamwork* index. Panel (d) compares firms with above- and below-median *Customer* index. See Table A.1 for variable descriptions.

Figure 6: Implicit Internal Rate of Returns (IRRs)

Table 1: Summary Statistics

Variable	#Obs	Mean	Median	Std	P25	P75
Panel A: Firm-level Variables						
Ret	7,198	-0.007	-0.001	0.065	-0.023	0.013
Nonremote	7,198	0.657	0.729	0.163	0.508	0.776
Teamwork	7,198	0.234	0.209	0.070	0.175	0.298
Customer	7,198	0.426	0.406	0.140	0.310	0.528
Nonremote_C	7,198	0.602	0.681	0.175	0.498	0.740
Nonremote_NC	7,198	0.642	0.697	0.165	0.469	0.783
Teamwork_C	7,198	0.257	0.261	0.069	0.203	0.302
Teamwork_NC	7,198	0.231	0.210	0.065	0.172	0.287
Customer_C	7,198	0.447	0.459	0.169	0.312	0.604
Customer_NC	7,198	0.398	0.394	0.128	0.284	0.490
USCOVID	7,198	0.148	0.134	0.130	0.000	0.251
GeoCOVID	7,198	0.102	0.056	0.117	0.000	0.185
Days since outbreak	7,198	36	37	27	14	59
Days since outbreak^2	7,198	2034	1369	1995	289	3481
ln(GeoDensity)	7,198	7.830	7.539	1.026	7.134	8.362
PropHHI	7,198	0.878	0.971	0.173	0.804	1.000
GeoHHI	7,198	0.106	0.053	0.146	0.020	0.123
Leverage	7,198	0.483	0.464	0.156	0.397	0.559
Cash	7,198	0.033	0.011	0.082	0.004	0.036
Size	7,198	6542	3935	7289	2046	8421
Tobin's q	7,198	1.471	1.328	0.496	1.162	1.640
LAG3MRET	7,198	0.040	0.044	0.063	0.006	0.074
InstOwn	7,198	0.851	0.902	0.213	0.735	1.003
Investment	7,198	0.084	0.027	0.308	-0.033	0.165
EBITDA/AT	7,198	0.021	0.020	0.013	0.016	0.025

Table 1: Summary Statistics (Continue)

Variable	#Obs	Mean	Median	Std	P25	P75
Panel B: Firm-State Variables						
NPI CAR (3-day)	2,631	-0.157	-0.115	0.180	-0.258	-0.038
NPI CAR (5-day)	2,631	-0.246	-0.206	0.229	-0.393	-0.073
ReOpen CAR (3-day)	2,597	0.011	-0.002	0.097	-0.056	0.063
ReOpen CAR (5-day)	2,597	0.008	-0.008	0.126	-0.073	0.082
Panel C: Analyst Forecast						
ln(1-Year EPS)	12,532	0.776	0.756	0.639	0.412	1.115
ln(Long-Term EPS)	3,973	0.301	0.255	0.307	0.104	0.432
Panel D: Property-Loan-Level Variables						
Mortgage Spreads	17,773	2.511	2.330	1.259	1.603	3.160
Nonremote (Building)	17,773	0.686	0.778	0.221	0.562	0.838
Teamwork (Building)	17,773	0.192	0.174	0.098	0.137	0.232
Customer (Building)	17,773	0.448	0.452	0.224	0.285	0.633
Property Book Value	17,773	71.012	21.634	162.955	4.750	72.000
Less Than 10 Years Old	17,773	0.071	0.000	0.257	0.000	0.000
Class A Property	17,773	0.090	0.000	0.286	0.000	0.000
Renovated	17,773	0.296	0.000	0.457	0.000	1.000
LTV	17,773	0.754	0.010	1.685	0.006	0.218
Time-to-Maturity	17,773	5.342	4.500	4.051	2.250	7.500
Cross-Collateralization	17,773	0.454	0.000	0.498	0.000	1.000
Fixed Rate	17,773	0.852	1.000	0.356	1.000	1.000

This table shows summary statistics (number of observations, mean, standard deviation (Std), and 25th, 50th, and 75th percentiles) of key variables used in our analysis. See Table A.1 for variable descriptions.

