# Peer Effects of Corporate Disclosure in Pandemic Era

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**Abstract**

We show that a peer firm's management forecast provides information for other firms in the same industry. Specifically, we show that a firm's management forecast is positively associated with the stock return of other firms in the same industry. Furthermore, we show that such peer effect is observed when peer firms are the first disclosure company in the industry. We also find that the peer effect is more pronounced among firms with higher information asymmetry. Finally, we find that the peer effect is observed only in 2020 and not in other years between 2001 and 2019. Overall, the analysis provides strong evidence of peer effects under the COVID-19 pandemic period. This paper suggests that management forecast of peer firm plays a vital role as useful information set for investors that have limited access to public information due to the global pandemic.



**Keywords**: information spillover; COVID-19 pandemic; management forecast

**JEL Classification**: M4, G14

## 1. Introduction

The literature has been argued that investors use disclosure of peer firms to improve the information set of other firms in the same industry (Foster 1981; Leuz and Wysocki, 2016 for review).[1] The information spillover from peer firms is especially useful for firms with high asymmetric information. Indeed, using firm-level events such as bond or equity issuances, Shroff et al. (2017) point out that the peer effect is positively associated with the degree of asymmetric information. However, public information would be useful not only for firm-specific events, but also for an economic-wide shock which limits the set of public information investors have.

The rapid spread of COVID-19 brought a high economic uncertainty. The pandemic made it difficult to evaluate its impact on the real economy. For example, the spread of the virus triggered a great paradigm shift in human lifestyle and business style , so-called a 'new normal', changing investors' expectation for future corporate earnings. Furthermore, it also reduced public information available for the investors. These situations changed investor preferences and led investors to seek alternative information source (Acharya and Steffen, 2020; Rameli and Wagner, 2020). If there exists the peer effect shown in previous literature, it is more valuable in the pandemic period when investors are less likely to access public information. Hence, in this study, we focus on COVID-19 pandemic as the economic-wide shock and investigate the peer effect during the pandemic period. The hypothesis is that peer information has an impact on the stock return of other firms in the same industry under the pandemic period. We focus on a stock price reaction because it reflects the public information of investors.

We use Japanese non-financial firms as our sample because of its unique features. The

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[1] Other stream of literature argues the information spillover from peer firms to the managerial decision of other firms in the same industry, such as investment (Bernard et al 2020), frequency of disclosure (Seo 2020), capital structure (Leary and Roberts, 2014), and dividend policy (Adhikari and Agrawal, 2018; Grennan, 2019).

institutional backgrounds provide us a nice testing ground on peer effects of management forecasts in uncertain economy. First, most of listed firms have fiscal year ending in March.[2] Security exchanges in Japan require listed firms to disclose the quick review of accounting information, *tanshin*, within two months after the accounting period end. Furthermore, stock exchange highly recommends managers to disclose *tanshin* within 45 days (until in the middle of May for the firms whose accounting period ends in March). The reporting timing overlaps the period of 'the first wave' when COVID-19 spread world-wide.[3] Many Japanese listed firms needed to report accounting information when the COVID-19 started significantly affecting the economy and the uncertainty increased.

Second, the stock exchanges in Japan strongly request listed firms to disclose the management forecasts. Following the request, most of the listed firms disclose their forecasts (Kato et al., 2009). Indeed, in fiscal year 2019, 95% of listed firms disclosed earnings forecasts.[4] The management forecast has been a useful information for investors. However, response to COVID-19 spread, more than the half of the firms did not disclose earnings forecasts in fiscal year of 2020. These drastic changes in reporting practices might lead investors to seek alternative information including peers' public information.

We define the peer information, *Peer Forecasts*, as peer's EPS forecast for the next fiscal year divided by realized EPS in the current fiscal year. *Peer Forecasts* increases as the peer firms are optimistic about the future and decreases as they are pessimistic. That is, investors might be able to catch a valuable information on the specific industry from a peer's forecast. Hence, investors will predict similar

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[2] Approximately 65% of Japanese listed firms regularly ends their fiscal year in March. Their market capital dominates 83% of all the listed firms.

[3] Indeed, the Japanese government declared a state of emergency policy on April 7th, which was lifted on March 14th. Strictly it is different from 'lock-down' policy (Economist, 2020). Under Japanese laws, government has no authority to restrict the move of individuals and close shops. Hence government requested individuals and companies to restrict movements.

[4] As comparison, only 43% of listed firms in U.S. discloses earnings forecasts (Matsumoto et al, 2020).

expectations for other firms in the same industry.

We estimate a model regressing a firm's stock return response on peer firms' management earnings forecast news. Using the sample period of fiscal year 2020, we find that the peer earnings forecasts positively relate to other firms' abnormal stock returns in the same industry. This result is consistent with our hypothesis that peer information is used under the pandemic period.

To examine the heterogeneity of the information spillover, we run several additional analyses. First, we divide the sample into two sub sample: sample where peer firms are the first disclosure company in the industry, and sample where peer firms are second or later disclosure firms. We find a positive relationship only in the subsample where peer firms are the first disclosure company in the industry. These results indicate that the peer information is useful when no other firms disclose earnings forecasts before. Second, the information spillover is pronounced for the firms with more serious asymmetric information. We divide the sample by the degree of information asymmetry in several ways, such as firm size, firm age, dividend payments, analyst coverages, and bond ratings. The positive relationship between peer information and abnormal stock return is more pronounced in the subsample with higher information asymmetry. The result implies that peer information is essential for firms that face high information asymmetry between management and investors.

Lastly, we show that the information spillover in 2020 is strongest of these 20 years. We investigate whether the positive relationship between peer information and abnormal stock return is a unique phenomenon in 2020 by extending the sample period from 2001 to 2020. We find that the positive relationship is observed only in 2020. In the other years, from 2001 to 2019, we do not find any evidence of peer information spillover. The results indicate that management forecast of peer firm plays a vital role as an information set for investors that have less public information due to the global pandemic.

The remainder of this paper is organized as follows. Section 2 shows theoretical background and develops testable hypotheses. Section 3 introduces the institutional background. Section 4 explains the research methodology, the data, and variables used in our empirical study. Section 5 presents our empirical findings. Section 6 concludes our study.

## 2. Hypothesis development

Our hypothesis is based on the arguments that (a) COVID-19 breakout increases economic uncertainty, and (b) economic uncertainty magnifies the importance of corporate disclosure for investors and (c) also magnifies the importance of peer information.

COVID-19 breakout increases economic uncertainty worldwide. Altig et al. (2020) show that economic uncertainty in the US and UK increases in response to COVID-19 breakout by using multiple uncertainty measures. To show the similar pattern in Japan, Figure 1 shows the evolution of economic uncertainty indices (implied volatility and economic policy uncertainty) from January 2000 through October 2020. Panel A draws monthly average of implied S&P 500 index returns volatility (*vix*) and implied Nikkei 225 index returns volatility (*vxj*). Japanese market index return implied volatility (*vxj*) jumps in February 2020. The spike is the second greatest level after Global Financial Crisis in October 2008.

Panel B shows the increases in monthly economic policy uncertainty (EPU) indices. Japanese EPU index does not look change drastically, compared with US or Global EPU. Since EPU index is adjusted within each country or area, we cannot compare EPU indices among multiple countries or areas. To show the within change in EPU, Table 1 reports each index before and after COVID-19 breakout. Japanese EPU increases by 81.2 percent (from 111 in January to 202 in April). This change is similar to the change in Global EPU (increase by 87.6 percent), but smaller than the US (increase by 133.1 percent). These findings suggest the great spike of economic uncertainty in Japan in the first half of 202, consistent with the findings in the US (Altig et al., 2020).

