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Analyst Forecasts during the COVID-19 Pandemic: Evidence from REITs

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Abstract: The COVID-19 pandemic disrupts capital markets and confuses decision makers. This event represents an opportunity to better understand how financial analysts forecast earnings. We focus on forecasts for Real Estate Investment Trusts (REITs) in the United States, since REITs are relatively transparent during normal times, and since the real estate sector, as a whole, displays wide variations in forecasts during the pandemic. Using data between October 2018 and November 2020, our regression analysis finds that the severity of the pandemic increases analysts' forecast error and dispersion. Government interventions have an offsetting effect, which is relevant during the more severe times. These results are robust to various measures of the severity of the pandemic. We also find that the pandemic has differential effects across property types, where forecast error rises by more, for REITs, when focusing on Hospitality and Industrial properties, and dispersion rises by more, for REITs, when focusing on Hospitality, Retail, and Technology properties.

Keywords: forecast; analysts; earnings; REITs; COVID-19; pandemic; information environment

JEL Classification: G17; G01; D84

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"It's difficult to make predictions, especially about the future."

1. Introduction

The COVID-19 pandemic challenges forecasters. This is a once-in-a-century pandemic, which governments try to control with constantly-changing rules. An incredible number of other unusual events in the United States (U.S.), during 2020, were associated with COVID-19. The U.S. unemployment rate tripled in one month, and the distribution of job losses differed noticeably from previous recessions. Interest rates dropped close to zero. The price of oil was *negative* for a short time. Daily habits for work, play, school, and home life changed by choice and by government regulation. The intersection of repeated and significant surprises means that we can learn by studying how forecasters responded to the challenge. Our paper studies the impact of the COVID-19 pandemic on the quality of earnings forecasts produced by financial analysts, and how the changes in forecast quality vary across different sectors. We also explore how government interventions, such as when businesses could be open and economic stimuli, moderate this impact.

The quality of analyst forecasting depends on two aspects of the information environment: public and private. During normal times, analysts collect information from a variety of public and private sources (e.g., Beyer and Guttman 2011; Lang and Lundholm 1996). Public information sources include government statistics, business press, and public reports from firms. Private information includes the information that individual analysts collect and generate through their own effort. It could, for example, be information obtained by corporate site visits, insights into local conditions, or cross-referencing the claims of management (e.g., Cheng et al. 2016). Each analyst combines those bits of information using methods they deem appropriate.

The pandemic changes the information environment facing analysts. In terms of the information which is publicly available, companies may not be able to produce as much public information about themselves as quickly as before; Chen et al. (2020) find evidence that sickness, due to the annual flu, constrains financial reporting. Further, analysts must quickly learn about new sources of public information, such as government information on the spread of the pandemic or epidemiology models showing disease dynamics. Analysts also need to anticipate the timing and severity of rarely used government policies. In terms of the information, which is collected privately, some of the usual sources of information may be blocked when people cannot meet in person. The unusual source of uncertainty, due to the COVID-19 pandemic, may also make traditional methods of analysis less effective.

Many events during the pandemic confuse or surprise many people. In addition to the examples noted above, supply chain issues create shortages for many products and disrupt international shipping. The persistence of the pandemic may make forecasting even harder since, while short disruptions are unsettling, short run adaptations cannot persist; the behaviors of people and businesses are likely to change more radically as the pandemic continues. Government interventions were, in some ways, unprecedented. Such surprises can be expected to change an analyst's perception about the range of possible outcomes, to make that range more dispersed, or to change the meaning of any one bit of information. Therefore, there are many reasons to expect the quality of analyst forecasts to change.

We study these effects in the real estate sector for a couple of reasons. During normal times, Real Estate Investment Trusts (REITs) are viewed as a stable investment platform which transfers the rent paid by tenants to investors relatively transparently.[1] Predictability simplifies the relationship between a firm's operations and the net present value of dividends, which may equal the stock price.[2] This information environment should make forecasting earnings of REITs relatively easy during normal times, especially when compared with forecasting earnings of companies active in other sectors, such as e-commerce, energy, or pharmaceuticals. If consumers cannot visit a retailer in a mall, if small businesses expand their presence in e-commerce, or if consumers buy much more from Amazon, then the effect on a retail or industrial REIT should be relatively easy for independent observers to predict.[3] Finally, focusing on this sector may help to resolve a big puzzle, Landier and Thesmar (2020), Figure 6 shows that the biggest change in short term earnings forecasts, during the pandemic, was in the real estate sector, and that the sector had one of the smaller changes in long term forecasts.

Our paper uses data on analyst forecasts of earnings, for REITs in the United States during 2019 and 2020, to investigate the change of forecast quality. The quality of analysts' forecasts is examined from two perspectives: Forecast Error and Forecast Dispersion. Our hypotheses focus on the effect of the severity of the pandemic, and we consider various measures of the severity, based on the number of cases or the number of deaths associated with COVID-19, both per month and cumulatively.

Governments intervened in many ways, and we investigate one of their effects. During 2020, many different kinds of policies were considered or implemented. Some policies were intended to control the spread of the disease and its severity. Other policies were intended to help people and businesses outlast the pandemic, even if nobody knew how long it would last. We use two measures of government interventions, provided by Hale et al. (2021). One measure is derived from 16 indicators which recognize government responses such as closing schools or workplaces, restrictions in movement (such as stay at home orders or recommendations concerning public transit), public health initiatives (including face covering, testing policies, contact tracing, and protecting the elderly), and economic stimuli (such as emergency income support and debt relief). A second measure focuses on the economic stimuli only.

We find that an increase in the severity of the pandemic decreases the quality of analyst forecasts. Surprisingly, we find that the greatest decreases in forecast quality are in a type of REIT which is generally seen as a loser because of the pandemic (i.e., Hospitality) and in a type of REIT which is generally seen as a winner because of the pandemic (i.e., Industrial). We also find that government interventions have a beneficial effect on forecast quality since they partially offset the direct negative effect of the pandemic during the more severe times. These results are robust to using a variety of alternative measures of the severity of the pandemic and of government interventions.

Our paper offers a number of contributions. First, our analysis of earnings forecasts by financial analysts adds to the growing body of work which studies the effect of the COVID-19 pandemic on stock markets. In addition to understanding the history, many authors have, and will, use the pandemic as an exogenous shock, or natural experiment, to reveal issues which cannot normally be studied rigorously. For example, Ding et al. 2021 study how stock returns in 61 countries react to the pandemic, and they connect that reaction to characteristics of the firms. Bilinski (2021) describes how different types of forecasts change during 2020, focusing his effort on the connection between stock prices and forecasts. Our paper explores the effect of changes in the information environment due to the pandemic, which differs from that of previous disease outbreaks (e.g., Baker et al. 2020). In this information environment, knowing how financial analysts behave would be instructive.

Next, we contribute to the literature on the effects of government policies. Many researchers have documented or commented on the real effects of the pandemic and of various government policies, such as Bloom et al. (2021), Klein and Smith (2021), or Bauer et al. (2020).[4] Independent of whether a policy increases or decreases expected earnings, we document that government interventions have a beneficial effect on forecast quality.

Finally, we complement the REIT literature by showing how performance during the pandemic varies according to the characteristics of the REITs (e.g., Ling et al. 2020; Lin et al. 2021). Our work offers insight into whether the pandemic's effects are more or less predictable, according to the type of business.

The next section reviews the literature on the effects of the COVID-19 pandemic, and it links those effects with the literature on the information environment and financial analysts. The following section offers our hypotheses and research design. Section 4 describes the data and sample selection. Section 5 presents the empirical findings. Section 6 discusses the robustness tests. The last section provides our conclusions.

