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Is silence golden sometimes?

Management guidance withdrawals during the COVID-19 pandemic

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Is Silence Golden Sometimes?

Management Guidance Withdrawals during the COVID-19 Pandemic

ABSTRACT

The many management guidance withdrawals during the COVID-19 pandemic have attracted considerable attention from the media, investors, and regulators. This study analyzes the determinants and consequences of these withdrawals. We find that guidance withdrawals are due to economic uncertainty, resulting from firms' exposure to the COVID-19 pandemic rather than poor financial performance. Also, the effect of COVID-19 exposure on guidance withdrawals is stronger when firms face higher litigation risk. Further, guidance withdrawals result in abnormally large trading volumes and high analyst forecast dispersion but do not harm stock prices or the level of analyst earnings forecasts. Overall we believe the findings have implications for understanding corporate disclosure practices during periods with heightened economic uncertainty.

Keywords: COVID-19 Pandemic; Economic Uncertainty; Management Guidance; Guidance Withdrawal; Analyst Forecasts

Is Silence Golden Sometimes?

Management Guidance Withdrawals during the COVID-19 Pandemic

1. Introduction

The novel coronavirus (COVID-19) pandemic has drastically affected the global economy and offers a unique setting to investigate firm and market behavior through periods with heightened economic uncertainty. During the pandemic, many U.S. public firms *withdrew* their quarterly and annual guidance on the firms' financial outlook. According to Intelligize, 851 companies announced the withdrawals of their management guidance between March 16 and May 31, 2020.[1] In contrast, guidance withdrawals were rare previously. The large increase in the number of withdrawals has attracted wide attention from investors, regulators, and the media (CNBC 2020; *The Wall Street Journal* 2020). However, this phenomenon is not well understood in the literature. In this study, we empirically analyze the determinants and consequences of these withdrawals. This knowledge is important for corporations and investors in forming their decisions in the case of similar future events.

The literature examines a similar but different type of firm behavior, guidance cessation (e.g., Houston, Lev, and Tucker 2010; Chen, Matsumoto, and Rajgopal 2011). Disclosure theory predicts that firms cease guidance in the presence of negative news (Dye 1985; Verrecchia 1983). Consistent with the theoretical prediction, prior findings suggest that firms that stop management guidance have poorer anticipated future financial performance. Their managers have less favorable news to disclose and thus stop issuing guidance for current and future quarters. Said differently, when a firm withdraws an outstanding guidance, it may resume its guidance after the situation

[1] See https://www.irmagazine.com/reporting/how-covid-19-affecting-earnings-guidance-and-dividend-payments

becomes clearer and more stable.[2] In fact, some firms that previously withdrew their guidance during the pandemic have already restarted providing guidance (*IR Magazine* 2021). Therefore guidance withdrawals are less likely driven by anticipated poor financial performance for the relatively long-term future.

We predict that firms withdraw their guidance due to uncertainty resulting from their exposure to the pandemic. The pandemic could deepen firms' economic uncertainty in several ways and prevent managers from providing accurate guidance. For example, the pandemic may have resulted in significant uncertainty about customers' demand and disrupt the supply chain. Firms also had to adapt to social distancing rules and a remote working environment. All these changes could have increased uncertainty faced by managers and thus motivated firms to withdraw their previously issued management guidance.

For our empirical analyses, we manually collect a sample of 272 firms that withdraw their financial guidance during March 2020 by extracting 8-K filings from the Securities and Exchange Commission EDGAR website and searching press releases in the FactSet News database. [3] To investigate determinants of the decision to withdraw, we also collect a sample of control firms that issued financial guidance by March 1, 2020, but did not withdraw the guidance from March 1, 2020, to June 30, 2020. We further adopt a measure of a firm's exposure to the COVID pandemic from Hassan et al. (2021) based on the frequency of COVID-related words in conference call transcripts. A manager is expected to discuss COVID more if his or her firm has greater exposure the pandemic. Consistent with our prediction and anecdotal evidence, we find that firms with greater COVID exposure are more likely to withdraw their guidance. We also find a higher

[2] We do not find any firms that announced cessation of future guidance in their press releases of guidance withdrawal. Also, Chen et al. (2011) exclude guidance withdrawals from their sample according to their footnote 4.
[3] The term "guidance" in our study refers to general financial guidance, which includes both earnings guidance and other types of financial guidance but does not include nonfinancial guidance.

probability of guidance withdrawal when a firm experiences a larger increase in stock price volatility and thus greater uncertainty during the pandemic. Further, the probability of guidance withdrawals is significantly higher for cyclical and labor-intensive industries that are expected to be more severely affected by the pandemic. However, we do not find a significant impact of anticipated future performance on guidance withdrawals. Therefore these findings support the prediction that the decision to withdraw guidance is due to exposure to the COVID pandemic and the resulting economic uncertainty rather than anticipated bad economic news.