**Figure 1 inserted here**

**Table 1 inserted here**

The importance of financial reporting increases with economic uncertainty. It is well known that stock market response to corporate disclosure, including earnings announcement and management forecasts (Beyer et al., 2010 for review). Recent studies the extent of price reaction to the information depends on economic uncertainty. Choi (2018) finds that the stock price response to earnings announcements increases with market volatility. Nagar et al. (2019) find that managers increase voluntary management forecasts during higher economically uncertain periods, and the increased forecasts, in turns, decrease investor information asymmetry. These findings suggest that both managers and investors consider corporate disclosure a more importance information source when uncertainty increases.

Economic uncertainty is also likely to magnify the importance of peer information. When uncertainty increases or information available for investors are limited, investors seek information relevant for investment decisions. The relevant information includes peer's financial reporting, since the peer firms tend to face similar economic conditions (Dye, 1990; Admati and Pfleiderer 2000). The importance of peer information depends on the firm's information environment. Shroff et al. (2017) find information asymmetry increases the importance of peer information for investors. Bergsma and Tayal (2020) find that firm-level risk measured with idiosyncratic volatility pronounces information spillover effects on peer firms.

Extending these arguments, we consider that uncertainty spike in response to COVID-19 breakout increases the information transfer to the firms in the same industry. We expect that economic uncertainty increases the importance of peer information for investors. Formally, we will test the following hypothesis:

*H1: Stock returns reflect the information of peer management forecasts during COVID-19 pandemic*

To examine the mechanism behind the hypothesis, we focus on heterogeneity of peer information transfer. In Hypothesis 1, we consider uniform COVID-19 effects on corporate information environment. However, the relative relevance of peer information is likely to be magnified when the information available for investors is limited. When the investors are able to access to the information, they do not have incentives to seek information in peer firms' financial reporting. When they do not have useful information source, peer's information can influence investor response to corporate disclosure. Shroff et al. (2017) find that asymmetric information increases the relative importance of peer information for investors. If these arguments hold, the information spillover of peer management forecasts should be pronounced for firms with serious asymmetric information. Formally, we will test the following hypothesis:

*H2: The information spillover during COVID-19 pandemic is pronounced than other years*.

## 3. Institutional Background

### *3.1. Corporate disclosure in Japan*

Japanese Financial Instruments Exchange Act regulates the main disclosure rule of Japanese listed firms, requiring them to report Japanese Form 10-K (J 10-K, hereafter). Stock Exchanges in Japan also enforces other several corporate disclosures. The Stock Exchange rule requires firms to report earnings announcement, so-called Timely Disclosure (*tanshin*). The stock exchange highly recommends managers to disclose *tanshin* within 45days from the accounting period end (until in the middle of May for firms which end the accounting period in March).

Management forecasts in Japan are effectively mandated. Tokyo Stock Exchange (TSE, hereafter) strongly encourages managers of listed firms to provide regular forecasts of sales and earnings. Following the TSE rule, most Japanese firms report management forecasts on *tanshin*. As we will see in the next section over 95% of Japanese listed firms regularly report management forecasts. Based on this practice, several prior studies have called that the forecasts are effectively mandated in Japan (Kato, Skinner, and Kunimura 2009; Verrecchia and Wang, 2011).

### *3.2. COVID-19 and corporate disclosure in Japan*

These Japanese institutional backgrounds provide us a nice research ground to examine the information spillover of management forecasts in the periods of COVID-19 pandemic. The COVID-19 breakout overlaps the periods when most Japanese firms need to announce their earnings. The governor of Tokyo prefecture (including the capital city of Japan) requested self-restraint on March 25th. Japanese government declared a state of emergency policy on April 7th, which was lifted on May 14th. Even though these social distancing measures in Japan are not as strict as in European countries or the US, they affect the wide range of human decisions. For instance, Figure A1 shows that human mobility sharply declined during the period. Figure 2 summarizes the timeline of required reporting and COVID-19 related policies in Japan.

**Table 2 inserted here**

**Figure 2 inserted here**

The COVID-19 break out also drastically changed financial reporting practices in Japan. First, Timely Disclosure delayed. Panel A of Table 2 reports the time trend of reporting lag, which represents the average days from fiscal year end through the day of *tanshin* announcement. The reporting lag gradually declined until 2019, suggesting that Japanese listed firms increase the speed of earnings announcement. However, in 2020, the reporting lag sharply increased. The average delay is 4.4 days from the previous year.

Second, most Japanese managements did not disclose their forecasts in 2020. Panel B of Table 2 shows that 95.9 percentage of Japanese listed firms report management forecasts before 2019. This is consistent with the argument of prior literature considering Japanese management forecasts effectively mandated. Surprisingly, however, only 41.3 percent of listed firms disclosed management forecasts in 2020.

These changes in information environment suggests that Japan could be a nice research ground to examine the effects of COVID-19 breakout and information spillover of management forecasts. Investors have limited access to both historical and future information in response to COVID-19 spread. This limited access to information motivates investors to seek alternative information source relevant for their investment decisions. And the peer's management forecasts could be a good information source. Thus, we consider that the worse information environment caused by COVID-19 breakout exogenously increases information spillover of management forecasts.

## 4. Research Design

### *4.1. Identification of Peer Effects*

To examine Hypothesis 1, we will estimate the following regression model:

$$CAR[t-1,t+1]_{it} = \alpha + \beta_1 Peer\ Forecast_{it} + \sum \gamma X_{i,2019} + \epsilon_{i,t} \qquad [1]$$

Where *i* and *t* index firms in the same industry with the peer firm, and years. The dependent variable is the three-days cumulative abnormal return from *t-1* to *t+1* of firm *i* where the date *t* is the announcement day of the peer firm. We use the market model to estimate abnormal returns. The estimation window is from January to December 2019. We require more than 200 trading days to estimate the beta.

The primary variable of interest is $Peer\ Forecast_{it}$ which is defined as the estimated EPS of the peer firm of firm *i* in 2021 divided by the realized EPS of firm *j* in 2020. It takes the value of one if the forecast EPS is precisely the same as the realized EPS and more (less) than one if forecast EPS is higher (lower) than realized EPS. If two or more firms disclose the forecast EPS at the same trading day, we compute the mean of the $Peer\ Forecast_{it}$ .

Hypothesis 1 predicts high management forecast of firm *j* is associated with a high abnormal stock return of firm *i*. We predict a positive coefficient for the $Peer\ Forecast_{it}$. Strictly, the null hypothesis is H0: $\beta_1 = 0$.

The vector *X* contains a set of control variables of firm *i*. The control variables account for firm-specific factors that would affect the asymmetric information, demand for information, and other characteristics, including profitability (EBITDA), firm size (ln(Total Assets)), financial leverage (Loan), an indicator for deficit firm (I(Deficit)), an indicator variable for firms report R&D expenditure (I(R&D Expenditure)), beta (Beta), market-to-book ratio (M/B), momentum (Momentum), volatility (Volatility), indicator for extreme forecasts(I(Extreme Forecasts)), and firm age(ln(Firm Age)). The control variables are one-year lagged values. Continuous variables are winsorized at the 1st and 99th percentiles. Definition of variables are in Appendix. Table 3 reports the summary statistics of variables in our sample.

We use the Nikkei three-digits Industry Classification that divides industries into 139 categories.

The peer effects could differ among industries because the degree of private information is different. Hence, we add industry dummy variables to control industry heterogeneity. Standard errors are robust to heteroskedasticity and clustered by industry. To mitigate a concern of simultaneity problem between a dependent variable and control variables, control variables are made from the accounting and stock return information in 2019.

The sample consists of firms whose peer firm discloses earnings forecasts between April to May 2020. The sample covers all listed firms but financial companies, ETFs, REITs, and those with less than 200 trading days in 2019.

To examine Hypothesis 2, we will estimate the following regression model:

$$CAR[t-1,t+1]_{it} = \alpha + \beta_1 Peer\ Forecast_{it} + \beta_2 I(y2020)_{\mathrm{t}} + \beta_3 Peer\ Forecast_{it} \times I(y2020)_t + \sum \gamma X_{i,t-1} + \epsilon_{it} \quad [2]$$

Now, the sample is all trading days from April and June from 2001 to 2020. The estimation model is similar to equation [1] but adds two new variables. One of the additional variables is $I(y2020)$ that takes the value of one for the observation in 2020. The second variable is the interaction term of $Peer\ Forecast_{it}$ and *I(y2020)*. Hypothesis 2 predicts high sensitivity to the management forecast of firm j on the abnormal stock return of firm *i*. Hence, we expect a positive coefficient for the interaction term. Strictly, the null hypothesis is H0: $\beta_3 = 0$.