2. Literature Review

The environment for buying and selling in a stock market is information rich, even if the remaining uncertainty causes investors to worry about risk. During normal times, analysts collect information from a variety of public and private sources to reduce that uncertainty. The fact that the pandemic is due to a disease never seen before means that analysts need to quickly learn about some unusual considerations, such as understanding epidemiology models of disease dynamics or anticipating the timing and severity of rarely-used government policies. This section notes some of the major events that happened during 2020 as a reminder of why forecasting earnings is difficult. We review the literature on the effects of the COVID-19 pandemic and link those effects with the literature on the information environment experienced by financial analysts who produce the forecasts. This section ends by discussing literature relevant to REITs.

2.1. The COVID-19 Pandemic and the Effects on Stock Markets

An incredible number of unusual events, associated with COVID-19, happened in the U.S. during 2020. Hundreds of thousands of people died because of the disease, tens of millions became sick, and many more were tested because they worried that they might be infected. Even now, the dynamics of how the disease spread remain confusing (e.g., see Avery et al. (2020) for more on epidemiological models). The news was very confusing for people not reading the latest medical publications because, as the evidence accumulated, the advice coming from authority figures changed. Daily habits for work, play, school, and home life changed by choice and by government regulation. To some people, the biggest surprise of 2020 may be that, within one year of the disease being discovered, two highly effective vaccines were developed, tested, authorized for use, and distributed.

Such disruptions affected the real economy, businesses, and the stock markets in both obvious and surprising ways. The national unemployment rate tripled between March and April. The savings rate rose to over 30 percent. The U.S. federal government passed the CARES Act, worth trillions of dollars in economic stimulus, after only a couple of days of public discussion. Each of these events had their own effects which a forecaster would have to account for. Uncertainty about the persistence of the pandemic may make forecasting even harder since short run adaptations must change in the long run; the behaviors of people and businesses would have to change more radically as the pandemic continues. Radical changes are inherently less predictable, due to a shortage of reliable or relevant data.

Stock markets indices fluctuated significantly. The Dow Jones Industrial Average (DJIA) fell by more than 30 percent within less than 30 trading days, with other indices changing similarly. During this time, the federal funds rate dropped by 150 basis points, and trading on the New York Stock Exchange was halted a couple of times due to the imposition of Level 1 circuit breakers. Later, between mid-March and the end of 2020, the DJIA rose by more than 50 percent.

In this environment, businesses act while investors buy or sell their investments, based on those actions plus the environment. Alfaro et al. (2020) find that unexpected changes in the trajectory of COVID-19 infections can be used to predict stock returns in US. Ding et al. (2021) consider how abnormal returns vary across firms in 61 countries. Their massive study considers the connections between many characteristics of a firm and investors' reaction in terms of stock returns. Fahlenbrach et al. (2020) confirm the benefits of financial flexibility during the pandemic, as evaluated by investors.

All forecasts depend on the available information. Baker et al. (2020) emphasize how the effects on stock markets, of the COVID-19 pandemic, differ from the effects of past outbreaks of disease, such as the outbreaks of flu during 1968, 1957–58, or even 1918–20, because of how markets process information. They conclude that news was the primary driver of volatility and price changes between mid-February 2020 and April 2020.

Bilinski (2021) describes how different types of forecasts changed during 2020, focusing his effort on the connection between stock prices and forecasts. In particular, he notes that "Forecasts issued during the pandemic associate with significantly lower accuracy" during the first and second quarters of 2020, and he concludes that "This effect is magnified in periods of increased information demand" (p. 17).

Landier and Thesmar (2020) add to this by studying how earnings forecasts, and discount rates varied during the early phase of the pandemic, while paying special attention to the term structure of forecasts. They conclude that, between mid-February and early May of 2020, the change in stock prices can be fully accounted for by changes in estimated earnings while, later, the effects can be accounted for by changes in the discount rate.

These papers emphasize the effects on stock market returns. Their conclusions and their methods of analysis reveal some of the special features of the pandemic that complicate the job of an analyst. At the same time, the dynamics of the pandemic represent changes which are unrelated to the characteristics of a REIT or of an analyst. We use this opportunity to focus on the question of how the quality of earnings forecasts by analysts, adapts to the new environment due to COVID-19.

2.2. Information Environment

While the pandemic creates changes unlike any previous event, prior research indicates how to think about the activities of a financial analyst. A rational expectations model provides a familiar, if excessively simple, starting point. In it, an analyst's forecast of earnings, at time t, based on the information available at time t, would be unbiased. Beyer et al. (2010) add to this perspective by reviewing the sources of bias in an analyst's report. Investors and analysts live in an information-rich environment where information comes from various sources.

During normal times, the information used by an analyst depends on the information environment where the sources of information fall into two broad categories: public and private (e.g., Beyer et al. 2010). Public information sources include government statistics, business press, and public reports from firms. Not all of the information about a firm is published by the firm. Private information sources may include site tours offered by companies and other insights into local conditions, which might verify the claims of management (e.g., Bae et al. 2008). These bits of information are studied by each analyst using methods they deem appropriate. Even if the benefits of forecasting are the same for all analysts, differences in the cost of analysis, or the abilities of an analyst, can lead to forecasts with different answers and with different precisions.

Researchers have considered the information environment in the past, but empirical research on this topic is challenging. Government regulations, such as the Sarbanes-Oxley Act of 2002, increased the amount of information disclosed by firms to the public. Often, this information is provided in machine-readable formats to simplify deeper analysis by interested parties.[5] An increase in disclosure should reduce the asymmetry of information between investors and management. That reduction should reduce a firm's cost of capital (e.g., Leuz and Wysocki 2016, pp. 545–46). The effects of mandated disclosure are not necessarily limited to the firm making the disclosure; public disclosures by some firms add contextual information, which can help investors evaluate other firms (e.g., Leuz and Wysocki 2016, p. 553). Yet, Coates (2007) argues that the Act has benefits that are real but hard to quantify, while the costs are hard to estimate. Later, Leuz and Wysocki (2016) and Beyer et al. (2010) argue that the effects of the Act are unresolved because regulations affect both costs and benefits to firms and because different researchers use different research designs, which affect the conclusions.

The pandemic changes the public information environment. Companies may not be able to produce as much public information about themselves as quickly as before; Chen et al. (2020) argue that the annual flu affects financial reporting by a company. In addition, analysts must quickly identify and become familiar with the most reliable sources of public information, such as government information on the spread of the pandemic or epidemiology models showing disease dynamics. Analysts also need to anticipate the timing and severity of rarely used government policies.

Researchers have also considered the environment for private information. The most obvious source of change, in this environment, comes from government rules and regulations, such as Regulation FD (Fair Disclosure) in 2000. Analysts routinely participate in public conference calls with a company's management, but Regulation FD restricts the opportunities for an individual analyst to meet with corporate management privately (e.g., Leuz and Wysocki 2016). Prohibiting selective disclosure to individuals raised concerns about a reduction in total information because other private information sources might not compensate for the reduction in information from management. Leuz and Wysocki (2016) and Beyer et al. (2010) suggest that the evidence on the effects of Regulation FD is mixed, with different studies reaching different conclusions, perhaps due to many confounding events. The pandemic, especially the various types of travel restrictions associated with it, limits access to many of the familiar sources of private information both in terms of frequency and the quality of data that can be discovered.

Given an information environment, Clement (1999) shows that the accuracy of an analyst's forecast is positively related to their experience and their employer's size while negatively related with the number of firms and industries covered by an analyst. In normal times, analysts would investigate familiar factors, which affect earnings, such as the actions of competitors, income trends for consumers, or the natural ups and downs of the business cycle. The challenge is that making a better forecast is costly because it takes time and effort to evaluate the information that exists, and it takes more time to gather information that is not widely available. Du (2020) shows that the pandemic affected the costs of different analysts differently: female analysts with children were "20% less likely to issue timely forecasts after school closures" during the COVID-19 pandemic.