Table 2: Social Distancing Indices and Abnormal Returns

	(1) *Ret*	(2) *Ret*	(3) *Ret*
Nonremote × *GeoCOVID*	-0.120***		
	(-4.729)		
Teamwork × *GeoCOVID*		0.225***	
		(3.553)	
Customer × *GeoCOVID*			-0.136***
			(-3.719)
Teamwork		-0.016**	
		(-2.151)	
Nonremote	0.011***		
	(3.506)		
Customer			0.015***
			(3.703)
GeoCOVID	0.021	-0.108***	0.002
	(1.547)	(-5.925)	(0.144)
Constant & Controls	Yes	Yes	Yes
Prop FE	Yes	Yes	Yes
R-squared	0.022	0.021	0.021
# Obs	7,198	7,198	7,198

This table shows regression results pertaining to the relationship between abnormal returns and the growth rate of geographically weighted COVID-19 cases interacted with fact-to-face (*FTF*) indices. *Ret* is daily abnormal returns. *Nonremote*, *Teamwork*, and *Customer* are the averages of property-level non-remote work, teamwork, and customer contact indices, weighted by the percentage of a firm's portfolio invested in each building at the end of 2019Q4, respectively. *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 the firm level. See Table A.1 for variable definitions and Table A.2 for suppressed constants and controls. Property-type fixed effects are included in the regression. *p<.1, **p<.05, ***p<.01.

Table 3: Social Distancing Indices and Abnormal Returns: Critical and Non-Critical Industries

Ret	(1) *Nonremote_C*	(2) *Nonremote_NC*	(3) *Teamwork_C*	(4) *Teamwork_NC*	(5) *Customer_C*	(6) *Customer_NC*
$GeoCOVID \times FTF$	-0.074***	-0.131***	0.107*	0.273***	-0.088**	-0.159***
	(-2.645)	(-4.749)	(1.717)	(3.706)	(-2.466)	(-4.069)
FTF	0.006**	0.012***	-0.002	-0.022**	0.010***	0.018***
	(2.295)	(3.510)	(-0.260)	(-2.482)	(2.693)	(3.941)
$GeoCOVID$	-0.012	0.027*	-0.082***	-0.119***	-0.016	0.008
	(-0.705)	(1.778)	(-4.654)	(-5.867)	(-0.995)	(0.523)
Constant & Controls	Yes	Yes	Yes	Yes	Yes	Yes
Prop FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.021	0.022	0.020	0.021	0.021	0.022
# Obs	7,198	7,198	7,198	7,198	7,198	7,198

This table shows regression results pertaining to the relationship between abnormal returns and the growth rate of geographically weighted COVID-19 cases interacted with social distancing indices (FTF) for critical and non-critical industries. *Ret* is daily abnormal returns. *Nonremote*, *Teamwork*, and *Customer* are averages of property-level non-remote work, teamwork, and customer contact indices, weighted by the percentage of a firm's portfolio invested in each building at the end of 2019Q4, respectively. The subscript $\_C$ ($\_NC$) indicates that an FTF index is constructed using critical (non-critical) industries only. $GeoCOVID$ 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 Table 2 and are suppressed. The numbers in parentheses are t-statistics. Standard errors are clustered at the firm level. See Table A.1 for variable definitions. Property-type fixed effects are included in the regression. *p<.1, **p<.05, ***p<.01.

Table 4: Market Reactions to Policy Interventions and Social Distancing

	(1)	(2)	(3)	(4)	(5)
Panel A: NPI					
	Non-Remote	*Teamwork*	*Customer*	*Non-Remote_C*	*Non-Remote_NC*
CAR (3-day)	-0.089***	0.248**	-0.235*	-0.021	-0.114**
	(-2.769)	(2.178)	(-1.976)	(-0.626)	(-2.142)
CAR (5-day)	-0.335***	0.889**	-0.244*	-0.043	-0.293**
	(-3.084)	(2.380)	(-1.705)	(-0.471)	(-2.226)
Panel B: Reopen					
	Non-Remote	*Teamwork*	*Customer*	*Non-Remote_C*	*Non-Remote_NC*
CAR (3-day)	0.043	-0.031	0.030	0.023	-0.014
	(1.425)	(-0.534)	(0.391)	(1.265)	(-0.515)
CAR (5-day)	0.005	0.040	0.060	0.029	-0.049
	(0.154)	(0.568)	(1.292)	(1.264)	(-1.642)