### *4.2. Data*

Management forecast data are obtained from two data sources because of the following two reasons. First, we need management forecasts data that contains a time of disclosure. Because our main dependent variable of interest is the abnormal returns, it is essential to understand when investors obtain the new information and reflect it in stock price. New information arrives after the stock market closes is reflected on the next day's stock price. Stock markets in Japan close at 3 p.m. Therefore, the new information disclosed after 3 p.m. is reflected in the next day's stock price. Second, to test hypothesis 2, we need a dataset covering the management forecast data from 2000.

Two data sources have pros/cons. The first source of management forecast is *eol* service provided by Pronexus. The advantage of *eol* is that it contains the time of the disclosures. A disadvantage of *eol* is that it is difficult to obtain the management forecast in the deep past. Hence, we use the date form *eol* when testing Hypothesis 1, which requires the management forecast data of 2020.

The second source of the management forecast is Nikkei NEEDS. Nikkei NEEDs also collects the detail of the management forecast. It covers the detailed items of the management forecast from 1997. It also contains the date of disclosures. However, it does not contain the time of disclosures. To conduct an event study, understanding the data of disclosure is essential to identify the event date. To enjoy the benefit, we use the Nikkei's management forecast data for testing Hypothesis 2, which requires the management forecast from 2001 to 2020.[5]

We use Nikkei Quick Astra Manager and Nikkei NEEDs to obtain various data such as accounting information, stock returns, bond rating, analyst forecasts, dividend information, and firm established year. Forecasters are restricted only to firms with the fiscal year end in March.

## 5. Results

### *5.1. Under COVID-19 Pandemic*

First, we begin our empirical analysis by examining whether a forecaster's disclosure is associated with other firms' abnormal stock returns in the same industry.

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[5] We do not use *eol* because obtaining the historical disclosure information is difficult on *eol*.

Table 4 presents the results from regressions of abnormal returns on peer information and control variables (Equation [1]). Column 1 reports the results from a regression of univariate estimation. The coefficient of *Peer Forecasts* is positive and marginally statistically significant at the 10% level, which is consistent with Hypothesis 1 that predicts peer information positively associates to the abnormal return of related firms in the same industry under the COVID-19 pandemic period. The coefficient of 0.241 implies that a one-percentage point increase of $Peer\ Forecast$ increases an 0.241 percentage point increase of abnormal return.

Column 2 adds control variables for firm characteristics. Including the full set of control variables increases the economic effect of the forecasts on peers' abnormal returns: the estimated coefficient is 0.289. In terms of economic magnitude, the coefficient of 0.289 implies that a one-standard deviation increase in *Peer Forecasts* is associated with an increase of 0.293 percentage points of cumulative abnormal returns, which is 0.036 standard deviation of CAR [-1,+1].

There is a concern that some outliers cause such a linear relationship. To mitigate such concern, we eliminate the sample those $Peer\ Forecast$ is top or bottom one percentiles. The estimated coefficients are reported in column 3. Like other columns, we find a positive association between the peer's forecast and abnormal stock return of other firms in the same industry. Now, the estimated coefficient increases to 0. 319, which implies that the economic significance is that a one-standard deviation increase in *Peer Forecasts* is associated with an increase of 0.0574 standard deviation of CAR[-1,+1].[6]

The coefficient estimates on the control variables are as follow. *Beta* has a negative coefficient indicating that firms with low market risk outperform others, which may imply that investors may refer low-risk firms under high uncertainty due to COVID-19 pandemic. Firms with a high market-to-book ratio

[6] Eliminating outliers changes the standard deviation of *CAR* and *Peer Forecast*.

outperform others partially because high-tech firms enjoyed the benefit of work-from-home policy under the quarantine period. On the other hand, the quarantine policy would severely impact firms in the traditional sector with low market-to-book ratios. The estimated coefficient of *Momentum* is negative, which is intuitive because the pandemic changed the lifestyle of people. Hence the high performers before the pandemic period are not necessarily enjoying high performance during the pandemic period. *Volatility* has positive coefficients. Lastly, Firm age is negatively associated with the abnormal stock return in our sample period.

**Table 4 inserted here**

### *5.2. Subsample analysis*

The assumption of our first hypothesis is that peer information influences other firm's stock returns. To verify this assumption, we test two types of additional analysis. First, the peer firms' management forecast information is valuable for firms that have not disclosed the information under less public information. In this situation, the value of peer information is precious and has a significant impact on other firms' stock returns in the industry. In this aim, we divide the sample by whether the disclosed peer firm' management forecast is the first disclosure in the industry during our sample period or not. Table 5 reports the results of the subsample analysis. Column 1 consists of the observations where peer firms are the first disclosure company in the industry, and Column 2 consists of the observations that those peer firms are second or later disclosure firms. As predicted, the estimated coefficient of *Peer Forecasts* is positive and statistically significant only in Column 1. The economic significance is that a one-standard deviation increase in *Peer Forecasts* is associated with an increase of 0.0732standard deviation of cumulative abnormal return. As shown in Column 2, peer information has less impact on firms' abnormal return in the same industry. Now, the estimated coefficient of *Peer Forecasts* is positive but statistically insignificant (*t*-statistics =0.84). Albeit statistical insignificance, the economic significance is that a one-standard deviation increase in *Peer Forecasts* is associated with an increase of 0.0302 standard deviation of CAR [-1,+1], which is lower than the *Peer Forecasts* in Column 1.

**Table 5 inserted here**

**Table 6 inserted here**

Second, we also divide the sample by the degree of asymmetric information. The peer information is vital for firms that face high asymmetric information. Then we divide the sample by several proxies of asymmetric information. Table 6 reports the estimated coefficients where sample is divided by firm size in Columns 1 and 2. We predict smaller size firms face higher information asymmetry. Hence the positive abnormal stock return would be observed in a small firm subsample when new information arrives. The economic significance in Column 1 is that a one-standard deviation increase in *Peer Forecasts* is associated with an increase of 0.062 standard deviation of cumulative abnormal return. On the other hand, the estimated coefficient of *Peer Forecasts* is positive, but statistically insignificant in the subsample of large firms (Column 2).

Next, we divide the sample by firm age (Columns 3 and 4). Younger firms are assumed to face higher asymmetric information with investors implying the impact of information spillover is high for younger firms. Consistent with the prediction, we find a positive abnormal return for the subsample of younger firms. The estimated coefficient of *Peer Forecasts* is positive and statistically significant in the younger firm subsample (Column 3), but statistically insignificant in the older firm subsample (Column

4). The economic significance of the younger firm subsample is that a one-standard deviation increase in *Peer Forecast*s is associated with an increase of 0.0887 standard deviations of cumulative abnormal return.

We also divide the sample by dividend payment. Column 5 reports the results of a sample of non-dividend payers, and Column 6 reports the results of the subsample of dividend payers. We find the positive association between peer's forecast and abnormal return of other firms in the same industry is observed for the subsample of non-dividend payers, but not for dividend-payers. The economic significance of the non-dividend payer subsample is that a one-standard deviation increase in *Peer Forecasts* is associated with an increase of 0.0593 standard deviations of cumulative abnormal returns.

We also point out that the peer's disclosure is vital for firms without analyst coverages. We divide the sample by the existence of analyst coverage. We access Nikkei Quick Analyst Forecast Data, which collects analyst reports published by major Japanese financial companies. We regard a firm is with analyst coverages when the Quick's Analyst Forecast data is updated between January 2016 to December 2019. We find that the forecast is positively associated with the abnormal return of other firms in the subsample of firms without analyst coverages (Column 7). The economic significance is that a one-standard deviation increase in *Peer Forecasts* is associated with an increase of 0.0487 standard deviations of cumulative abnormal return. However, the estimated coefficient of *Peer Forecasts* is positive but statistically insignificant in the subsample of firms with analyst coverage (Column 8).