Lang and Lundholm (1996) examine the relationship between corporate disclosure practices and the properties of analysts' earnings forecasts. They emphasize the distinctions between analysts as information intermediaries and as information producers. Beyer and Guttman (2011) offer a theoretical model with a detailed consideration of the interactions amongst investors, companies, and the analysts which study those companies. They characterize a Perfect Bayesian Equilibrium in which an informed analyst balances the benefits of forecasting against the costs of making erroneous forecasts. They argue that the degree of bias varies with the informative signal, with the reaction of investors (indicated by trading volume), and with the reaction of the company's managers.

2.3. The Effects of COVID-19 on REITs

Akinsomi (2021) documents how REIT returns varied during the first phase of the COVID-19 pandemic in the United States, with large decreases in stock price for all types of REITs except data centers. Ling et al. (2020) use county-level data on the spread of the pandemic, and associated government policies, to study abnormal returns of REITs between 21 January and 15 April 2020. They find that Retail and Residential type REITs reacted most negatively to an increase in the number of COVID-19 cases locally. They infer that investors placed a greater weight on the effect on controlling the spread than on the localized effect on current business activities. Xie and Milcheva (2020) complement this study and, in Hong Kong, find that location specific effects are relevant to stock returns. Chu et al. (2021) also show that location matters, using Chinese data, and demonstrate the benefits of having a diversified portfolio. Ling et al. (2021) build on their previous work to examine how institutional investors react to local shocks. They argue that the location of the investor affects expectations, leading to an overreaction.

Lin et al. (2021) focus on the capital structure of a REIT and compare the experience of the pandemic to the experience of the 2007–2009 Global Financial Crisis (GFC). They find that well-prepared REITs send a signal of competence that is rewarded. They emphasize that this logic applies to the financial crisis but not to the pandemic because the pandemic was unpredictable. Van Dijk et al. (2020) focus on the effects of the pandemic on market liquidity in eight large American cities. Both argue that the effects of the pandemic exceed those of the GFC.

Earnings may affect the liquidity of a firm and its use of funds. Using the REIT Modernization Act of 2001 as a natural experiment, Gupta (2022) shows that allowing REITs to retain more of their earnings represents a positive shock to internal funds. This shock did not change REITs' investments but did reduce their security issuance (both debt and equity) and leverage.

Some papers have considered the effect of uncertainty per se. For example, Gholipour et al. (2021) use a vector autoregression (VAR) model to study how the REIT index covaries with housing prices, GDP growth, the unemployment rate in the United States and a measure of economic uncertainty between 1989 and 2017. Their analysis of impulse responses shows that, over a period of 20 quarters, an increase in economic uncertainty has a negative effect on the index. In a variance decomposition analysis, they show that the effects of past REIT index have the dominant effect initially, and the effect of uncertainty becomes relatively more important later. Because of data limitations, they are not able to study whether the uncertainty associated with the pandemic differs in kind or degree.

The fact that different researchers look at REITs in different ways, and find economically and statistically significant results, reinforces our belief that studying activities in this sector is interesting. The facts, that the real estate sector is not homogenous, and the pandemic has different effects on different types of businesses, mean that studying this sector could help to understand how analysts assess the future.

3. Hypotheses and Research Design

We study how the quality of analysts' forecasts change during the COVID-19 pandemic. The pandemic created challenges for analysts in many ways. First, the "once-in-a-century" pandemic changed the information environment dramatically. For example, in terms of the public information, companies may not be able to produce as much public information about themselves as quickly as before (Chen et al. 2020). Analysts must learn how to evaluate new sources of public information, such as government information on the spread of the pandemic. Analysts also need to anticipate the timing and severity of rarely used government policies. In terms of private information, some of the usual sources of information may be blocked when people cannot meet in person. A study of the timeline of the pandemic reveals many events which could add confusion.

The persistence of the pandemic may also make forecasting harder since short run adaptations cannot persist. In a short run, some inputs to production are fixed. Business decisions in the short run would be based on incomplete information about the disease and, especially if the interruption is expected to be relatively short-lived, managers would focus on simple actions, which are easy to reverse. The behaviors of people and businesses would have to change more radically as the pandemic continues and, therefore, less predictably. As the pandemic continues or becomes more severe, the perspective of managers would shift to a long run perspective which considers other types of questions, such as whether to leave the market, new aspects of consumer behavior, or, if staff reductions continue, how to coordinate them with other aspects of business operations. The unusual source of uncertainty may also mean that traditional methods of analysis are less effective. These surprises and unusual considerations can be expected to change the quality of analysts' forecasts. We examine the quality of analysts' forecasts from two perspectives: Forecast Error and Forecast Dispersion. We offer the following hypothesis:

Hypothesis 1 (H1). *An increase in the severity of the COVID-19 pandemic increases forecast error and dispersion.*

We measure the severity of the pandemic using various measures of the number of cases, or the number of deaths, due to COVID-19.

Our second hypothesis considers the effects of government interventions which were, in some ways, unprecedented. Governments intervened often, and many different kinds of policies were considered or implemented. Some policies were intended to control the spread of the disease and its severity. Other government policies, such as income support for selected types of people or businesses, were intended to help people and businesses continue. Lockdowns, travel restrictions, and physical distancing may not have been intended to reduce a business's revenue or to increase its costs, but they had those effects. Government restrictions limit the spread of a disease by reducing interaction, but business is all about interacting (i.e., buying and selling).

We argue that one effect of these policies is to reduce uncertainty. Even if restrictions have a negative effect on the level of earnings, a restriction is a binding constraint on behavior: more restrictions reduce the discretion of people and businesses by a greater degree. Therefore, more restrictions reduce the degree of uncertainty for an analyst.

A stimulus policy would help people and businesses continue by managing the transition with less financial disruption which, therefore, would reduce uncertainty for analysts. More financial resources reduce the stress on managers which enables them to consider their options, and the consequences, more carefully. For example, laying off restaurant staff who may be accustomed to part-time work, or shifting schedules, is a short run decision which can be reversed easily. Shifting to a take-out or delivery service requires more planning if the shift is to be successful. In an office setting, a short run solution might be to ask people to work from home for a couple of days or weeks. As the pandemic continues, a company would need to think about upgrading their communication infrastructure, renegotiating bank loans and leases, adapting the processes used to supervise subordinates, or updating their ten-year corporate strategic plan. Gupta (2022) notes that internal funds are less expensive than external funds. Especially during a crisis, avoiding the need to borrow is important. Government support gives companies money, which can be used to coordinate their activities better. When disclosing their decisions to the investment community, the senior managers of a company are better able to explain why their actions are reasonable. The managers of a company would also be able to communicate with their landlords (i.e., a REIT), which would therefore be able to offer more detailed insights to its investors and analysts. Therefore, the government stimulus should improve the quality of public information about a company, making earnings forecasts less sensitive to idiosyncratic differences amongst analysts.

An important feature of the government interventions is that the number and strictness of interventions are correlated with the severity of the pandemic. At times, when the pandemic is more severe, governments add more restrictive policies which become stricter. At the same time, the existing policies are more likely to be enforced more energetically, because of a desire to do something to control the spread of the disease, due to increased media attention and attention from the senior government leaders who initiate a policy. In addition, an increase in the severity of the pandemic would cause a policy to continue for longer. The same argument applies to government policies intended to stimulate the economy, since the political pressure to stimulate is greater when more people need help. Therefore, the effect of a government policy, on analyst forecasts, is likely to be bigger at times when the pandemic is more severe.

For these reasons, our second hypothesis does not focus on the effect of government interventions alone. Our hypothesis focuses on an interaction effect.