This table shows weighted least squares regression results pertaining to the relationship between firm-state-level cumulative abnormal returns (CAR) and social distancing indices (FTF). State-level total book values are used as the sampling weights. *CARs* are constructed based on two event windows, indicated by (-1,1) and (-2,2), which represent, respectively, 3- and 5-day windows around the announcements of state-level non-pharmaceutical interventions (NPI) and reopenings. *Nonremote*, *Teamwork*, and *Customer* are the averages of property-level non-remote work, teamwork, and customer contact indices, weighted by the percentage of a firm's state-level portfolio invested in each building at the end of 2019Q4, respectively. The subscript $\_C$ ($\_NC$) indicates that an FTF index is constructed using critical (non-critical) industries only. Control variables are the same as those used in Table 2 and are suppressed. The numbers in parentheses are t-statistics. Standard errors are clustered at the firm level. See Table A.1 for variable definitions. Property-type fixed effects and state fixed effects are included in the regression. *$p<.1$, **$p<.05$, ***$p<.01$.

Table 5: Social Distancing Indices and Analyst Forecast

	(1)	(2)	(3)	(4)	(5)
Panel A: 1-Year					
	Nonremote	*Teamwork*	*Customer*	*Nonremote_C*	*Nonremote_NC*
Outbreak	-0.924***	1.674***	-0.433*	-0.290	-1.044***
	(-4.617)	(4.399)	(-1.787)	(-1.258)	(-4.829)
NPI	-0.932***	1.680***	-0.436*	-0.293	-1.052***
	(-4.631)	(4.389)	(-1.789)	(-1.266)	(-4.838)
ReOpen	-1.295***	2.429***	-0.600*	-0.481	-1.454***
	(-4.994)	(5.021)	(-1.707)	(-1.500)	(-5.082)
Panel B: Long-Term					
	Nonremote	*Teamwork*	*Customer*	*Nonremote_C*	*Nonremote_NC*
Outbreak	-0.280**	0.469	-0.145	-0.025	-0.327***
	(-2.350)	(1.610)	(-1.371)	(-0.264)	(-2.661)
NPI	-0.279**	0.474	-0.145	-0.025	-0.326***
	(-2.352)	(1.626)	(-1.380)	(-0.265)	(-2.663)
ReOpen	-0.436***	0.893**	-0.256*	-0.105	-0.486***
	(-3.166)	(2.445)	(-1.880)	(-0.925)	(-3.452)

This table shows regression results pertaining to the relationship between analyst forecasts and the post-COVID indicators ($POST$) interacted with social distancing indices (FTF). EPS is the log of forecasted earnings per share (EPS) by analyst j for firm i over forecast period τ. *Nonremote*, *Teamwork*, and *Customer* are the averages of property-level non-remote work, teamwork, and customer contact indices, weighted by the percentage of a firm's portfolio invested in each building at the end of 2019Q4, respectively. The subscript $\_C$ ($\_NC$) indicates that an FTF index is constructed using critical (non-critical) industries only. *Outbreak*, *NPI*, and *ReOpen* are post-COVID indicators of (1) January 21, (2) the earliest date on which a non-pharmaceutical intervention (NPI) was announced in localities in which a firm owns properties, and (3) the earliest date of reopening in any state in which a firm owns properties, respectively. The numbers in parentheses are t-statistics. Standard errors are clustered at the firm level. See Table A.1 for variable definitions. Analyst fixed effects, firm fixed effects, and analysts' forecast-week fixed effects are included in the regression. *p<.1, **p<.05, ***p<.01.