We further consider the role of litigation risk in moderating the relation between guidance withdrawal and economic uncertainty due to COVID exposure. Practitioners emphasize the importance of guidance withdrawals in mitigating possible litigation costs (e.g., SEC 2020). The cost of issuing inaccurate guidance is greater for firms facing greater litigation risk. Therefore we predict that, in the presence of high litigation risk, firms' decisions to withdraw guidance become more sensitive to their exposure to the COVID pandemic. Consistent with our expectation, we find that firms with higher litigation risk are more likely to withdraw guidance due to their exposure to the pandemic. This finding suggests that, even during the pandemic, litigation risk plays an important role in shaping firms' disclosures.

To understand the consequences of guidance withdrawals, we next examine the trading-volume and stock price reactions to guidance withdrawal announcements. Following prior research (e.g., Beaver 1968), abnormal trading volumes are calculated based on the ratio of average daily trading volume in the event window to that in a benchmark period. We find that the announcements significantly increase abnormal trading volumes. This finding is consistent with investors responding to withdrawals of management guidance as an important event. We further examine how investors react to the announcements based on stock returns. If investors view guidance withdrawals as a signal of poor anticipated future performance, we expect negative stock price reactions to the withdrawals. However, on the other hand, if investors believe that withdrawals are driven by the difficulty in issuing accurate estimates rather than by bad news, stock prices may not react negatively. Using alternative measures of stock returns, we do not find evidence of significant negative stock-price reactions to guidance withdrawals. In other words, investors do not generally interpret the withdrawal announcements as bad news. Therefore, investors appear to understand the difficulty in issuing accurate estimates during the pandemic.

We also investigate equity analysts' reactions to guidance withdrawals. Our regression model with firm fixed effects find that guidance withdrawals significantly increase analyst forecast dispersion, consistent with studies that find higher difficulty for analysts in forecasting firms without management guidance (Lang and Lundholm 1996; Barron, Kim, Lim, and Stevens 1998). In contrast, we do not observe a significant change in earnings per share (EPS) forecast estimates after guidance withdrawals. This finding further supports the argument that investors do not generally interpret guidance withdrawals during the pandemic as bad economic news. However, a caveat here is that underlying economic uncertainty may explain both a firm's decision to withdraw its guidance and changes in trading volume and analyst forecast dispersion.

Finally, we provide several additional analyses. First, our inferences remain if we alternatively measure a firm's exposure to COVID-19 based on the sentiment of the firm's COVID-related news reports or the strictness of lockdown-style policies in the firm's headquarters state. Second, our conclusions are robust to controlling for industry-fixed effects. Third, we identify 11 firms that withdrew their guidance during the two years prior to the pandemic and 54 firms that ceased their guidance in the year prior to the pandemic. Relative to these firms, firms that withdrew during the pandemic also have greater exposure to the pandemic but do not report different financial performance. In addition, we do not find evidence of significant herding in firms' decisions to withdraw their guidance.

Our study has implications for firm disclosure practices and investors during the COVID-19 pandemic as well as similar future events and makes several contributions to the voluntary disclosure literature. First, our paper contributes to the literature by empirically analyzing the many guidance withdrawals during the pandemic. As discussed above, this phenomenon has attracted attention from investors and regulators. We find that the withdrawals are due to economic uncertainty rather than poor anticipated financial performance. We also find that the stock market and analysts do not penalize guidance withdrawal decisions per se, indicating that the market understands that withdrawal decisions are likely to be attributed to extreme uncertainty rather than private negative news. Such knowledge could help firms evaluate the benefits and costs of guidance withdrawals in similar future events.

Second, studies have examined the effect of uncertainty on firm decision-making or stock market behavior. For example, Joos, Piotroski, and Srinivasan (2016) show that the 2008 financial crisis raises analysts' awareness of firms' exposures to macroeconomic uncertainty. Bloom et al. (2019) find that uncertainty due to Brexit significantly reduces U.K. firms' productivity. We contribute to this line of literature by providing evidence that economic uncertainty due to the COVID pandemic affects corporate disclosures and increases firms' tendency to withdraw their guidance. Given the precedent during the COVID pandemic, guidance withdrawals may become more common in the future. Therefore our findings contribute to understanding and prediction of how heightened economic uncertainty and similar future events will affect firms' disclosures. Waymire (1985) examines how uncertainty (measured by firm-level earnings volatility) relates to management guidance. He finds that firms with more volatile earnings provide less guidance.