Lastly, we divide the sample by bond rating. Columns 9 and 10 are divided by the existence of bond rating. We access Nikkei Quick Analyst Forecast Data that collects the bond rating information of Japanese companies. We find the positive association between peers' forecast and abnormal return of other firms in the same industry is observed for the subsample of firms without a bond rating (Column 9). The economic significance is that a one-standard deviation increase in *Peer Forecasts* is associated with an increase of

0.0634 standard deviation of cumulative abnormal returns. However, in the subsample of firms with the bond rating (Column 10), the estimated coefficient of *Peer Forecasts* is positive, but statistically insignificant.

Next, we examine whether the estimated coefficients of *Peer Forecasts* in a high asymmetric information subsample are different from those in a low asymmetric information subsample. To this aim, we estimate the following equation.

$$CAR[t-1,t+1]_{it} = \alpha + \beta_1 Peer\ Forecasts_{it} + \beta_2 Asyn.Infor_{it} + \qquad [3]$$

$$\beta_3 Peer\ Forecast_{it} \times Asyn.Infor_{it} + \sum \gamma X_{i,2019} + \epsilon_{i,t}$$

If the estimated coefficients between two subsamples are different, $\beta_3$ should be significantly different from zero. Panel B of Table 6 reports the estimated coefficients except for the control variables. Interestingly, estimated coefficients of interaction terms are statistically insignificant. In Panel A of Table 6, all coefficients of *Peer Forecasts* are positive and statistically significant in high asymmetric information subsample and insignificant in low asymmetric information subsample. Therefore, we can say peer information is associated with abnormal stock returns for high asymmetric information firms. However, we cannot argue whether the impact of peer information for firms with high asymmetric information is different from that for low asymmetric information.

### 5.3. *Pre- and during Pandemic*

As so far, the empirical findings point out the importance of disclosure of management forecast by peer firms. One may have a concern that it is not the phenomena in the COVID-19 pandemic period. Hence, we extend our sample period

To make the assumptions consistent with previous estimations for equation 1, we restrict the sample in the following ways. First, we limit peer firms that the accounting period finishes in March. The sample period is all trading days of April to June each year from 2001 to 2020.

Table 7 reports the estimated coefficients of panel analysis. Column 1 reports the results of univariate analysis. The estimated coefficient of $Peer\ Forecast$ is positive and statistically significant at the 1% level. However, adding the set of control variable weaken the results. Column 2 reports the results with additional control variables. Now the coefficient of $Peer\ Forecast$ is positive, but insignificantly different from zero. These results indicate the peer effect is sensitive by the specification.

Columns 3 and 4 divide the sample by period. Column 3 is with observations from 2001 to 2019, and Column 4 is only observations in 2020. The positive correlation between the peer's disclosure and abnormal return is observed in the only subsample of 2020. In this case, we find that *Peer Forecasts* is positively associated with the cumulative abnormal return of non-disclosure firms at the 1% level. The difference is also observed with the interaction term approach in column 5. We add an indicator variable that takes the value of one for the observations in 2020 and its interaction term with *Peer Forecasts.* The interaction term is positive and statistically significant at the 1% level, which implies that the peer effect is critical only under the pandemic period.

We also show that the forecasts in 2020 are different from other years in another way. Specifically, we run the following estimation.

$$\begin{aligned} CAR[t-1,t+1]_{it} &= \alpha + \beta_1 Peer\ Forecasts_{it} + \textstyle\sum_{y=2002}^{2020} \gamma_y I(y) \\ &\quad + \textstyle\sum_{y=2002}^{2020} \delta_y I(y) \times Peer\ Forecasts_{it} + \sum \gamma X_{i,t-1} + \epsilon_{it} \end{aligned} \qquad [4]$$

We add year indicator variables and interaction terms between year indicators and $Peer\ Forecast$. $I(y)$ is a year indicator that takes the value of one for the observations in year $y$. The variable of interest is the interaction terms between year indicators and *Peer Forecasts*, which capture the year variant sensitivity of peer information on the abnormal return of other firms in the same industry.

Figure 3 plots the estimated coefficients of the interaction terms $\delta_y$ by year. The estimated coefficients of interaction terms are positive and statistically significant in 2013 and 2020, and economic impact is high in 2020.

Interestingly, we find no peer effects in the global financial crisis period: the estimated coefficients of interaction terms in 2008 or 2009 are not statistically significant. As we have shown, the VIX indicator (*vix*) in 2008 is as high as in the COVID-19 pandemic period. It may be because the time investors have enough time to evaluate the impact of the shock. Lehman Brothers bankrupted on September 15th, 2008. Because most Japanese firms end the fiscal year in March, there are six months of duration between the severe period of the crisis and the fiscal year close. Such a long period would enable investors to collect information of public information of firms.

**Table 7 inserted here**

## 6. Conclusion

In this paper, we examine the importance of peer effects under the COVID-19 pandemic period. Specifically, we find peer firm's management forecast is positively associated with the stock return of firms in the same industry. Furthermore, such peer effect is pronounced for first disclosure in the industry and firms with high asymmetric information. We also find that the peer effect is observed only in 2020 and not in other years between 2001 and 2019.

Overall, the analysis provides strong evidence of peer effects under the COVID-19 pandemic period. This paper suggests that peer firm disclosure of management forecasts plays a vital role when a pandemic happens.

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**Appendix**

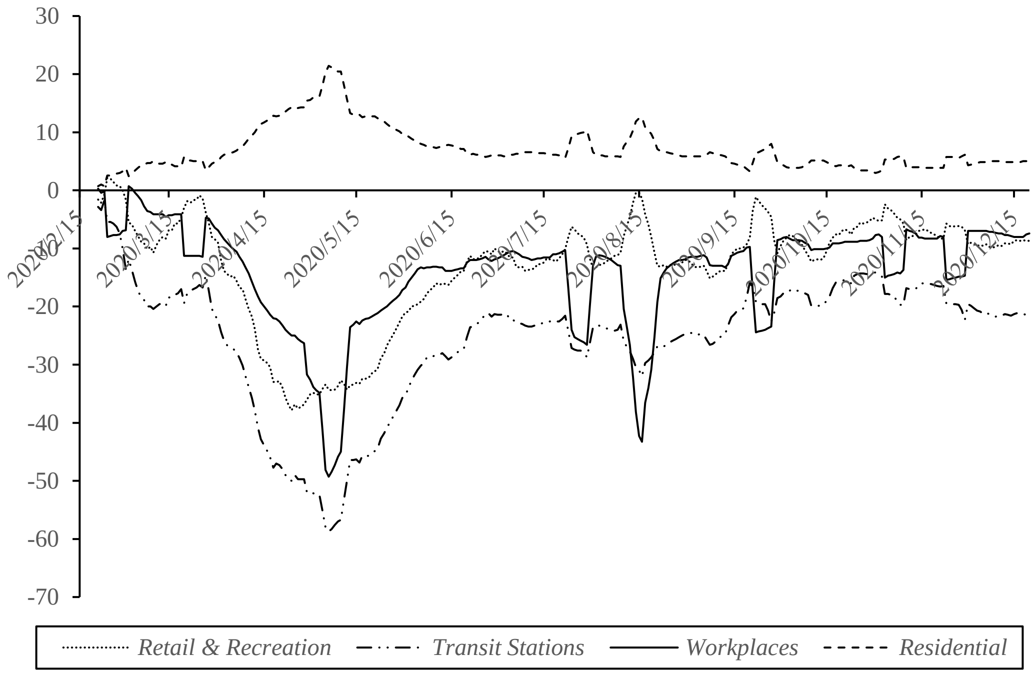



**Figure A1 Human mobility in Japan (7-day moving average):**
This figure draws the time-series of Google's COVID-19 Community Mobility Reports from February 15th through December 20th. We obtain the data from COVID-19 Community Mobility Reports' website (https://www.google.com/covid19/mobility/).