Hypothesis 2 (H2). *Government interventions moderate the impact of the COVID-19 pandemic on forecast error and dispersion.*

To test the above two hypotheses, we use the following models:[6]

$$FE_{it} = \beta\ Severity_t + \gamma\ GovRes_t * Severity_t + \delta\ Controls_{it} + \varepsilon_{it} \quad (1)$$

$$FD_{it} = \beta\ Severity_t + \gamma\ GovRes_t * Severity_t + \delta\ Controls_{it} + \varepsilon_{it} \quad (2)$$

where *FE* (*FD*) represents Forecast Error (Forecast Dispersion), i and t denote the REIT and the month, respectively. *Severity* represents the severity of the pandemic, and *GovRes* represents the government intervention policies. We control for a variety of firm-level variables and use indicator variables to denote the property types. The details of how each variable is measured are provided in the next section. This model is estimated using ordinary least squares, where the standard errors are clustered at the firm level. We are most interested in the coefficients β and γ. Hypothesis 1 implies $\beta > 0$ while Hypothesis 2 implies that $\gamma < 0$.

4. Data and Sample Selection

This section discusses the data and sample used in our study, which focuses on the REITs in the United States. We use several databases, including I/B/E/S, Compustat, CRSP, and Thomson Reuters 13F. We start from the I/B/E/S database, using quarterly earnings forecasts produced by financial analysts between October 2018 and November 2020. Table 1 shows that the initial sample has 105,670 firm-month observations. We merge it with data from Compustat, CRSP, and Thomson Reuters 13F and then retain only observations for REITs. We exclude observations not being covered by CRSP, any observations with missing information from Compustat, and observations with non-REITs. Our final sample has 2688 firm-month observations. In the regressions, our sample is further reduced because we use lagged values of control variables and because of missing values of forecast dispersion.[7]

Table 1. Sample Selection.

	Observations
All firm-month observations of U.S. public firms with I/B/E/S analyst earnings forecasts from October 2018 to November 2020	105,670
Less:	
Observations of firms that are not covered by CRSP	(11,573)
Observations of firms that are not covered by COMPUSTAT	(3910)
Observations of firms that are not REITs	(87,499)
Total sample	2688

The table describes the sample selection in this study.

We examine the forecasting quality of financial analysts during the pandemic from two perspectives: Forecast Error (*FE*) and Forecast Dispersion (*FD*). *FE* is calculated as the absolute value of the difference between an analyst's forecasted earnings and a REIT's actual earnings, multiplied by 100, scaled by the month-end stock price, and then averaged across analysts for each firm and each month. *FD* is calculated as the standard deviation of earnings forecasts across analysts for each firm and each month, multiplied by 100 and scaled by the month-end stock price. For each REIT and each month, if an analyst makes more than one forecast, only the last forecast is retained.

The measures of *FE* and *FD* are different. Because *FE* is computed as an absolute value, it emphasizes the errors which differ from zero. Because *FD* is computed as a standard deviation, it emphasizes the differences amongst analysts from the mean. If different analysts access different sources of private information, or if they give different weights to different bits of information, they would produce different forecasts. The arithmetic used to compute *FD* tends to emphasize outliers and large deviations from the mean.

We measure the severity of the pandemic using various measures of the number of cases, or the number of deaths, due to COVID-19 both per month and cumulatively. The information on the number of cases and deaths comes from the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University.[8] The variables of interest, *Ln(Cum Cases)* or *Ln(Cum Deaths)* are the natural logarithm of one plus the average cumulative COVID-19 cases (or deaths) for each month. For robustness checks, we also use the natural logarithm of one plus the number of new COVID-19 cases (*Ln(New Cases)*), or the new COVID-19 deaths (*Ln(New Deaths)*), reported in each month.

To examine the effects of government intervention policies associated with the pandemic, we use the government response indices provided by Hale et al. (2021): Oxford COVID-19 Government Response Tracker (OxCGRT).[9] The government response index, *GovRes*, is derived from 16 indicators. It recognizes responses such as closing schools, workplaces or public events, restrictions in movement, and public health initiatives (including vaccines and face covering), as well as economic stimulus measures (such as emergency income support and debt relief). This index weights the different components equally. We also use a second government policy variable, *EcoMeasure*, which only focuses on the economic stimuli to check the robustness of our analysis. In our regression analyses, we calculate them as the average of the daily values for each month.

Following the prior literature, we use a variety of control variables plus ten indicator variables to recognize differences amongst ten sectoral specializations of a REIT, including office, industrial, retail, residential, diversified, hospitality, health care, self-storage, specialty, and technology (Ling et al. 2020). The control variables focus on the characteristics of the REITs, since we do not have any information on the identity or demographic characteristics of the analysts.

The precise definitions of the control variables are provided in the Appendix A, including the use of lagged values. The level of *Institutional Holding* is associated with corporate governance issues (Ding et al. 2021) and whether the REIT is well managed (Xu and Ooi 2018). A well-managed firm is less likely to surprise analysts or investors, including institutional investors. The *Size* of a REIT is likely to have many effects, not all of which go in the same direction. Firm size may be a proxy for the amount of public information (e.g., Beyer et al. 2010; Lang and Lundholm 1996). If so, then forecasts concerning larger firms would tend to be more accurate. Larger firms would be less sensitive to localized effects, if the REIT's portfolio of properties is properly diversified. Larger firms would be more sensitive to sources of risk due to operations or to the senior management of that REIT (e.g., Beracha et al. 2019a, 2019b; Highfield et al. 2021), especially when that management is challenged by an unusual situation such as the pandemic. Therefore, we do not offer a specific prediction concerning the effect of firm size.

It is clear that *Leverage* is relevant for any firm (Ling et al. 2020; Chen et al. 2021). The effect of leverage on earnings forecast is unclear, since greater leverage does not always increase earnings. In theory, firms which borrow more would be subject to more oversight by financial markets. This reason suggests that earnings forecasts for such firms would be more accurate.[10] Such firms may also be punished more severely for taking on risks, which managers would want to hide. Since the consequences of risky actions are more evident during bad times, the forecasts of more highly leveraged firms may be less accurate during the pandemic. The review by Letdin et al. (2019) notes that the relationship between leverage and returns is more complicated for REITs. For example, they note that an increase in leverage increases the sensitivity of REIT returns to general stock market returns (i.e., beta), and that may be relevant during the pandemic. In addition, for tax reasons, REITs pay out most of their earnings as dividends. Therefore, unlike other types of businesses, those who lend to REITs may tend to focus more on the value of immobile and tangible collateral and to focus less on retained, current, or future earnings. Gupta (2022) offers some evidence supporting this perspective.

Many researchers include market to book ratio (*MB*) (e.g., Chen et al. 2021). *MB* is a measure of growth, but growth is not always predictable. We follow prior literature by including measures of return on assets (*ROA*) and *Stock Return*, as measures of firm fundamentals (e.g., Ding et al. 2021; Chen et al. 2021). Our control variables also include the *Volatility* of stock returns because, independent of the pandemic, past volatility indicates that markets may be unsure about a REIT's future prospects (e.g., Chen et al. 2021). *Analyst Coverage* may also affect the average quality of forecasts for a number of reasons. Having more analysts means that there is both a greater chance of an outlier and that its effect could disappear into an average, since our data focuses on the forecast quality for a REIT and not for an analyst. Finally, the *Forecast Horizon* could be relevant since being able to offer a forecast closer to the time when earnings are reported means that an analyst can use more current data, which tends to reduce errors. We follow common practice and use lagged values in our regressions to reduce concerns about endogeneity.

Table 2 describes the data we use. Each observation represents one REIT for one month. Since our data cover 26 months (October 2018 to November 2020), the numbers of cases, or deaths, due to the COVID-19 equals 0 for the first 15 months. Our data cover the first and second waves, plus part of the third wave, of the pandemic in the United States. Panel A shows summary statistics. The distribution of Forecast Error (*FE*) and Forecast Dispersion (*FD*) across months and REITs is skewed: the mean of each variable is much greater than its median. Our data have been winsorized at the 1 percent and 99 percent levels. Panel B reports correlation coefficients. As we note in the discussion of Hypothesis 2, the unsurprising finding is that the various measures of the severity of the pandemic are highly correlated with the measure of government policies.

Table 2. Summary Statistics and Correlation Coefficients.