Table 6: Property-Level Social Distancing Indices and Mortgage Spreads

Mortgage Spread	(1) *Nonremote*	(2) *Nonremote*	(3) *Teamwork*	(4) *Teamwork*	(5) *Customer*	(6) *Customer*
POST × FTF (Building)	-0.122	-0.122	-0.587***	-0.567***	0.036	0.036
	(-1.362)	(-1.369)	(-2.762)	(-2.698)	(0.462)	(0.462)
FTF (Building)	-0.215*	-0.236**	-0.475*	-0.474*	-0.326***	-0.326***
	(-1.788)	(-2.024)	(-1.834)	(-1.886)	(-3.401)	(-3.401)
Property Book Value		-0.409***		-0.370***		-0.393***
		(-3.130)		(-2.771)		(-3.003)
Less Than 10 Years Old		-0.292***		-0.304***		-0.294***
		(-4.041)		(-4.173)		(-4.041)
Class A Property		-0.315**		-0.312**		-0.316**
		(-2.288)		(-2.292)		(-2.303)
Renovated		-0.075		-0.074		-0.074
		(-1.639)		(-1.625)		(-1.624)
LTV	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(-1.250)	(-1.257)	(-1.278)	(-1.284)	(-1.237)	(-1.237)
Time-to-Maturity	-0.041***	-0.040***	-0.040***	-0.038***	-0.040***	-0.040***
	(-7.813)	(-7.622)	(-7.644)	(-7.431)	(-7.703)	(-7.703)
Cross-Collateralization	0.062	0.031	0.060	0.030	0.033	0.033
	(0.761)	(0.388)	(0.739)	(0.371)	(0.410)	(0.410)
Fixed Rate	0.010	0.020	0.012	0.018	0.022	0.022
	(0.116)	(0.228)	(0.132)	(0.201)	(0.249)	(0.249)
Constant	2.857***	2.968***	2.797***	2.893***	2.938***	2.938***
	(23.456)	(24.453)	(28.653)	(29.048)	(30.001)	(30.001)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Prop FE (Building)	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.566	0.573	0.567	0.574	0.574	0.574
# Obs	17,773	17,773	17,773	17,773	17,773	17,773

This table shows regression results pertaining to the relationship between property-level mortgage spreads and the post-COVID indicators (*POST*) interacted with social distancing indices (*FTF*). *Mortgage Spread* is the difference between the mortgage rate and the Treasury rate with the same or closest maturity. *Nonremote*, *Teamwork*, and *Customer* are the property-level non-remote work, teamwork, and customer contact indices, respectively. *POST* indicates 2020Q1 or 2020Q2. The numbers in parentheses are t-statistics. Standard errors are clustered at the property level. See Table A.1 for variable definitions. Date fixed effects, state fixed effects, building-property-type fixed effects, and firm fixed effects are included in the regression. *$p<.1$, **$p<.05$, ***$p<.01$.

Table 7: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Parent Company			*Independent versus Corporate*					
	Non-Remote (Parent Co.)	*Teamwork* (Parent Co.)	*Customer* (Parent Co.)	*Non-Remote* (Indep.)	*Non-Remote* (Corp.)	*Teamwork* (Indep.)	*Teamwork* (Corp.)	*Customer* (Indep.)	*Customer* (Corp.)
Panel A: Abnormal Returns									
GeoCOVID × FTF	-0.103***	0.220**	-0.152***	-0.146***	-0.141***	0.329***	0.254***	-0.181***	-0.151***
	(-3.299)	(2.476)	(-3.493)	(-5.417)	(-5.035)	(4.473)	(3.198)	(-3.583)	(-5.361)
Panel B: Policy Interventions									
CAR (3-day) NPI	-0.140*	0.333**	-0.183**	-0.143***	-0.107**	0.261*	0.142	-0.174*	-0.082
	(-1.968)	(1.980)	(-2.017)	(-2.641)	(-2.007)	(1.942)	(1.024)	(-1.782)	(-1.103)
CAR (3-day) Reopen	0.037	-0.064	0.063*	0.046	0.044	-0.051	-0.052	0.082*	-0.004
	(1.460)	(-0.977)	(1.661)	(1.331)	(1.498)	(-0.674)	(-0.783)	(1.748)	(-0.137)
Panel C: Analyst Forecast									
1-Year (Outbreak)	-0.652*	1.962**	-0.419	-1.058***	-0.143	2.347***	0.003	-0.587**	-0.293
	(-1.670)	(2.003)	(-1.488)	(-4.154)	(-0.390)	(4.317)	(0.003)	(-1.987)	(-1.165)
Long-Term (Outbreak)	-0.337***	0.919**	-0.299*	-0.310**	-0.019	0.662*	0.127	-0.242	-0.079
	(-2.667)	(2.402)	(-1.901)	(-2.427)	(-0.216)	(1.887)	(0.534)	(-1.586)	(-0.886)