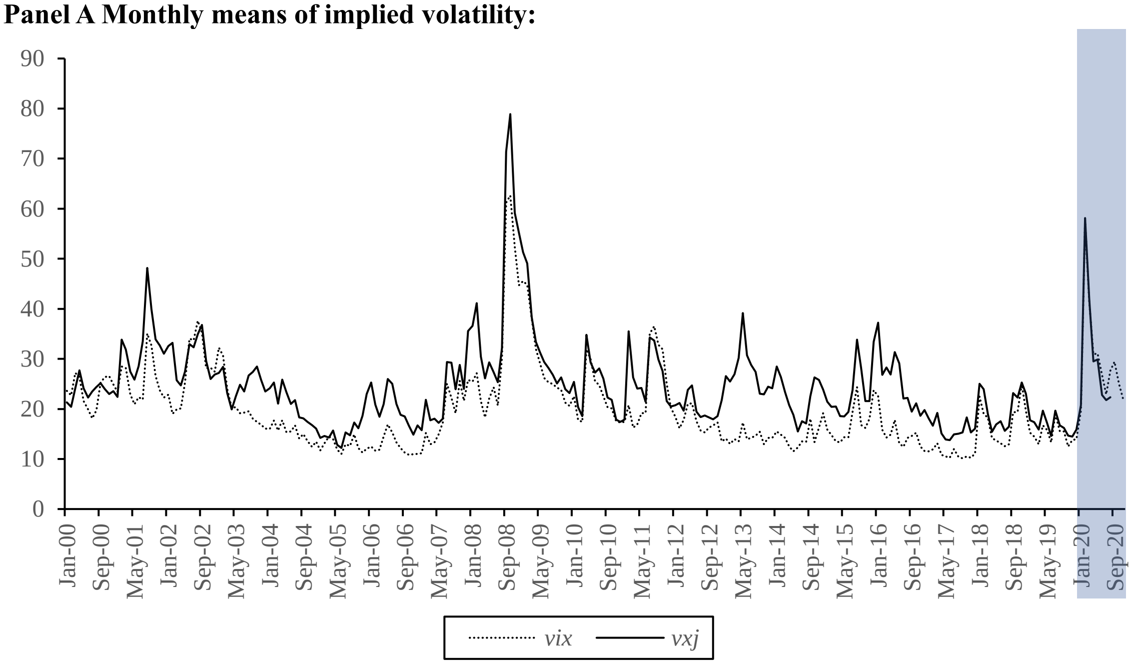
**Table A 1 Definition of variables**

This table describes the variable definition used in our main analysis.

| Variables | Definition |
|---|---|
| Dependent variables | |
| *CAR[-1,+1]* | Three days cumulative abnormal return from date *t-1* to *t+1*. Date *t* is the date the peer firm discloses the management forecast. Abnormal return is estimated using a market model. The estimation window is trading days from January to December 2019. We require more than 200 trading days to estimate the beta. |
| Explanatory variables | |
| *Peer Forecasts* | Management forecast of EPS in 2021 divided by realized EPS in 2020. |
| *EBITDA/Assets* | Defined as EBITDA divided by total assets. EBITDA is defined as sum of operating profit, and depreciation and amortizations. |
| *ln(Total Assets)* | Natural logarithm of total assets. |
| *Loan* | Total liabilities divided by total assets. |
| *Market-to-book ratio* | Market value of assets divided by total assets. Market value of assets is defined as the sum of the market value of equity and total liabilities. |
| *I(Deficit)* | This variable takes the value of one for firms that report operating losses, and zero otherwise. |
| *I(R&D)* | This variable takes the value of one for firms that reports a none-zero value of R&D expenditure, and zero otherwise. |
| *Beta* | Beta value computed from the market model with daily return in 2019. Market model is conducted for firms with more than 200 trading days in 2019. |
| *Momentum* | Raw return calculated by daily return in 2019. |
| *Volatility* | Standard deviation of daily return in 2019. |
| *I(Extreme Forecasts)* | Takes the value of one for forecaster's *Forecast* is 1 and 99 percentiles. |
| Macroeconomic Uncertainty | |
| *vxj* | Monthly averabe of implied Nikkei 225 index returns volatility, obtained from MMDS web page (http://www-mmds.sigmath.es.osaka-u.ac.jp/structure/activity/vxj.php). |
| *vix* | Monthly average of implied S&P 500 index returns volatility, obtained from Cboe web page (https://ww2.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data). |
| *JPN_epu* | Monthly economic policy uncertainty in Japan developed by Arbatli et al. (2019), obtained from Economic Policy Uncertainty web page (https://www.policyuncertainty.com/index.html ). |
| *US_epu* | Monthly economic policy uncertainty in the US developed by Baker et al. (2016), obtained from Economic Policy Uncertainty web page. |
| *GL_epu* | Monthly economic policy uncertainty in the US developed by Baker et al. (2016), obtained from Economic Policy Uncertainty web page. |

## Tables and Figures

**Panel A Monthly means of implied volatility:**




**Panel B Monthly EPU:**

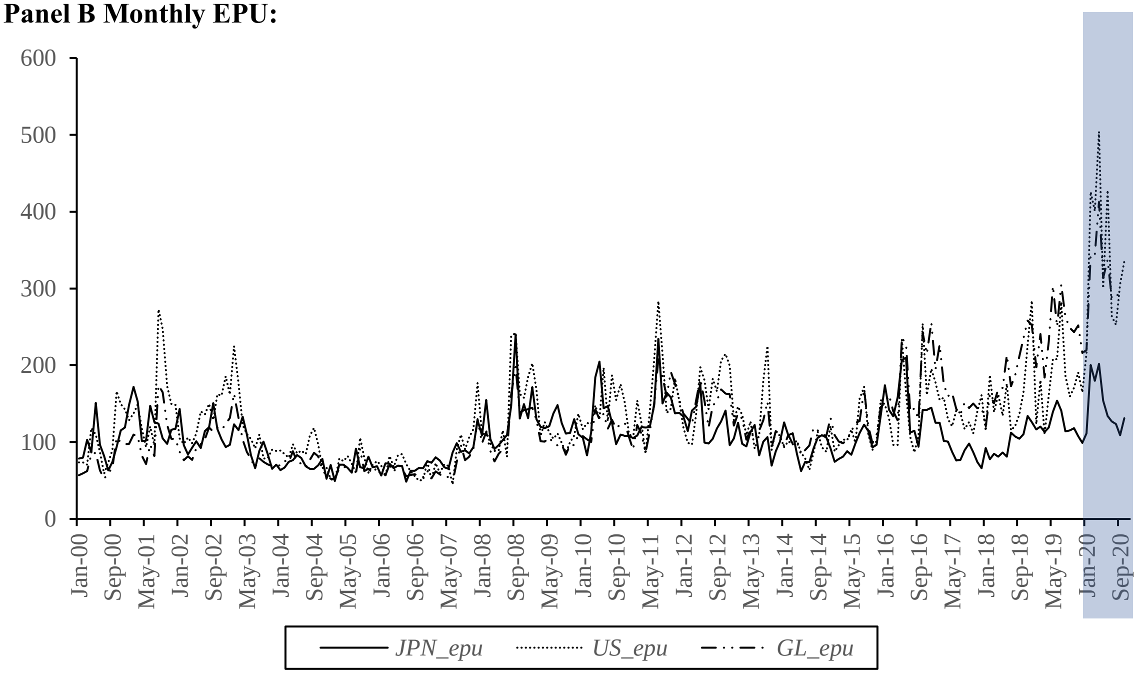



**Figure 1 Time-series of macroeconomic uncertainty:**
These figures show that time-series trend of indeses of macroeconomic uncertainty from January 2000 through October 2020. Panel A plots monthly average of implied S&P 500 index returns volatility (*vix*) and implied Nikkei 225 index returns volatility (*vxj*). Panel B plots monthly economic policy uncertainty indices of Japan, the US, and global level (JPN_epu, US_epu, and GL_epu, respectively).