Panel A. Summary Statistics.						
Name	**#Obs.**	**Mean**	**Std. Dev.**	**25th**	**Median**	**75th**
FE	2688	1.06	3.24	0.09	0.23	0.64
FD	1958	0.27	0.60	0.04	0.09	0.21
Ln(Cum Cases)	2688	5.21	6.77	0	0	14.20
Ln(Cum Deaths)	2688	3.84	5.35	0	0	11.37
Ln(New Cases)	2688	5.08	6.43	0	0	13.65
Ln(New Deaths)	2688	3.57	4.82	0	0	10.05
Cum Cases	2688	1,166,034	2,288,984	0	0	1,462,345
Cum Deaths	2688	40,335	69,172	0	0	86,813
New Cases	2688	407,513	690,741	0	0	850,218
New Deaths	2688	10,552	16,996	0	0	23,109
GovRes	2688	22.01	29.59	0	0	62.93
EcoMeasure	2688	19.62	28.63	0	0	62.50
Institutional Holding	2688	0.82	0.20	0.76	0.88	0.9350
Size	2688	8.59	0.96	7.97	8.53	9.13
Leverage	2688	0.50	0.15	0.41	0.47	0.58
MB	2688	1.49	0.55	1.11	1.39	1.69
ROA	2688	0.0045	0.0185	0.0011	0.0053	0.0094
Stock Return	2688	−0.0048	0.1140	−0.0488	0.0019	0.0475
Volatility	2688	0.0240	0.0232	0.0109	0.0156	0.0256
Analyst Coverage	2688	2.49	0.61	2.20	2.56	2.94
Forecast Horizon	2688	0.14	1.07	−1	0	1

Panel B. Correlation Coefficients.														
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1 *FE*	1													
2 *FD*	0.59	1												
3 *Ln(Cum Cases)*	0.10	0.21	1											
4 *Ln(Cum Deaths)*	0.09	0.21	0.99	1										
5 *GovRes*	0.10	0.22	0.99	0.99	1									
6 *Forecast Horizon*	−0.04	−0.03	−0.14	−0.13	−0.13	1								
7 *Institutional Holding*	−0.19	−0.16	0.08	0.10	0.09	0.00	1							
8 *Stock Return*	−0.16	−0.13	−0.14	−0.12	−0.15	0.09	0.01	1						
9 *Volatility*	0.26	0.42	0.59	0.61	0.65	−0.14	0.01	−0.36	1					
10 *Size*	−0.15	−0.19	0.03	0.03	0.03	−0.03	0.23	0.01	−0.06	1				
11 *Leverage*	0.17	0.25	0.05	0.05	0.05	0.00	−0.14	−0.01	0.15	−0.08	1			
12 *MB*	−0.23	−0.33	−0.15	−0.16	−0.15	0.03	0.10	0.03	−0.22	0.32	0.03	1		
13 *ROA*	−0.21	−0.38	−0.14	−0.14	−0.13	−0.01	0.01	0.00	−0.14	0.21	−0.23	0.36	1	
14 *Analyst Coverage*	−0.19	−0.22	0.01	0.01	0.01	0.03	0.24	0.04	−0.10	0.58	−0.11	0.32	0.21	1

This table presents summary statistics in Panel A and correlation coefficients in Panel B for the sample, in this study, from October 2018 to November 2020. Detailed variable definitions are provided in the Appendix A.

5. Empirical Findings

This section presents and discusses our empirical results. First, we show our findings concerning the impact of the COVID-19 pandemic on forecast error and forecast dispersion. Then, we show how the impact differs across different property types.

5.1. The Impact of the COVID-19 Pandemic on Forecast Error

Table 3 shows that Forecast Error (*FE*) increases with the severity of the pandemic. The difference between column 1 and column 2 is the difference between measuring severity according to the cumulative number of cases and the cumulative number of deaths, respectively. The effect of an increase in severity on Forecast Error is positive, and statistically significant, at the 1% level. An increase in government interventions significantly offsets the effect of the pandemic on Forecast Error.

Table 3. The COVID-19 Pandemic and Forecast Error.

	FE	***FE***
	(1)	(2)
Ln(Cum Cases)	0.2745 ***	
	(3.22)	
*GovRes*Ln(Cum Cases)*	−0.0045 ***	
	(−3.30)	
Ln(Cum Deaths)		0.3359 ***
		(2.77)
*GovRes*Ln(Cum Deaths)*		−0.0056 ***
		(−2.82)
Forecast Horizon	0.0051	−0.0198
	(0.14)	(−0.54)
Institutional Holding	−2.5968 ***	−2.7875 ***
	(−2.75)	(−2.92)
Stock Return	−1.6756 *	−1.8504 *
	(−1.71)	(−1.83)
Volatility	27.9225 ***	27.0415 ***
	(3.20)	(3.11)
Size	0.1644	0.1712
	(1.03)	(1.07)
Leverage	2.8855 *	2.8233 *
	(1.89)	(1.85)
MB	−0.7934 **	−0.7767 **
	(−2.27)	(−2.25)
ROA	−28.8939 *	−29.0649 *
	(−1.68)	(−1.70)
Analyst Coverage	−0.5933 *	−0.5819 *
	(−1.73)	(−1.70)
Property Type	Yes	Yes
Observations	2326	2326
Adjusted R^2	0.2829	0.2789

This table presents regression results of analyst forecast error (*FE*) on the cumulative number of COVID-19 cases and deaths, as well as their interactions with government policy variable, for the sample of firm-month observations during the pandemic. All variables are as defined in the Appendix A. The numbers in parentheses are t-statistics. Standard errors are clustered at the firm level. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Both of these findings are consistent with our hypotheses. These findings indicate that the experience of the pandemic is more complicated than a claim that "there was some confusion initially which, with the benefit of time and learning, was overcome". Regardless of any initial surprise or confusion, the confusion amongst analysts increased as the disease spread. Government interventions help to reduce uncertainty.

The control variables offer some interesting insights into economic and statistical significance. An increase in *Institutional Holding* decreases *FE*, while an increase in the *Volatility* has a positive relationship with *FE*. Both variables have a high degree of statistical significance (at the 1% level). Based on our previous discussion, the direction of both effects is as expected: in the first case, because institutional ownership is associated with a REIT being well-run and, in the second case, because past volatility in stock returns suggests some underlying uncertainty on the part of market participants. Using the standard deviations for each variable reported in Panel A of Table 2 enables us to compare the economic significance of the different regressors on a shared dependent variable. Our regression analysis implies that the effect on *FE*, of an increase in the severity of the pandemic, is three or four times larger than the effect of an increase in *Institutional Holding* or *Volatility*.[11] This difference is true regardless of whether the severity is measured by cases or deaths. The market to book ratio (*MB*) is also statistically significant and, with a negative coefficient, indicates that analysts who study REITs with a relatively high growth make smaller errors when forecasting.

5.2. The Impact of the COVID-19 Pandemic on Forecast Dispersion

Table 4 studies the change in the dispersion of forecasts. Forecast dispersion (*FD*) depends on the differences in the information being used and in the methods of analysis amongst analysts. We find that an increase in the severity of the pandemic has a positive, and statistically significant, effect on *FD* at the 1% level. Government interventions have an offsetting effect, which is also statistically significant. Further, the effect of severity based on the number of cases (i.e., column 1) is much smaller than the effect of severity based on the number of deaths (i.e., column 2).[12] These results suggest that, due to limiting access to many familiar sources of private information, and to the unusual uncertainties during the pandemic, there are big differences amongst analysts in terms of the quality of data and methods of analysis.

Table 4. The COVID-19 Pandemic and Forecast Dispersion.