However, the association between earnings volatility and management guidance could be endogenous, as both are affected by managers' decisions. We examine the considerably more exogenous event of the COVID pandemic and investigate how variations in the exposure to the pandemic affect firms' tendency to withdraw their guidance. Therefore, we believe that our study provides strong evidence on the effect of uncertainty on corporate disclosures.

2. Literature review

2.1 Voluntary disclosure

Information asymmetry between corporate insiders and external capital providers induces significant agency problems (e.g., Bartov, Bodnar, and Kaul 1996). A manager can alleviate concerns resulting from information asymmetry by communicating with external information users through voluntary disclosure (Graham, Harvey, and Rajgopal 2005; Beyer, Cohen, Lys, and Walther 2010; Kimbrough and Louis 2011; Hope and Liu 2021). In this way, high-quality voluntary disclosure facilitates efficient asset allocation and increases shareholder value (Baginski, Conrad, and Hassell 1993; De Franco, Hope, and Larocque 2015).

Management earnings forecasts are among the most important voluntary disclosures that firms can use to guide market expectations of their prospects (e.g., Nagar, Nanda, and Wysocki 2003). These forecasts can guide the market expectation of profits and are perceived to be informative by investors (Patell 1976; Penman 1980; Waymire 1984) and analysts (Ajinkya and Gift 1984; Jennings 1987; Baginski and Hassell 1990). Beyer et al. (2010) show that on average 15.67 percent of the variance in quarterly stock returns occurs on days when management guidance is issued, implying that these forecasts convey material economic news to investors (see also De Franco and Hope 2011).

Research documents various motives for managers' decisions to issue earnings forecasts. Trueman (1986) proposes that managers issue forecasts to enable investors to better assess the managers' ability to anticipate economic environmental changes. Accordingly, managers issue earnings forecasts to signal their ability (Trueman 1986). Managers' economic incentives, such as stock-based compensation plans, insider trading profits, and stock option awards, also play an important role (e.g., Noe 1999; Aboody and Kasznik 2000; Miller and Piotroski 2000; Nagar, Nanda, and Wysocki 2003; Cheng and Lo 2006). At the firm level, potential litigation threats incentivize managers to voluntarily disclose bad news through forecasts as well (Skinner 1994). Also, as an effort to lower the cost of financing, firms with greater needs for external financing are more likely to issue forecasts (e.g., Frankel, McNichols, and Wilson 1995). Further, to reduce the cost of investors' information acquisition and narrow the information gap, managers are more likely to provide earnings forecasts when economic policy uncertainty is greater (e.g., Nagar, Schoenfeld, and Wellman 2019) or when there is more firm-specific information (e.g., Gong, Li, and Zhou 2013).

2.2 Economic consequences of management guidance

A large body of research documents stock market consequences of managerial earnings guidance. Disclosure theory suggests that firms withhold forecasts in the presence of unfavorable information (Verrecchia 1983; Dye 1985; Verrecchia 2001; Dye 2001). For example, Verrecchia (1983) shows that only managers of firms with news above a certain threshold disclose their news and that managers withhold bad news below the threshold. Therefore investors would view the issuance of forecasts as a positive signal. Consistent with this prediction, Lev and Penman (1990) show that firms with particularly good earnings news distinguish themselves from others by issuing earnings forecasts. On average, the stock market reacts positively to management earnings forecasts. Management guidance also benefits firms by reducing information asymmetry between informed and uninformed investors and by improving firms' information environment in the capital market. The reduced information asymmetry decreases stock illiquidity, bid-ask spreads, and the cost of equity financing (Coller and Yohn 1997; Baginski and Rakow 2012; Balakrishnan, Billings, Kelly, and Ljungqvist 2014).