This table shows regression results pertaining to the relationships between abnormal returns and post-COVID indicators (*POST*) interacted with social distancing indices (*FTF*) in Panel A, between firm-state-level cumulative abnormal returns (CAR) and social distancing indices (*FTF*) in Panel B, and between analyst forecasts and post-COVID indicators (*POST*) interacted with social distancing indices (*FTF*) in Panel C. For columns (1)-(3), *Nonremote*, *Teamwork*, and *Customer* are constructed based on the corresponding *FTF* index of a tenant's parent company. *Indep.* and *Corp.* indicate that an *FTF* index is constructed using independent businesses or corporations only. The numbers in parentheses are *t*-statistics. Standard errors are clustered at the firm level. See Table A.1 for variable definitions. *p<.1, **p<.05, ***p<.01.

Appendix 1: Matching Tenants to Properties

In this appendix we explain the algorithm we used to match business listings to properties. We began by matching business listings to properties using street addresses in 2019Q4. We collected 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: institution name (KeyField: 220568), property type (KeyField: 225476), address line (KeyField: 220574), net book value (KeyField: 221784), initial cost (KeyField: 221778), and historic cost (KeyField: 221782). We dropped any listing that lacked data indicating a business street address (KeyField: 261530), the primary NAICS 6-digit code (KeyField: 261977), or the leased area (KeyField: 261527).

First, we standardized street addresses for both property-level and listings data. For instance, "123 ABC Street" and "123 A B C St, Suite 4" would both be transformed to "123 ABC St." This step allows us to match properties and listings using their street addresses directly. To ensure that a match is exact, we checked the distance between properties and listings using latitude and longitude coordinates as reported by S&P Global for both properties and listings. We deleted observations that were separated by a distance greater than 1 mile.

Some properties and listings were not directly linked, even after standardizing street addresses. For example, a given property record in the S&P Global Real Estate Properties might be comprised of several units or buildings. For instance, "5102-5114/5116-5142 Joanne Kearney Blvd" is the street address of a warehouse property in Tampa, Florida. If a tenant (a listing) occupies only a single building, "5103 Joanne Kearney Blvd," we could not directly link the tenant to the warehouse property using street addresses. To resolve this issue, we first calculated similarity scores separately for the text portion of the street addresses of properties and listings. In the earlier example, as the text portion of both addresses consists of "Joanne Kearney Blvd," both property and tenant have a similarity score of 1. We restricted our focus to observations with similarity scores larger than 0.7.

Next, we extracted street numbers from the addresses. For instance, "5102-5114/5116-5142 Joanne Kearney Blvd" would have four numbers, including 5102, 5114, 5116, and 5142. "5103

Joanne Kearney Blvd" is in the warehouse because it falls within in the range of 5102 and 5114, but "5200 Joanne Kearney Blvd" is not.

Finally, we manually verified the matched propertytenant observations. This left us with an initial sample of 33,023 properties owned by 132 unique equity REITs traded on NYSE, AMEX, and Nasdaq matched to 310,609 tenant listings.