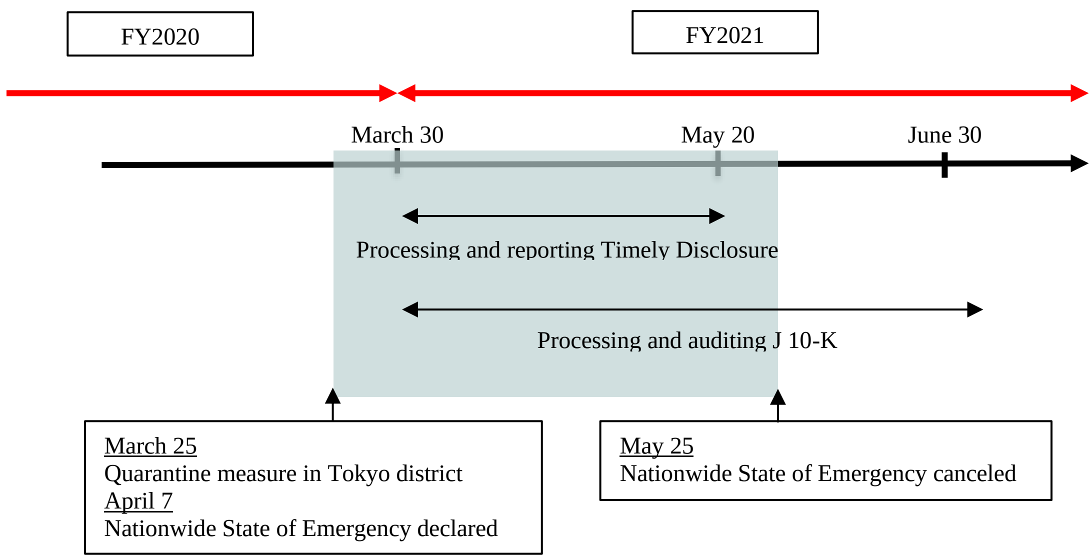



**Figure 2 Fiscal year end and social distancing measures in Japan:**
This figure describes the timeline of financial reporting and social distancing measures in Japan.

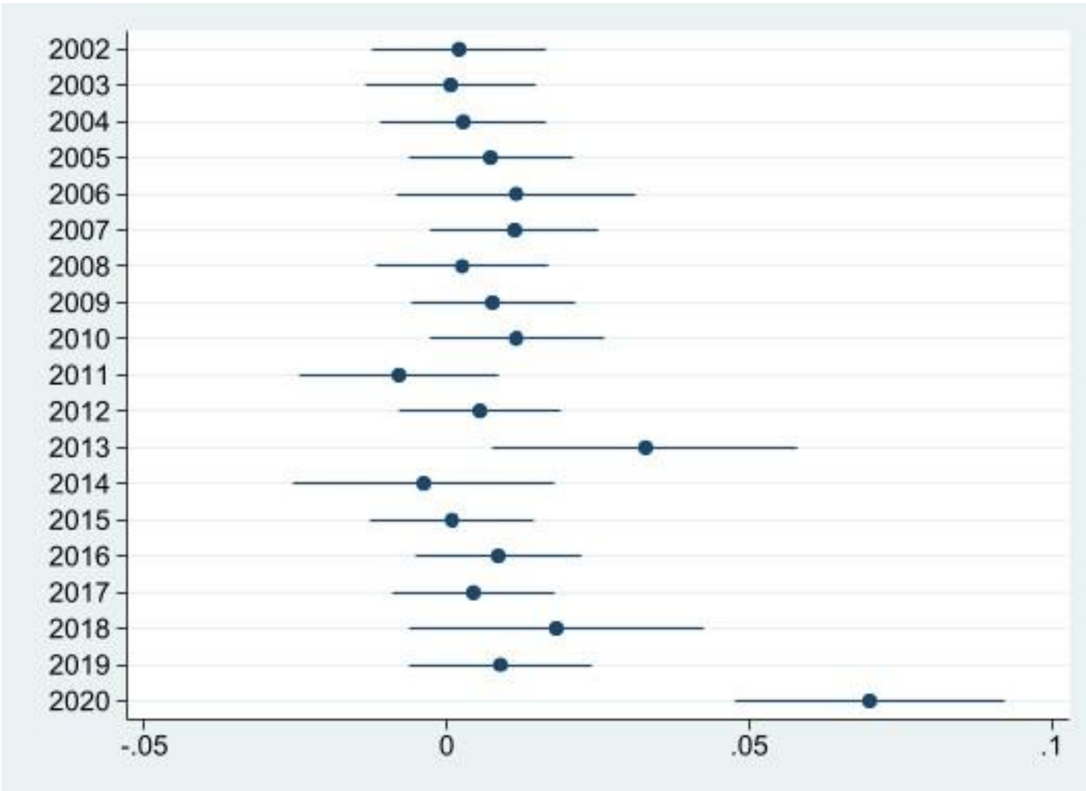



**Figure 3 Coefficient of *Peer Forecasts in year-by-year estimations.***
This figure plots the estimated coefficients of the interaction term between *Peer Forecasts* and year dummy variables. The dots express the estimated coefficients and the lines express the 95 percent confidential intervals.

**Table 1 Time trend of economic uncertainty**

This table shows the time-series of economic uncertainty measures. Column (1) reports the mean value of each measure from November 2019 through January 2020. Column (2) reports the values in January 2020. Column (3) reports the mean values from March through May in 2020. Columns (4) shows the maximum values of the measures after March 2020 (in the month reporting in Column (5)). Column (6) shows the percent change in each measure from January 2020.

| | Before COVID-19 | | Post COVID -19 | | | |
|---|---|---|---|---|---|---|
| | (1) Mean 2019Nov -2020Jan | (2) 2020Jan | (3) Mean 2020Mar -2020May | (4) Peak | (5) Peak Month | (6) Peak/ 2020Jan (%) |
| **Implied Volatility** | | | | | | |
| *vix* (Monthly Average) | 13.4 | 13.9 | 43.4 | 57.7 | 2020 Mar | 414.2 |
| *vxj* (Monthly Average) | 15 | 15.8 | 43.2 | 58.1 | 2020 Mar | 366.7 |
| | | | | | | |
| **EPU** | | | | | | |
| *JPN_epu* | 106 | 111 | 179 | 202 | 2020 Apr | 181.2 |
| *US_epu* | 190 | 216 | 402 | 504 | 2020 Apr | 233.1 |
| *GL_epu* | 229 | 220 | 357 | 413 | 2020 Apr | 187.6 |