	FD	***FD***
	(1)	(2)
Ln(Cum Cases)	0.0418 ***	
	(3.57)	
*GovRes*Ln(Cum Cases)*	−0.0007 ***	
	(−3.28)	
Ln(Cum Deaths)		0.0667 ***
		(3.63)
*GovRes*Ln(Cum Deaths)*		−0.0011 ***
		(−3.43)
Forecast Horizon	0.0236 *	0.0221
	(1.67)	(1.59)
Institutional Holding	−0.4490 ***	−0.4681 ***
	(−3.28)	(−3.43)
Stock Return	0.1277	0.1269
	(0.48)	(0.48)
Volatility	9.3716 ***	9.3776 ***
	(5.78)	(5.77)
Size	0.0206	0.0223
	(0.63)	(0.68)
Leverage	0.7283 ***	0.7250 ***
	(2.99)	(3.00)
MB	−0.1541 *	−0.1514 *
	(−1.82)	(−1.80)
ROA	−13.0778 ***	−13.1033 ***
	(−4.86)	(−4.88)
Analyst Coverage	−0.0231	−0.0229
	(−0.24)	(−0.24)
Property Type	Yes	Yes
Observations	1688	1688
Adjusted R^2	0.5076	0.5066

This table presents regression results of analyst forecast dispersion (*FD*) on the cumulative number of COVID-19 cases, and deaths, as well as their interactions with government policy variable, for the sample of firm-month observations during the pandemic. All variables are as defined in the Appendix A. The numbers in parentheses are t-statistics. Standard errors are clustered at the firm level. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The effects of *Institutional Holding* and *Volatility* are qualitatively similar to those reported in Table 3. At the same time, the coefficient on *Leverage* has a positive sign, and the coefficient on *ROA* has a negative sign. These results suggest that REITs with higher leverage are more difficult for analysts to analyze, and earnings forecasts are more dispersed, while REITs that generate a high return on assets are easier for analysts to analyze and tend to have less dispersion. Both Tables 3 and 4 suggest that a REIT's *Size* has a positive, but insignificant, effect on either *FE* or *FD*. Prior research suggests that firm size may be a proxy for the quantity of public information (Beyer et al. 2010), but our earlier discussion suggests that additional effects may be relevant for REITs' operations (e.g., Highfield et al. 2021) especially during the pandemic. Similarly, the coefficient on *Leverage* is positive even if some research argues that more highly leveraged firms would tend to have more accurate earnings forecasts, due to increased oversight by lenders. We note that the review by Letdin et al. (2019) identifies some unexpected relationships between leverage and returns in REITs. Lin et al. (2021) also suggest that the logic used to evaluate uncertainty during the pandemic differs from the kind of logic normally used by financial markets during normal times, or even during the Global Financial Crisis.

5.3. The Differential Effects of the COVID-19 Pandemic across Property Types

Table 5 shows how the severity of the pandemic changes the Forecast Error and Forecast Dispersion across different property types of REITs and that our results are not dominated by one type being an outlier. The table shows, directly, that each of the coefficients differs from zero, which is consistent with what was found in Tables 3 and 4: an increase in severity increases Forecast Error and Dispersion. Individually, the value of most of the property type coefficients reported are similar to the comparable coefficients reported in Tables 3 and 4 (i.e., 0.2745 and 0.3359 or 0.0418 and 0.0667, respectively). We conclude that the effects of the pandemic, on the quality of forecasts, are widespread across property types.

The estimated effect on Forecast Error (column 1 in Panel A) is largest for Hospitality REITs and for Industrial REITs. The differences between Hospitality and four of the other eight types are statistically significant at the 5% level, and at the 10% level for the other four. The difference in estimated effect between the Industrial type and Diversified type is statistically significant at the 10% level, but differences with other types in a one-on-one comparison are not statistically significant.

The estimated effect on Forecast Dispersion (column 2 in Panel A) is largest for Hospitality REITs. The differences between that type and each of the other types individually is statistically significant at the 1% level. Unlike the results for Forecast Error, the second largest coefficient in column 2 of Panel A is Retail. Technology is a close third, with the order being reversed in Panel B. Surprisingly, given column 1, the coefficient, regarding the interaction effect with Industrial REITs, is one of the closest to 0. The results in Panel B are similar when measuring the severity of the pandemic using the number of deaths instead of the number of cases.

The Industrial and Technology sectors seem to be the two biggest winners during the pandemic, based on the growth of home delivery, video conferencing, plus the use of digital media, and based on cumulative abnormal returns during the early stages of the pandemic (Ling et al. 2020). The Hospitality and Retail sectors seem to be the pandemic's two biggest losers, based on the effects of travel restrictions and lockdowns. Yet, forecast quality in those four sectors tends to be the most sensitive to the severity of the pandemic. It may seem obvious, now, that the travel, restaurant, and retailing sectors would be forced to change. It may seem obvious, now, that disruptions in business travel, (home) schooling, and corporate meetings of all kinds would create opportunities for Zoom and its competitors. Our results show something more. Regardless of the average opinion concerning earnings by firms in those sectors, the coefficients show a growing difference in opinion amongst analysts concerning REITs in those sectors as the severity of the pandemic grew.

Table 5. The Differential Effects of the COVID-19 Pandemic across Property Types.

Panel A. Cumulative number of COVID-19 cases.		
	FE	***FD***
	(1)	(2)
*Office*Ln(Cum Cases)*	0.2334 ***	0.0339 ***
	(2.79)	(2.82)
*Industrial*Ln(Cum Cases)*	0.3053 ***	0.0283 **
	(3.09)	(2.27)
*Retail*Ln(Cum Cases)*	0.2525 ***	0.0388 ***
	(3.24)	(3.00)
Residential Ln(Cum Cases)*	0.2731 ***	0.0339 **
	(3.05)	(2.50)
Diversified Ln(Cum Cases)*	0.2100 ***	0.0202 *
	(2.66)	(1.90)
Hospitality Ln(Cum Cases)*	0.4278 ***	0.0900 ***
	(3.39)	(4.27)
Health Care Ln(Cum Cases)*	0.2699 ***	0.0358 ***
	(3.42)	(2.74)
Self-Storage Ln(Cum Cases)*	0.2260 ***	0.0269 **
	(2.83)	(2.20)
Specialty Ln(Cum Cases)*	0.2151 ***	0.0369 ***
	(2.84)	(2.78)
Technology Ln(Cum Cases)*	0.2622 ***	0.0375 ***
	(3.17)	(2.68)
GovRes Ln(Cum Cases)*	−0.0043 ***	−0.0006 ***
	(−3.24)	(−2.84)
Control Variables	Yes	Yes
Property Type	Yes	Yes
Observations	2326	1688
Adjusted R^2	0.2935	0.5331
Panel B. Cumulative number of COVID-19 deaths.		
	FE	***FD***
	(1)	(2)
*Office*Ln(Cum Deaths)*	0.2894 **	0.0555 ***
	(2.30)	(2.97)
*Industrial*Ln(Cum Deaths)*	0.3607 ***	0.0492 **
	(3.02)	(2.57)
*Retail*Ln(Cum Deaths)*	0.3074 **	0.0598 ***
	(2.58)	(3.30)
*Residential*Ln(Cum Deaths)*	0.3313 **	0.0546 ***
	(2.61)	(2.77)
*Diversified*Ln(Cum Deaths)*	0.2604 **	0.0387 **
	(2.26)	(2.30)
*Hospitality*Ln(Cum Deaths)*	0.4898 ***	0.1278 ***
	(3.23)	(4.22)
*Health Care*Ln(Cum Deaths)*	0.3319 ***	0.0583 ***
	(2.78)	(2.95)
*Self-Storage*Ln(Cum Deaths)*	0.2760 **	0.0467 **
	(2.34)	(2.46)
*Specialty*Ln(Cum Deaths)*	0.2618 **	0.0591 ***
	(2.30)	(2.97)
*Technology*Ln(Cum Deaths)*	0.3209 ***	0.0603 ***
	(2.64)	(2.79)
*GovRes*Ln(Cum Death)*	−0.0053 ***	−0.0010 ***
	(−2.69)	(−2.99)
Control Variables	Yes	Yes
Property Type	Yes	Yes
Observations	2326	1688
Adjusted R^2	0.2855	0.5328