Table A.1: Variable Definition

Variable	Source	Definition
Panel A: Firm-Level Variables		
Ret	S&P Global	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 from firm i on day t. M_t denotes daily returns on the S&P 500 index.
Nonremote	S&P Global, Dingel & Neiman	The firm-level non-remote work index, calculated as the average property-level non-remote work index, weighted by the percentage of a firm's portfolio allocated to each county at the end of 2019Q4.
Teamwork	S&P Global, Dingel & Neiman	The firm-level teamwork index, calculated as the average property-level teamwork index, weighted by the percentage of a firm's portfolio allocated to each county at the end of 2019Q4.
Customer	S&P Global, Dingel & Neiman	The firm-level customer index, calculated as the average property-level customer index, weighted by the percentage of a firm's portfolio allocated to each county at the end of 2019Q4. .
Critical	Papanikolaou & Schmidt	Critical industries, or industries that are allowed to stay open during the COVID-19 crisis based on Cybersecurity and Infrastructure Security Agency (CISA) guidance.
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 a 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 $ln(1 + \#Cases_{l,t} - ln(1 + \#Cases_{l,t-1}$.
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.
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.
PropHHI	S&P Global	The Herfindahl Indexes of each firm's property weights in each of the ten property categories, including office, industrial, retail, residential, diversified, hospitality, health care, self-storage, specialty, and technology, at the end of 2019Q4.
GeoHHI	S&P Global	The Herfindahl Indexes of each firm's property weights across the U.S. counties at the end of 2019Q4.
Leverage	S&P Global	The sum of total long-term debt and debt in current liabilities divided by the book value of assets at the end of 2019Q4.
Cash	S&P Global	The ratio of cash and cash equivalents to the 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.
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 non-cash assets during 2019Q4.
EBITDA/AT	S&P Global	The ratio of EBITDA to book value of total assets at the end of 2019Q4.

A.1: Variable Definition (Continue)

Variable	Source	Definition
Panel B: Firm-State Variables		
NPI CAR (3-day)	S&P Global	Cumulative abnormal returns (CARs) from day t-1 to t+1. The event date t is the earliest date a major non-pharmaceutical intervention (NPI) was announced in the state in which a firm owns properties.
NPI CAR (5-day)	S&P Global	Cumulative abnormal returns (CARs) from day t-2 to t+2. The event date t is the earliest date a major non-pharmaceutical intervention (NPI) was announced in the state in which a firm owns properties.
ReOpen CAR (3-day)	S&P Global	Cumulative abnormal returns (CARs) from day t-1 to t+1. The event date t is the earliest reopening announcement in the state in which a firm owns properties.
ReOpen CAR (5-day)	S&P Global	Cumulative abnormal returns (CARs) from day t-2 to t+2. The event date t is the earliest reopening announcement in the state in which a firm owns properties.
Panel C: Analyst Forecast		
ln(1-Year EPS)	I/B/E/S	The logarithm of the analyst forecasts of earnings per share (EPS) for the period ending next December.
ln(Long-Term EPS)	I/B/E/S	The logarithm of the analyst forecasts of earnings per share (EPS) over the next business cycle.
Panel D: Property-Loan-Level Variables		
Mortgage Spread	S&P Global	The difference between the mortgage rate and the Treasury rate with the same or closest maturity to the mortgage rate.
Nonremote (Building)	S&P Global	The property-level non-remote index, calculated as the average tenant-level non-remote index, weighted by the percentage of a property's leased area occupied by each tenant at the end of 2019Q4. Tenant-level non-remote index equals $1 - \%$ *jobs that can be performed at home*
Teamwork (Building)	S&P Global	The property-level teamwork index, calculated as the average tenant-level teamwork index, weighted by the percentage of a property's leased area occupied by each tenant at the end of 2019Q4.
Customer (Building)	S&P Global	The property-level customer index, calculated as the average tenant-level customer index, weighted by the percentage of a property's leased area occupied by each tenant at the end of 2019Q4.
Property Book Value	S&P Global	Building size, or the depreciated book value of a property (in million USD).
Less than 10 Years Old	S&P Global	An indicator variable that equals one if a property is less than 10 years old and zero otherwise.
Class A Property	S&P Global	An indicator variable that equals one if a property is Class A and zero otherwise.
Renovated	S&P Global	An indicator variable that equals one if a property was renovated and zero otherwise.
LTV	S&P Global	The loan-to-value (LTV) ratio, calculated as the ratio of the unpaid principal balance to the depreciated book value of a property pledged as collateral, both gauged in the year of origination.
Time-to-Maturity	S&P Global	The difference between the year of maturity and the year of origination of a mortgage.
Cross-Collateralization	S&P Global	An indicator variable that equals one if a mortgage is cross-collateralized by multiple properties and zero otherwise.
Fixed Rate	S&P Global	An indicator variable that equals one if a mortgage is a fixed-rate debt contract and zero otherwise.