**Table 2 Summary Stats of forecast in 2020**

**Panel A. Timely Disclosure delay:**

| | | Distribu-tion | | | | | |
|---|---|---|---|---|---|---|---|
| FY | Mean of reporting lag | -30days | 31-60days | 61-90days | 91-120days | 121-150days | 151- days or non-disclosed |
| 2001 | 50.96 | 0.0384 | 0.8978 | 0.0153 | 0 | 0 | 0.0485 |
| 2002 | 49.34 | 0.0492 | 0.8762 | 0.0125 | 0.0004 | 0.0004 | 0.0613 |
| 2003 | 47.73 | 0.0729 | 0.8677 | 0.0015 | 0 | 0.0004 | 0.0575 |
| 2004 | 46.25 | 0.0980 | 0.8573 | 0.0033 | 0.0007 | 0 | 0.0407 |
| 2005 | 45.04 | 0.1177 | 0.8300 | 0.0044 | 0.0004 | 0 | 0.0475 |
| 2006 | 44.18 | 0.1273 | 0.8292 | 0.0007 | 0.0004 | 0.0004 | 0.0421 |
| 2007 | 42.73 | 0.1263 | 0.8126 | 0.0050 | 0.0004 | 0 | 0.0557 |
| 2008 | 41.64 | 0.1333 | 0.8113 | 0.0007 | 0 | 0.0014 | 0.0532 |
| 2009 | 41.01 | 0.1411 | 0.7981 | 0.0026 | 0.0004 | 0.0022 | 0.0557 |
| 2010 | 40.28 | 0.1480 | 0.7920 | 0.0008 | 0.0027 | 0.0004 | 0.0562 |
| 2011 | 40.11 | 0.1031 | 0.7299 | 0.0255 | 0.0514 | 0.0314 | 0.0588 |
| 2012 | 39.37 | 0.1275 | 0.7906 | 0.0016 | 0.0016 | 0.0028 | 0.0759 |
| 2013 | 39.32 | 0.1363 | 0.7971 | 0.0016 | 0.0028 | 0.0024 | 0.0597 |
| 2014 | 39.46 | 0.1302 | 0.8046 | 0.0012 | 0.0016 | 0.0016 | 0.0608 |
| 2015 | 39.97 | 0.1339 | 0.8018 | 0.0016 | 0.0016 | 0.0008 | 0.0602 |
| 2016 | 39.54 | 0.1380 | 0.7954 | 0.0004 | 0.0041 | 0.0021 | 0.0600 |
| 2017 | 39.43 | 0.1341 | 0.8020 | 0.0017 | 0.0017 | 0.0029 | 0.0577 |
| 2018 | 39.23 | 0.1272 | 0.7996 | 0.0033 | 0.0017 | 0.0017 | 0.0665 |
| 2019 | 39.81 | 0.1237 | 0.8061 | 0.0013 | 0.0017 | 0.0017 | 0.0656 |
| **2020** | **44.23** | **0.0464** | **0.4848** | **0.0185** | **0.0287** | **0.1842** | **0.2374** |

**Panel B. Management forecast disclosure:**

| | disclosed | | non-disclosed | | |
|---|---|---|---|---|---|
| FY | # | frac | # | Frac | #Total |
| 2001 | 2,618 | 0.976 | 64 | 0.024 | 2,682 |
| 2002 | 2,631 | 0.966 | 92 | 0.034 | 2,723 |
| 2003 | 2,651 | 0.971 | 78 | 0.029 | 2,729 |
| 2004 | 2,647 | 0.979 | 58 | 0.021 | 2,705 |
| 2005 | 2,661 | 0.973 | 74 | 0.027 | 2,735 |
| 2006 | 2,691 | 0.976 | 66 | 0.024 | 2,757 |
| 2007 | 2,724 | 0.972 | 78 | 0.028 | 2,802 |
| 2008 | 2,678 | 0.970 | 83 | 0.030 | 2,761 |
| 2009 | 2,608 | 0.968 | 86 | 0.032 | 2,694 |
| 2010 | 2,526 | 0.966 | 89 | 0.034 | 2,615 |
| 2011 | 2,109 | 0.827 | 442 | 0.173 | 2,551 |
| 2012 | 2,387 | 0.954 | 115 | 0.046 | 2,502 |
| 2013 | 2,371 | 0.956 | 108 | 0.044 | 2,479 |
| 2014 | 2,357 | 0.962 | 94 | 0.038 | 2,451 |
| 2015 | 2,331 | 0.960 | 96 | 0.040 | 2,427 |
| 2016 | 2,327 | 0.956 | 107 | 0.044 | 2,434 |
| 2017 | 2,313 | 0.960 | 96 | 0.040 | 2,409 |
| 2018 | 2,301 | 0.957 | 104 | 0.043 | 2,405 |
| 2019 | 2,287 | 0.956 | 106 | 0.044 | 2,393 |
| **2020** | **980** | **0.413** | **1,392** | **0.587** | **2,372** |

| | | | | | |
|---|---|---|---|---|---|
| Total | 48,198 | 0.934 | 3,428 | 0.066 | 51,626 |
| Total (2020 excluded) | 47,218 | 0.959 | 2,036 | 0.041 | 49,254 |

**Table 3 Descriptive Statistics**

This table reports summary statistics of variables used in analysis

| Variable Name | N. | Mean | St. Dev. | Q1 | Median | Q3 |
|---|---|---|---|---|---|---|
| CAR | 27,573 | 0.722 | 4.725 | -1.918 | 0.325 | 2.972 |
| Peer Forecasts | 27,573 | 0.785 | 1.014 | 0.559 | 0.862 | 1.022 |
| EBITDA | 27,573 | 0.089 | 0.102 | 0.052 | 0.090 | 0.133 |
| ln(Total Assets) | 27,573 | 9.911 | 1.707 | 8.668 | 9.783 | 10.929 |
| Loan | 27,573 | 0.444 | 0.208 | 0.279 | 0.433 | 0.592 |
| I(Deficit) | 27,573 | 0.001 | 0.026 | 0 | 0 | 0 |
| I(R&D Expenditure) | 27,573 | 0.448 | 0.497 | 0 | 0 | 1 |
| HHI | 27,573 | 815.031 | 543.724 | 610.204 | 610.204 | 825.437 |
| Beta | 27,573 | 0.840 | 0.487 | 0.469 | 0.838 | 1.166 |
| M/B | 27,573 | 2.245 | 3.377 | 0.968 | 1.334 | 2.274 |
| Momentum | 27,573 | 0.128 | 0.649 | -0.155 | 0.013 | 0.241 |
| Volatility | 27,573 | 2.299 | 1.017 | 1.562 | 2.111 | 2.926 |
| I(Extreme Forecast) | 27,573 | 0.010 | 0.097 | 0 | 0 | 0 |
| ln(Firm Age) | 27,573 | 3.533 | 0.705 | 2.996 | 3.689 | 4.094 |

**Table 4 Peer Disclosure and Abnormal Return under Covid-19 Pandemic**

This table reports the results from an OLS model relating the sensitivity of forecaster s' disclosure on their industry-peers' abnormal returns. The sample period is April to June 2020. Observation consists of firms those peer firm discloses earnings forecasts. The standard errors computed by the *t*-statistics with adjusting for heteroskedasticity and industry clustering are reported in parenthesis. All specifications include industry-fixed effects. Symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | [1] | [2] | [3] |
|---|---|---|---|
| Peer Forecasts | 0.241* | 0.289* | 0.319* |
| | (0.133) | (0.157) | (0.162) |
| EBITDA | | -0.727** | -0.721** |
| | | (0.294) | (0.297) |
| ln(Total Assets) | | -0.0663** | -0.0648** |
| | | (0.0270) | (0.0285) |
| Loan | | 0.303 | 0.314 |
| | | (0.215) | (0.211) |
| I(Deficit) | | 2.243* | 2.313* |
| | | (1.180) | (1.173) |
| I(R&D Expenditure) | | 0.0687 | 0.0703 |
| | | (0.0616) | (0.0623) |
| Beta | | -0.511*** | -0.513*** |
| | | (0.130) | (0.131) |
| M/B | | 0.0609*** | 0.0604*** |
| | | (0.00730) | (0.00671) |
| Momentum | | -0.547*** | -0.546*** |
| | | (0.0918) | (0.0912) |
| Volatility | | 0.228*** | 0.228*** |
| | | (0.0552) | (0.0558) |
| I(Extreme Forecast) | | -1.045 | |
| | | (0.957) | |
| ln(Firm Age) | | -0.231*** | -0.241*** |
| | | (0.0867) | (0.0815) |
| Constant | 0.530*** | 1.715*** | 1.708*** |
| | (0.105) | (0.426) | (0.418) |
| Numbre of Observations | 27,974 | 27,573 | 27,311 |
| R-Squared | 0.023 | 0.036 | 0.036 |