Management guidance also affects analysts' forecasts (Baginski and Hassell 1990; Williams 1996). Lang and Lundholm (1993) suggest that voluntary disclosure decreases analysts' information acquisition costs and promotes more analyst following. This finding has motivated subsequent studies to investigate the interaction between analyst activities and disclosure practices. For example, Cotter, Tuna, and Wysocki (2006) document that analysts react quickly to management guidance and are more likely to issue meetable or beatable earnings forecasts for firms with public guidance. Kim and Song (2015) find evidence that management earnings forecasts influence the timing and precision of analyst forecasts. Further, studies suggest that earnings guidance benefits firms by reducing litigation risk (Skinner 1994, 1997) and by improving the firm's reputation for being transparent and increasing investors' credibility of its financial reporting and disclosure practices (e.g., Williams 1996; Graham et al. 2005).

2.3 Guidance cessations

Studies have examined firms' decisions to cease management forecasts in earlier periods. As discussed above, theory suggests that managers withhold bad news (Verrecchia 1983; Dye 1985; Verrecchia 2001; Dye 2001). Firms may use proprietary costs as a reason for not disclosing their information or may argue that no private information has been received. However, due to uncertainty about managers' information endowment, investors can hardly unravel the nature of the news (Dye 1985). Therefore, investors would interpret silence as withholding negative economic news, and firms will suffer from negative capital market consequences if they do not disclose information (Grossman 1981; Milgrom 1981). Further, Dye (1998) predicts that, when fewer investors are informed, firms are more likely to be penalized by investors for not disclosing.

Consistent with the theoretical predictions, Houston, Lev, and Wu (2010) conclude that poor performance is the main reason for guidance cessation in their sample. In particular, firms that stop guidance have decreased earnings, poor records of meeting or beating analyst consensus forecasts, and low anticipated earnings. They also document lower analyst coverage, higher analyst forecast dispersion, and lower forecast accuracy after firms stop guidance. Similarly, Chen et al. (2011) find that firms with worse performance, greater performance uncertainty, and fewer informed investors (proxied by analyst followings) are more likely to stop issuing management guidance. Further, firms that publicly announce the non-guidance decision experience a negative three-day stock return around announcement and a deterioration of information environments. Chen et al. (2011) do not find significant effects of litigation risk and institutional ownership on the probability of guidance cessation.

2.4 Guidance withdrawals during the COVID pandemic

From the beginning of 2020, the COVID-19 pandemic has resulted in heightened uncertainty in the capital market. In a public statement issued on April 8, 2020, the SEC emphasized the importance of financial disclosure in ensuring investor confidence during this special period and urged firms to provide forward-looking disclosure about their performance and outlook.[4] This statement suggests that such disclosure would benefit not only investors and companies but also the coordination of the whole economy. However, in contrast to the SEC guidance, many U.S. firms *withdrew* their quarterly and annual guidance on firms' financial outlook. According to Intelligize, 851 companies announced the withdrawals of their guidance between March 16 and May 31, 2020.[5] Withdrawals were rare before the pandemic. Based on our news search, only 11 firms withdrew their guidance in 2018 and 2019. Thus the many withdrawals during the pandemic has attracted attention from investors, regulators, and the media (CNBC 2020; *The Wall Street Journal* 2020).

We are interested in examining guidance withdrawals during the pandemic. As discussed above, a closely related line of literature has examined guidance cessations and suggests that managers opportunistically stop providing guidance due to anticipated poor future operating performance (e.g., Houston et al. 2010 and Chen et al. 2011). Different from guidance cessations, withdrawals occur when firms recall previously issued guidance. A withdrawing firm may resume its guidance when the situation becomes clearer and more stable. We include examples of guidance withdrawal announcements in Appendix A. None of these example firms suggest that they will stop providing guidance in the future. We also manually check other firms and do not find any firm that announced cessation of future guidance in its press releases of guidance withdrawal. In fact, some firms that previously withdrew their guidance have already restarted providing guidance (*IR Magazine* 2021). Therefore withdrawals are less likely used to opportunistically withhold anticipated poor future financial performance.

Instead, we argue that guidance withdrawals are due to firms' exposure to the COVID pandemic. The pandemic could deepen firms' economic uncertainty in several ways and make it