Table A.2: Social Distancing Indices and Abnormal Returns

	(1) *Ret*	(2) *Ret*	(3) *Ret*
GeoCOVID × *Nonremote*	-0.120***		
	(-4.729)		
Nonremote	0.011***		
	(3.506)		
GeoCOVID × *Teamwork*		0.225***	
		(3.553)	
Teamwork		-0.016**	
		(-2.151)	
GeoCOVID × *Customer*			-0.136***
			(-3.719)
Customer			0.015***
			(3.703)
GeoCOVID	0.021	-0.108***	0.002
	(1.547)	(-5.925)	(0.144)
Days since outbreak	-0.000***	-0.000***	-0.000***
	(-3.818)	(-3.863)	(-3.991)
Days since outbreak^2	0.000***	0.000***	0.000***
	(6.400)	(6.338)	(6.494)
ln(GeoDensity)	0.000**	0.000**	0.000***
	(2.429)	(2.418)	(2.699)
PropHHI	0.002*	0.002*	0.001
	(1.741)	(1.815)	(1.597)
GeoHHI	0.002*	0.002**	0.002*
	(1.668)	(1.981)	(1.791)
Leverage	-0.006***	-0.006***	-0.005***
	(-5.186)	(-5.401)	(-4.899)
Cash	-0.004***	-0.004**	-0.005***
	(-2.678)	(-2.374)	(-2.945)
ln(Size)	0.000	0.000	0.000
	(0.269)	(0.142)	(0.317)
Tobin's q	0.001***	0.001**	0.001***
	(2.622)	(2.526)	(2.622)
LAG3MRET	0.000***	0.000***	0.000***
	(19.739)	(20.656)	(21.322)
InstOwn	0.000	0.000	0.000
	(0.089)	(0.134)	(0.038)
Investment	0.000	0.000	0.000
	(0.956)	(0.588)	(0.857)
EBITDA/AT	0.002	0.004	-0.001
	(0.154)	(0.257)	(-0.100)
Constant	-0.005*	0.006*	-0.004
	(-1.760)	(1.843)	(-1.485)
Prop FE	Yes	Yes	Yes
R-squared	0.022	0.021	0.021
# Obs	7,198	7,198	7,198

This table shows the coefficient estimates on the constant and control variables that are suppressed in Table 2. The numbers in parentheses are t-statistics. Standard errors are clustered at the firm level. See Table A.1 for variable definitions. Property type fixed effects are included in the regression. *$p<.1$, **$p<.05$, ***$p<.01$.

Table A.3: Social Distancing Indices and Abnormal Returns, the Impact of Property Type

	(1) *Nonremote*	(2) *Teamwork*	(3) *Customer*
Panel A: Without Prop FE	-0.156***	0.320***	-0.164***
	(-6.455)	(5.278)	(-4.810)
Panel B: Without Office	-0.203***	0.318***	-0.145***
	(-5.921)	(3.513)	(-3.616)
Panel C: Without Industrial	-0.157***	0.334***	-0.166***
	(-6.538)	(5.517)	(-4.443)
Panel D: Without Retail	-0.121***	0.204**	-0.109**
	(-4.041)	(2.335)	(-2.212)
Panel E: Without Others	-0.168***	0.360***	-0.196***
	(-5.620)	(5.571)	(-5.091)
Panel F: Seven Property Types	-0.156***	0.319***	-0.164***
	(-6.445)	(5.268)	(-4.805)

This table summarizes results of robustness tests for Table 2. Panel A shows results with no property-type fixed effects. Panels B through E show results by deleting one property type at a time. Panel F shows results by using seven property types. See Table A.1 for variable definitions. Property type fixed effects are included in the regression. *p<.1, **p<.05, ***p<.01.