This table presents regression results of analyst forecast error (*FE*) and dispersion (*FD*) on the cumulative number of COVID-19 cases (Panel A) and deaths (Panel B), as well as their interactions with ten indicator variables of property types for the sample of firm-month observations during the pandemic. For brevity, we only report the results of our key variables of interest. All variables are as defined in the Appendix A. The numbers in parentheses are t-statistics. Standard errors are clustered at the firm level. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

In some ways, our work complements the work of others. For example, Ling et al. (2020) study differences in performance amongst property types of REITs, due to the pandemic and associated government policies. They find that the abnormal returns of Retail and Residential type REITs react most negatively to an increase in the number of cases locally. The estimated effect on Industrial type REITs varies with the timeframe and the measure of abnormal returns. Similar to our finding, they find that "non-pharmaceutical interventions" by government lessened the negative effects on REITs' abnormal returns, especially when the number of cases, locally, was higher. Our work also complements that of Ding et al. (2021) and of Lin et al. (2021), who find that being financially well-prepared has benefits. This finding is consistent with the old real estate adage that "Cash is King". Their work may support our finding that REITs with greater leverage displayed lower forecast quality.

6. Robustness Checks

This section shows that our findings concerning Hypotheses 1 and 2 are not sensitive to using alternative measures of the severity of the pandemic or of government intervention policies.

In Table 6, we use a different way to measure the severity of the pandemic: it replaces the cumulative count of cases, or deaths, by the number of new cases, or deaths, for each month. If, unintentionally, a cumulative count acts as a time trend, our previous results could be a sign that forecasting became harder as time passes for some reason unrelated to the pandemic. Using the number of new cases or new deaths in a month avoids this issue. Similar to Tables 3 and 4, Table 6 finds that Forecast Error and Dispersion increase as severity increases. Table 6 also shows that government interventions offset this effect.

Table 6. Robustness Analysis–Alternative Measures of the Pandemic Severity.

	FE	*FE*	*FD*	*FD*
	(1)	(2)	(3)	(4)
Ln(New Cases)	0.2317 ***		0.0346 ***	
	(3.24)		(3.47)	
*GovRes*Ln(New Cases)*	−0.0039 ***		−0.0006 ***	
	(−3.31)		(−3.10)	
Ln(New Death)		0.3403 ***		0.0563 ***
		(3.07)		(3.56)
*GovRes*Ln(New Death)*		−0.0060 ***		−0.0010 ***
		(−3.08)		(−3.25)
Forecast Horizon	0.0038	−0.0196	0.0231	0.0209
	(0.10)	(−0.54)	(1.64)	(1.51)
Institutional Holding	−2.5743 ***	−2.6867 ***	−0.4465 ***	−0.4537 ***
	(−2.74)	(−2.88)	(−3.28)	(−3.38)
Stock Return	−1.6917 *	−1.7252 *	0.1243	0.1391
	(−1.72)	(−1.72)	(0.47)	(0.52)
Volatility	28.7516 ***	29.9094 ***	9.5096 ***	9.8517 ***
	(3.13)	(3.01)	(5.68)	(5.56)
Size	0.1645	0.1710	0.0208	0.0225
	(1.03)	(1.07)	(0.63)	(0.68)
Leverage	2.8795 *	2.8157 *	0.7273 ***	0.7226 ***
	(1.89)	(1.86)	(2.99)	(3.00)
MB	−0.7972 **	−0.7797 **	−0.1551 *	−0.1533 *
	(−2.28)	(−2.26)	(−1.83)	(−1.82)
ROA	−29.1054 *	−29.4392 *	−13.1235 ***	−13.2089 ***
	(−1.70)	(−1.72)	(−4.86)	(−4.88)
Analyst Coverage	−0.5907 *	−0.5786 *	−0.0224	−0.0215
	(−1.72)	(−1.69)	(−0.23)	(−0.23)
Property Type	Yes	Yes	Yes	Yes
Observations	2326	2326	1688	1688
Adjusted R^2	0.2833	0.2813	0.5076	0.5075

This table presents regression results of analyst forecast error (*FE*) and dispersion (*FD*) on the number of new COVID-19 cases, and deaths, as well as their interactions with government policy variable, for the sample of firm-month observations during the pandemic. All variables are as defined in the Appendix A. The numbers in parentheses are t-statistics. Standard errors are clustered at the firm level. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7 considers the effects of only the economic policies used by governments. The conceptual difference in measures is that *EcoMeasure* focuses exclusively on policies related to economic stimuli and not on restrictive policies, such as stay-at-home orders or public health initiatives. In terms of the raw data, there is less variation in this measure of government initiatives during the pandemic. As in our main analysis, the coefficients on the interaction variables are negative and statistically significant for both Forecast Error and Forecast Dispersion. Our hypotheses concerning the quality of analyst forecasts are confirmed again. The main difference between Tables 3 and 7 or Table 4 is that, even though the measures of government policy are about the same, on average, and have a similar range, the relevant coefficients in Table 7 are smaller.

Table 7. Robustness Analysis—The Effects of Economic Stimuli.

	FE	***FE***	***FD***	***FD***
	(1)	(2)	(3)	(4)
Ln(Cum Cases)	0.1132 **		0.0163 ***	
	(2.57)		(2.98)	
*EcoMeasure*Ln(Cum Cases)*	−0.0020 ***		−0.0003 ***	
	(−2.93)		(−2.91)	
Ln(Cum Deaths)		0.1143 *		0.0211 ***
		(1.96)		(2.62)
*EcoMeasure*Ln(Cum Deaths)*		−0.0022 **		−0.0004 ***
		(−2.39)		(−2.82)
Forecast Horizon	−0.0114	−0.0239	0.0206	0.0201
	(−0.31)	(−0.66)	(1.51)	(1.47)
Institutional Holding	−2.7078 ***	−2.8221 ***	−0.4680 ***	−0.4806 ***
	(−2.82)	(−2.92)	(−3.35)	(−3.45)
Stock Return	−1.8447 *	−2.0089 *	0.0989	0.0849
	(−1.83)	(−1.93)	(0.36)	(0.31)
Volatility	25.5475 ***	25.2538 ***	8.9591 ***	8.9438 ***
	(3.06)	(3.02)	(5.76)	(5.73)
Size	0.1697	0.1722	0.0217	0.0225
	(1.06)	(1.07)	(0.65)	(0.68)
Leverage	2.8851 *	2.8387 *	0.7300 ***	0.7268 ***
	(1.89)	(1.86)	(3.00)	(3.00)
MB	−0.7849 **	−0.7797 **	−0.1524 *	−0.1515 *
	(−2.26)	(−2.25)	(−1.81)	(−1.80)
ROA	−29.4005 *	−29.4431 *	−13.1449 ***	−13.1545 ***
	(−1.71)	(−1.72)	(−4.87)	(−4.88)
Analyst Coverage	−0.5910 *	−0.5822 *	−0.0234	−0.0231
	(−1.72)	(−1.70)	(−0.24)	(−0.24)
Property Type	Yes	Yes	Yes	Yes
Observations	2326	2326	1688	1688
Adjusted R^2	0.2802	0.2778	0.5058	0.5049

This table presents regression results of analyst forecast error (*FE*) and dispersion (*FD*) on the cumulative number of COVID-19 cases, and deaths, with consideration of the economic stimulus measure (*EcoMeasure*), for the sample of firm-month observations during the pandemic. All variables are as defined in the Appendix A. The numbers in parentheses are t-statistics. Standard errors are clustered at the firm level. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

7. Concluding Remarks

The COVID-19 pandemic has widespread and diverse effects. Those effects were not well-understood in the beginning, and the spread of the disease depends on mechanisms other than the usual rules. Therefore, this event created an opportunity to study how financial analysts adapt. We focus on their forecasts for earnings of Real Estate Investment Trusts (REITs) in the United States, because forecast earnings can be compared to actual earnings frequently and because earnings forecasts for the real estate sector fell dramatically during the initial phase of the pandemic, as well as because REITs are relatively transparent tools to transfer money from property tenants to investors. We measure the severity of the pandemic by the number of cases or deaths. We found that an increase in the severity of the pandemic reduces the quality of forecasts, both when measured as the average absolute error and when measured as the standard deviation or dispersion across analysts. Further, we show that the quality of forecasting does not vary equally across all property types. For the forecast error, the biggest effects are seen both in a sector that suffered from the pandemic (i.e., Hospitality) and in a sector that benefited from the pandemic (i.e., Industrial). For the forecast dispersion, the biggest effects are seen in sectors focusing on Hospitality, Retail, and Technology. We also document that government interventions have a beneficial effect on forecast quality.