[4] See https://www.sec.gov/news/public-statement/statement-clayton-hinman
[5] See https://www.irmagazine.com/reporting/how-covid-19-affecting-earnings-guidance-and-dividend-payments

difficult for managers to provide accurate guidance. For example, firms need to change their operating models and adapt to social distancing rules and remote work during the pandemic. Due to COVID-mitigation measures (e.g., stay-at-home orders) and uncertainty in the job market, customers' demands may also change and become more uncertain. The supply chain could be affected by travel restrictions and labor shortages. All these changes could increase uncertainty faced by managers and motivate firms to withdraw their management guidance. Anecdotal examples support the prediction that uncertainty resulting from exposure to the COVID pandemic determines guidance withdrawal decisions. For example, on March 24, 2020, AAR Corp. stated: "Given the current macro uncertainty from the impact of COVID-19, we believe it is prudent to withdraw our guidance for the balance of the year."[6] Similarly, on March 17, 2020, Nordstrom Inc. announced: "Due to heightened uncertainty relating to the impacts of COVID-19 on the Company's business operations, including the duration and impact on overall customer demand, the Company is withdrawing its 2020 guidance."[7]

Prior to the pandemic, firms rarely withdrew their guidance. During normal times, investors cannot distinguish managers who have unfavorable information and withhold it from managers who do not have precise information (e.g., Dye 1985). Thus it is difficult for firms to successfully communicate that they do not have precise information due to uncertainty during normal times. However, the heightened exogenous uncertainty during the COVID pandemic likely facilitates firms credibly communicating with investors that they do not have accurate forward-looking information. Based on these discussions, we formally state out first prediction (P1) as follows.

[6] See http://investors.aarcorp.com/static-files/409e9ae7-d45a-4ff4-a8aa-505604837c6f

[7] See https://press.nordstrom.com/news-releases/news-release-details/nordstrom-provides-business-update-related-coronavirus

P1: Firms withdraw their guidance due to their exposure to the COVID pandemic and the resulting uncertainty rather than anticipated poor financial performance.

We also aim to underst the role of litigation risk in shaping corporate disclosure. Litigation related to poor financial guidance is common. For example, shareholders recently sued Rocket Companies due to misleading guidance in June 2021. Rocket, the parent of Quicken Loans and Rocket Mortgage, is a Detroit-based holding company consisting of personal finance and consumer service brands. According to the *Detroit Free Press* (2021), the lawsuit "claims that Rocket executives were extremely optimistic to the point of deception and fraud earlier this year when forecasting the anticipated 'gain on sale' margin for its mortgage loans." The gain on sale margin is commonly viewed as a core measure of profitability in the industry. But the firm's earnings results for the first quarter of 2021 showed their margins were declining sharply. Rocket went public in 2020 and lacks experience of past shareholder litigation. Therefore its executives may have failed to realize the potential litigation risk related to their financial guidance. Similarly, in recent lawsuits against Merit Medical Systems Inc. and Vroom Inc., shareholders alleged that their financial forecasts were made without a reasonable basis.[8,9] In another 2020 lawsuit, shareholders of GoPro Inc. claimed that the firm failed to disclose that it would not be able to reach its previously issued guidance (e.g., Willkie Farr & Gallagher LLP 2021). Therefore withdrawing inaccurate forecasts is important for managing litigation risk.

[8] See https://www.globenewswire.com/en/news-release/2021/04/20/2213142/12089/en/NYSE-MMSI-Shareholder-Notice-Update-in-Lawsuit-against-Merit-Medical-Systems-Inc-announced-by-Shareholders-Foundation.html

[9] See https://www.globenewswire.com/fr/news-release/2021/05/08/2225868/1087/en/SHAREHOLDER-ALERT-Pomerantz-Law-Firm-Reminds-Shareholders-with-Losses-on-their-Investment-in-Vroom-Inc-of-Class-Action-Lawsuit-and-Upcoming-Deadline-VRM.html

Anecdotal evidence suggests that litigation risk helps shape firms' decisions to withdraw guidance during the pandemic. For example, the SEC (2020) suggests that "companies often are cautioned to limit their forward-looking disclosures, and particularly specific estimates . . . to limit legal risk." A former deputy general counsel of the SEC, Andrew N. Vollmer, further suggested that providing forward-looking disclosure during the pandemic could "lead to securities class actions of questionable merit."[10] The cost of providing inaccurate guidance is greater for firms facing greater litigation risk. Therefore we predict that, in the presence of high litigation risk, firms' decisions to withdraw guidance become more sensitive to their exposure to the COVID pandemic. This second prediction (P2) is formally stated as follows.

P2: The effect of exposure to the COVID pandemic on guidance withdrawal is more pronounced for firms with higher litigation risk.