**Table 5 Main Result: Pandemic Period**

This table reports the estimated coefficient by subsample analysis. Sample in column 1 is without a prior announcement by peer firms. Sample in column 2 is with a prior announcement by peer firms. The sample period is April to June 2020. The standard errors computed by the *t*-statistics with adjusting for heteroskedasticity and industry clustering are reported in parenthesis. All specifications include industry-fixed effects. Symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| Peer's disclosure is … | first | second or later |
|---|---|---|
| | [1] | [2] |
| Peer Forecasts | 0.355** | 0.126 |
| | (0.155) | (0.150) |
| EBITDA | -0.883*** | 0.958 |
| | (0.320) | (0.816) |
| ln(Total Assets) | -0.0838*** | 0.0209 |
| | (0.0268) | (0.0284) |
| Loan | 0.448** | -0.125 |
| | (0.195) | (0.273) |
| I(Deficit) | 2.219** | |
| | (1.086) | |
| I(R&D Expenditure) | 0.0815* | 0.171 |
| | (0.0456) | (0.118) |
| Beta | -0.419*** | -0.762*** |
| | (0.144) | (0.106) |
| M/B | 0.0361*** | 0.0894*** |
| | (0.00990) | (0.0118) |
| Momentum | -0.485*** | -0.683*** |
| | (0.115) | (0.0488) |
| Volatility | 0.190*** | 0.313*** |
| | (0.0613) | (0.0378) |
| I(Extreme Forecast) | -1.491 | -0.310 |
| | (0.973) | (0.745) |
| ln(Firm Age) | -0.0670 | -0.508** |
| | (0.0837) | (0.198) |
| Constant | 1.477*** | 1.461* |
| | (0.425) | (0.826) |
| Numbre of Observations | 19,270 | 8,303 |
| R-Squared | 0.031 | 0.053 |

**Table 6 Subsample Analysis: Sample of Pandemic Period**

This table reports various subsample analyses by the degree of asymmetric information. In Panel A, sample is divided by firm size (columns [1] and [2]), firm age (columns [3] and [4]), dividend payment (columns [5] and [6]), analyst coverage (columns [7] and [8]), and bond rating (columns [9] and [10]). The sample period is April to June 2020. The standard errors computed by the *t*-statistics with adjusting for heteroskedasticity and industry clustering are reported in parenthesis. All specifications include industry-fixed effects. Symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A

| | Small | Large | Young | Old | Non-Div. Payers | Div. Payers |
|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] |
| Peer Forecasts | 0.335** | 0.221 | 0.445*** | 0.0129 | 0.368*** | 0.272 |
| | (0.144) | (0.162) | (0.127) | (0.115) | (0.0716) | (0.175) |
| Constant | 2.229*** | -0.413 | 1.720*** | 0.284 | 2.026*** | 1.011** |
| | (0.277) | (0.567) | (0.426) | (1.278) | (0.492) | (0.508) |
| Control Variables | *yes* | *yes* | *yes* | *yes* | *yes* | *yes* |
| Number of Observations | 17,201 | 10,372 | 19,217 | 8,356 | 5,567 | 22,006 |
| R-Squared | 0.026 | 0.050 | 0.029 | 0.046 | 0.025 | 0.038 |

| | W/O Analysts | With Analysts | W/O Bond | With Bond |
|---|---|---|---|---|
| | [7] | [8] | [9] | [10] |
| Peer Forecasts | 0.214** | 0.328 | 0.306* | 0.260 |
| | (0.101) | (0.199) | (0.161) | (0.170) |
| Constant | 2.489*** | 1.669*** | 1.916*** | 2.203*** |
| | (0.484) | (0.569) | (0.411) | (0.628) |
| Control Variables | *yes* | *yes* | *yes* | *yes* |
| Number of Observations | 10,610 | 16,963 | 25,052 | 14,942 |
| R-Squared | 0.032 | 0.044 | 0.033 | 0.047 |

Panel B

| | [1] | [2] | [3] | [4] | [5] |
|---|---|---|---|---|---|
| *Asyn. Infor. Var* is ... | Small | Young | Non-Dividends | Analyst Cov. | Bond Rating |
| Peer Forecasts | 0.251 | 0.131 | 0.320*** | 0.258** | 0.298* |
| | (0.158) | (0.148) | (0.107) | (0.121) | (0.159) |
| *Asyn. Infor. Var* | 0.143** | -0.236* | 0.0155 | 0.295*** | 0.145 |
| | (0.0587) | (0.130) | (0.0709) | (0.0634) | (0.0966) |
| *Asyn. Infor. Var* x Peer Forecasts | 0.0630 | 0.226 | -0.0388 | 0.0489 | -0.0876 |
| | (0.0402) | (0.143) | (0.0762) | (0.113) | (0.0845) |
| Control Variables | *yes* | *yes* | *yes* | *yes* | *yes* |
| Numbre of Observations | 27,573 | 27,573 | 27,573 | 27,573 | 27,573 |
| R-Squared | 0.036 | 0.036 | 0.036 | 0.037 | 0.036 |

**Table 7 Result of Panel Data: 2001 to 2020.**

This table reports the results of panel data. I(2020) is indicator variable that takes the value of one for observations in 2020. The sample period is all daily trading dates in April to June of each year from 2001 to 2020. The standard errors computed by the *t*-statistics with adjusting for heteroskedasticity and industry clustering are reported in parenthesis. All specifications include industry fixed effects. Symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | [1] | [2] | [3] | [4] | [5] |
|---|---|---|---|---|---|
| Peer Forecasts | 0.000297*** | 0.000134 | 0.000122 | 0.119*** | 0.000141 |
| | (0.000106) | (0.000110) | (0.000109) | (0.0186) | (0.000110) |
| I(2020) | | | | | 0.270*** |
| | | | | | (0.0387) |
| Peer Forecasts x I(2020) | | | | | 0.0663*** |
| | | | | | (0.00903) |
| EBITDA | | 0.219 | 0.283 | -1.141** | 0.232 |
| | | (0.211) | (0.233) | (0.529) | (0.212) |
| ln(Total Assets) | | 0.00935 | 0.0101 | -0.0587*** | 0.00909 |
| | | (0.00727) | (0.00767) | (0.0222) | (0.00725) |
| Loan | | 0.0103 | 0.0367 | 0.0578 | 0.0173 |
| | | (0.0522) | (0.0568) | (0.182) | (0.0520) |
| I(Deficit) | | -1.910** | -1.797** | | -1.879** |
| | | (0.872) | (0.865) | | (0.869) |
| I(R&D Expenditure) | | -0.0338 | -0.0404* | 0.0494 | -0.0322 |
| | | (0.0238) | (0.0245) | (0.0844) | (0.0236) |
| Beta | | -2.53e-05** | -2.69e-05** | -0.000143* | -2.35e-05** |
| | | (1.09e-05) | (1.11e-05) | (8.41e-05) | (1.09e-05) |
| M/B | | 0.166*** | 0.211*** | -0.575*** | 0.156*** |
| | | (0.0233) | (0.0244) | (0.0758) | (0.0233) |
| Momentum | | -0.111*** | -0.138*** | 0.00616 | -0.113*** |
| | | (0.0155) | (0.0195) | (0.0127) | (0.0158) |
| Volatility | | 0.200*** | 0.195*** | 0.274*** | 0.204*** |
| | | (0.00873) | (0.00929) | (0.0234) | (0.00866) |
| I(Extreme Forecast) | | 0.0814** | 0.0848** | -2.357*** | 0.0628* |
| | | (0.0373) | (0.0376) | (0.687) | (0.0376) |
| ln(Firm Age) | | -0.0412* | -0.00174 | -0.139*** | -0.0220 |
| | | (0.0212) | (0.0233) | (0.0535) | (0.0212) |
| Constant | 0.0970*** | -0.359*** | -0.00174 | -0.139*** | -0.0220 |
| | (0.00709) | (0.114) | (0.0233) | (0.0535) | (0.0212) |
| Numbre of Observations | 812,721 | 660,364 | 629,930 | 30,434 | 660,364 |
| R-Squared | 0.001 | 0.009 | 0.010 | 0.027 | 0.009 |