The fact that we found different effects for different types of REITs indicates one of the practical implications of our work. Forecast quality decreases, asymmetrically, as the pandemic becomes more severe, indicating different increases in perceived risk. Therefore, a wise investor would diversify their portfolio in a way that recognizes distinctions amongst perceived winners (e.g., Industrial and Technology REITs) and amongst perceived losers (e.g., Hospitality and Retail REITs). This implication can be extended to challenging times in the future.

Understanding how analysts react to changes in uncertainty during a pandemic offers insights beyond events in 2020 for several reasons. In theory, investors use an analysts' forecast to make decisions. The effects of forecasts on investors and of the decisions on an investor's wealth often depend on environmental factors, such as the degree of uncertainty. Joos et al. (2016) study how well analysts understand the risks associated with a firm's fundamental value. They show that, even if point estimates seem to be optimistic, "assessments of state-contingent valuation risk seem to be unbiased". Many forecasters face a more fundamental problem than estimating the parameters of a forecasting model precisely or without bias: they are unsure of the model to be estimated. Linnainmaa et al. (2016) argue that one solution is to adjust the reported forecast over time gradually. The rate of adjustment would depend on the balance between uncertainty in the environment and concerns about model risk. The relevance of such effects to capital markets depends on how investors interpret analysts' forecasts and on the information asymmetry between them, all of which vary with the underlying uncertainty (see, for example, Veenman and Verwijmeren 2018). The lessons of the pandemic will take many years to learn and to apply.

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Appendix A

Table A1. Variable Definitions.

Dependent Variables	
FE	Analyst Forecast Error (*FE*) is calculated as the absolute value of the difference between an analyst's forecasted earnings and a REIT's actual earnings, multiplied by 100, scaled by the month-end stock price, and then averaged across analysts for each firm and each month.
FD	Analyst Forecast Dispersion (*FD*) is calculated as the standard deviation of earnings forecasts across analysts for each firm and each month, multiplied by 100 and scaled by the month-end stock price.The samples used in the Forecast Dispersion regressions are smaller since forecast dispersion cannot be calculated in months with only one analyst reporting a forecast.
COVID-19 Variables	
Ln(Cum Cases)	Natural logarithm of one plus the average number of cumulative COVID-19 cases in each month.
Ln(Cum Deaths)	Natural logarithm of one plus the average number of cumulative COVID-19 deaths in each month.
Ln(New Cases)	Natural logarithm of one plus the number of new COVID-19 cases in each month.
Ln(New Deaths)	Natural logarithm of one plus the number of new COVID-19 deaths in each month.
Government Policy Variables	
GovRes	We use the government response indices provided by Hale et al. (2021): Oxford COVID-19 Government Response Tracker (OxCGRT). The government response index is derived from 16 indicators. It recognizes responses such as closing schools, workplaces or public events, restrictions in movement, and public health initiatives (including vaccines and face covering) as well as economic stimulus measures (such as emergency income support and debt relief). The variable *GovRes* is calculated as the average of the daily values for each month.
EcoMeasure	Economic support index is the average of two economic indicators for government response to the COVID-19 situation. The variable *EcoMeasure* is calculated as the average of the daily values for each month.
Control Variables	
Forecast Horizon	The number of months from the month in which the forecast is made to the end of the fiscal quarter for each firm.
Institutional Holding	The total number of common shares of each firm held by financial institutions divided by the total numbers of common shares outstanding, as most recently filed by financial institutions.
Stock Return	Stock return in the previous month for each firm.
Volatility	The standard deviation of daily stock returns calculated for the previous month for each firm.
Size	Natural logarithm of total assets reported in the previous fiscal quarter for each firm.
Leverage	Long-term debt divided by total assets in the previous fiscal quarter for each firm.
MB	The sum of the market value of equity and long-term debt divided by total assets in the previous fiscal quarter for each firm.
ROA	Income before extraordinary items divided by total assets in the previous fiscal quarter for each firm.
Analyst Coverage	Natural logarithm of one plus the number of analysts covering the firm in the previous year for each firm.
Office, Industrial, Retail, Residential, Diversified, Hospitality, Health Care, Self-Storage, Specialty, and Technology	Indicator variables for property types.

Notes

1 https://www.reit.com/investing/why-invest-reits (accessed on 18 September 2021). In addition, a REIT's owners benefit because a REIT can reduce or eliminate corporate income tax liability if they pay out 90 percent of taxable income to investors as dividends.

2 Das et al. (2015) note that studying real estate assets may generate more precise insights than for common stocks. On one hand, there is an active market in a securitized market (i.e., REIT) and in an unsecuritized market (i.e., buildings) simultaneously. On the other hand, the market for buildings is notoriously inefficient and illiquid.

3 Our work focuses on forecasting earnings, while other work considers the problem of forecasting stock prices. A large body of work considers the determinants of the expected returns to investing in REITs: see especially the recent review by Letdin et al. (2019). As a related issue, others (e.g., Das et al. 2015) have noted that REITs have assets which can be evaluated independent of the Trust.

4 Government sources include https://www.bls.gov/cps/effects-of-the-coronavirus-COVID-19-pandemic.htm and https://www.usa.gov/coronavirus (accessed on 18 September 2021).

5 https://www.sec.gov/news/speech/speech-bauguess-050318 (accessed on 18 September 2021). Additionally, Paredes (2003) discusses the possibility of information overload.

6 Formally, our regression model includes all of the indicator variables denoting the property types of REITs. Since including all of the indicator variables and the intercept would create a situation with perfect multicollinearity, we omit the intercept. This choice has no effect on the properties of the other coefficients.

7 The samples used in the Forecast Dispersion regressions are smaller since forecast dispersion cannot be calculated in months with only one analyst reporting a forecast for a firm.

8 https://github.com/CSSEGISandData/COVID-19 (accessed on 18 September 2021).

9 https://www.bsg.ox.ac.uk/research/research-projects/COVID-19-government-response-tracker#data (accessed on 18 September 2021).

10 Leverage may also be a proxy for the intensity of competition in an industry (e.g., Chen et al. 2020). We suggest that this issue is not relevant for quarterly earnings forecasts of a REIT since, even if the payments vary over time, the relationship between a landlord and a tenant is governed by a longer term lease contract while the total space owned by a REIT is fixed in the short run.

11 If *GovRes* = 0, then the estimated effect of a one standard deviation increase in *Ln(Cum Cases)* on *FE* is $0.2745 \times 6.77 = 1.86$, while the estimated effect of a one standard deviation increase in *Institutional Holding* on *FE* is $-2.5968 \times 0.20 = -0.52$ and the estimated effect of a one standard deviation increase in *Volatility* on *FE* is $27.9225 \times 0.0232 = 0.65$.

12 If *GovRes* = 0, then the estimated effect of a one standard deviation increase in *Ln(Cum Cases)* on *FD* is $0.0418 \times 6.77 = 0.28$, while the estimated effect of a one standard deviation increase in *Ln(Cum Deaths)* on *FD* is $0.0667 \times 5.35 = 0.36$.

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