3. Determinants of guidance withdrawals

3.1 Sample

We gather management guidance data from the IBES Guidance database, stock-return data from CRSP, and data on control variables from Compustat, CRSP, Thomson Reuters 13F, and IBES. We collect firms' withdrawal announcements from form 8-K filings in the SEC EDGAR database and from press releases in the FactSet News database.[11] Specifically, in SEC EDGAR, we first use Perl to identify all the form 8-Ks starting from January 1, 2020. Then we search for 8-Ks with keywords "COVID/coronavirus/pandemic," "outlook/guidance," and "withdraw/withdrew." Then we search for press releases on guidance withdrawals in the FactSet

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[10] See https://www.mercatus.org/bridge/commentary/secs-COVID-19-disclosure-guidance-litigation-trap

[11] FactSet has been used to collect corporate financial news in several recent studies (e.g., Brendel and Ryans 2021; Ng et al. 2021).

News database using keywords “guidance” and “withdraw.” Based on suggestions by the FactSet data team, we require that the distance between the two keywords “guidance” and “withdraw” be within 10 words of each other. [12] Further, we read through all the identified 8-K filings and press releases to ensure that the announcements relate to guidance withdrawals. Thus we identify a sample of 272 withdrawal announcements in March 2020.[13] Out of the 272 firms, 250 generally refer to financial guidance and do not mention a specific type of guidance in their announcements. Only 22 firms specifically mention that they withdrew their earnings guidance.

The distribution of withdrawal announcements by date is shown in Figure 1. The first three firms announced their withdrawal decisions due to COVID-19 on March 2, 2020. Not surprisingly, there are more announcements in the second half of the month, as more firms became affected by the pandemic. March 26 has the highest single-day number of withdrawal announcements (30 observations).

We report the distribution of the 272 withdrawing firms by the Fama-French 49 industry classifications in Table 1. The 272 firms are from 39 industries, suggesting that the impact of COVID-19 on firms’ disclosures is widespread. Consistent with our expectations, we find that cyclical and labor-intensive industries have more guidance withdrawals. In particular, the three industries with the most guidance withdrawals are (1) trading, (2) retail, and (3) restaurants, hotels, and motels.

To examine the determinants of management guidance withdrawals, we also identify a sample of control firms. A firm is identified as a control firm if it issued one financial guidance by

[12] The FactSet News database includes both corporate press releases and other news reports written by journalists. All our observations from the FactSet News database are based on firms’ press releases. Around 51% of withdrawal announcements are extracted from the FactSet News database.
[13] We do not find firms that withdrew management guidance in January or February of 2020. Accordingly, the withdrawal announcements in March 2020 may be unexpected by investors.

March 1, 2020, for one period ending after March 31, 2020, and did not announce withdrawals from March 1, 2020, to June 30, 2020.[14] Thus control firms are not willing to withdraw guidance or at least view withdrawals as being less urgent. In other words, control firms choose not to withdraw guidance, unlike those firms that withdraw their guidance during March 2020. After further eliminating observations with missing control variables used in the regression model, our sample comprises 264 firms with guidance withdrawals in March 2020 (withdrawing firms) and 457 control firms.

3.2 Regression model

We use the following Logit regression Model (1) to assess the firm-level determinants of guidance withdrawals.

$$\begin{aligned} Withdrawal = {} & \beta_0 + \beta_1\ COVID\_exposure + \beta_2\ \Delta StockVolatility + \beta_3\ \Delta ROA + \beta_4\ StockReturn + \beta_5\ Size \\ & + \beta_6\ Leverage + \beta_7\ Operating\ Leverage + \beta_8\ Cash + \beta_9\ Multinational + \beta_{10}\ Beta \\ & + \beta_{11}\ AnalystCoverage + \beta_{12}\ Institutional\ Ownership + \beta_{13}\ Cyclical \\ & + \beta_{14}\ LaborIntensity + \beta_{15}\ High\ R\&D. \qquad (1) \end{aligned}$$

The dependent variable *Withdrawal* is an indicator variable set to 1 if a firm withdrew its financial guidance during March 2020 and 0 for control firms. To test our prediction 1, we adopt a measure of a firm's exposure to COVID-19 (*COVID_exposure*) from Hassan et al. (2021). *COVID_exposure* is calculated based on the frequency of COVID-related words in the transcript of the last conference call before the withdrawal announcement for a withdrawing firm or before the end of March for a control firm. A manager is expected to have more discussions related to COVID if the firm is more significantly affected by the pandemic. We use this measure for our

[14] For a firm in the fiscal year of 2019, its fiscal-year ending month could be from July 2019 to June 2020. Thus none of the control firms withdrew their guidance during fiscal year 2019.

primary tests because it reflects managers' perception of COVID exposure, and these managers decide to withdraw guidance or not. We predict that greater exposure increases the probability of guidance withdrawals. Therefore the coefficient on *COVID_exposure* is expected to be positive.

We also include the change in a firm's stock price volatility during the pandemic (Δ*StockVolatility*) as a measure of uncertainty resulting from COVID. Specifically, if a firm withdraws its guidance on date *t*, Δ*StockVolatility* is calculated as the standard deviation of daily abnormal returns from *t*-15 to *t*-1 scaled by that from *t*-30 to *t*-16. For a control firm without guidance withdrawal, Δ*StockVolatility* is calculated as the standard deviation of daily abnormal returns from March 16 to March 30 scaled by that from March 1 to March 15. Abnormal returns are calculated using the Fama-French three-factor model. If a greater increase in a firm's uncertainty and stock price volatility leads to more withdrawals, we expect a positive coefficient on Δ*StockVolatility*.

We include two proxies for anticipated performance: a firm's change in return on assets (ROA) from the current quarter to the same quarter in the next year (Δ*ROA*) and abnormal stock returns from the beginning of the pandemic in January 2020 to the end of February 2020 (*StockReturn*). Δ*ROA* is calculated as the firm's ROA in the same quarter of the next year minus that in the current quarter, which is the quarter which March 2020 belongs to. If guidance withdrawals are due to poor anticipated financial performance, we expect negative coefficients on both variables.

Following prior research, we include several control variables that capture firm characteristics related to guidance withdrawal decisions (Houston et al. 2010; Chen et al. 2011). First, we control for several variables associated with economic uncertainty or risk. *Size* is the natural logarithm of market capitalization as of the last quarter, which is the quarter before the current quarter that March 2020 belongs to. *Leverage* equals the ratio of total debt to assets in the last quarter. *Operating Leverage* is calculated as selling, general, and administrative expenses divided by total assets in the prior quarter, which is the fiscal quarter before the current quarter that March 2020 belongs to. *Cash* is the cash and cash equivalents scaled by total assets in the prior quarter. A firm with a larger size, lower leverage, lower operating leverage, and higher cash holdings have more resources and greater capacity to mitigate potential macroeconomic shocks and stabilize operations. Therefore we expect these firms to face lower uncertainty. Further, *Multinational* is an indicator variable for multinational firms. Multinationals are more complex and consequently may face greater uncertainty. *Beta* is a firm's systematic market beta over the last year. Macroeconomic conditions are expected to have a greater impact on firms with higher betas.

Second, to capture variation in information environment, we include *Analyst Coverage* as the number of analysts covering a firm before the withdrawal announcement for a withdrawing firm or before the end of March for a control firm. We also include *Institutional Ownership*, which is the percentage of institutional ownership at the end of March 2020. Firms with more analysts and higher institutional ownership likely have more informed investors (e.g., Chen et al. 2011). Therefore it is likely easier for these firms to communicate with investors that they do not have precise information.

In addition, we include three industry attributes that measure industry-level variation in exposure to COVID. First, *Cyclical* is an indicator for cyclical industries whose performance is more sensitive to macroeconomic conditions (e.g., Faccio and Xu 2015). These industries are more likely to be impacted by the macroeconomy uncertainty during the COVID pandemic. Second, we adopt a measure of industry-level labor intensity (*LaborIntensity*) from Dewenter and Malatesta

(2001). Labor-intensive industries are more likely to be affected by social distancing rules and other COVID-mitigation measures. Third, we include an indicator for industries with high research and development (R&D) intensity (*High R&D*). Industries with more intangibles can more easily transition to the remote working environment and therefore are expected to be harmed less. We expect the probability of withdrawals to be higher in cyclical and labor-intensive industries but lower in high-R&D industries. Detailed variable definitions are included in Appendix C.

3.3 Empirical analyses

We provide descriptive information for our sample used to estimate Model (1) in Panel A of Table 2.[15] The mean of *Withdrawal* is 0.37, indicating that 37 percent of our sample firms announce guidance withdrawal during March 2020. The median value for *COVID_exposure* in our sample is 0.33, which is comparable to the reported value of Hassan et al. (2021).

Panel B of Table 2 reports comparative statistics between withdrawing and control firms. Consistent with our expectations, we find that withdrawing firms have significantly higher exposure to the pandemic (*COVID_exposure*) and higher increases in stock price volatility (*ΔStockVolatility*) than control firms. Also, we do not observe significant differences in Δ*ROA* and *StockReturn* between control firms and withdrawing firms. Further, we find that withdrawing firms are more (less) likely to be from cyclical and labor-intensive (high R&D) industries. Importantly, we find that withdrawing firms resemble control firms for several control variables, such as size, beta, and analyst coverage. Therefore, we believe that the control firms are a good control set to

[15] Given that our sample is relatively small, winsorization or truncation could result in loss of information and biases. Therefore, we use the Grubbs tests for potential outliers to ensure that our findings are not attributable to extreme values (e.g., Barbato et al. 2011). We perform the tests for each individual variable separately. The results suggest no outliers in our sample at the 99 percent confidence level. In untabulated tests, our inferences remain if we winsorize the sample at the top and bottom 1 percentiles.

analyze the impact of COVID exposure and uncertainty on guidance withdrawals while controlling for other firm attributes.

We further report the Pearson correlations in Panel C. We find that *Withdraw* is significantly and positively correlated with *COVID_exposure* (0.231) and *ΔStockVolatility* (0.153). Also, *Withdraw* is not significantly correlated with Δ*ROA* or *StockReturn*. These findings all support our prediction that withdrawals are due to exposure to the pandemic and the resulting uncertainty rather than poor anticipated performance. Further, *Withdraw* significantly and positively correlates with *Cyclical* and *Labor Intensity* but negatively correlates with *High R&D*.

Table 3 presents the results from estimating Model (1). Standard errors are clustered by industry to account for within-industry correlation of residuals. Panel A reports regression results of tests of the three possible industry-level determinants. Consistent with our expectations, we find that the probability of guidance withdrawals is significantly higher in cyclical industries and in industries with higher labor intensity. Also consistent with our expectation, the coefficient on *High R&D* is negative. These findings support the prediction that exposure to COVID determines guidance withdrawals.

Panel B further tests the firm-level determinants. The first column does not include the three industry attributes. We observe a significant and positive coefficient on *COVID_exposure* (0.926, *t*-statistic = 3.387). The coefficient on *ΔStockVolatility* is also positive and significant at the 1 percent level (9.241, *t*-statistic = 3.461). These findings are consistent with our prediction that exposure to the pandemic and the resulting economic uncertainty increase the probability of guidance withdrawals. Further, we observe insignificant coefficients on Δ*ROA* and *StockReturn*. Therefore, the withdrawal decisions are not attributable to poor anticipated future performance.

The second column further estimates the full model (1) after including the three industry attributes. Similar to Column (2), we observe significant and positive coefficients on *COVID_exposure* and *ΔStockVolatility*. Coefficients on Δ*ROA* and *StockReturn* remain insignificant. The marginal effect of *COVID_exposure* is 0.177. Thus, when *COVID_exposure* increases by one standard deviation (0.55), the probability of withdrawal increases by approximately 10 percent. Therefore, the effect of exposure on guidance withdrawals is also economically significant.

Coefficients on other variables generally comport with our expectations as well. For example, the coefficients on *Size* and *Cash* are both negative, and the coefficients for *Lev* and *OperatingLeverage* are positive. Thus, smaller firms with lower cash holding and higher leverage are more likely to stop guidance. These firms likely face greater uncertainty. Also, firms with more analyst following and higher institutional ownership are significantly more likely to withdraw management guidance.

3.4 Moderating role of litigation risk

In Table 4, we test our second prediction by estimating Model (1) after splitting the sample based on litigation risk. We adopt three measures of litigation risk. The first is an indicator for firms that have shareholder lawsuits in the prior three years (*PriorLawsuit*). To construct this measure, we manually collect shareholder lawsuit data from Stanford Securities Class Action Clearinghouse. The second (*FPS*) is an indicator for industries with high litigation risk (e.g., Francis et al. 1994), which is set to 1 if the firm is in the biotech (SIC codes 2833–2836 and 8731–8734), computer (3570–3577 and 7370–7374), electronics (3600–3674), or retail (5200–5961) industry and 0 otherwise. In addition, the third measure (*Litigation*) is the ex-ante probability of litigation for the prior fiscal year, estimated using the coefficients from the litigation risk model 3 of Kim and Skinner (2012). *High Litigation* (*Low Litigation*) is an indicator for firms with *Litigation* above (below or equal to) median.[16]

Similar to Table 3, we also estimate the model with and without the industry attributes in the two panels, respectively. In both panels, we find more positive coefficients on *COVID_exposure* in subsamples with high litigation risk. We use Chi-squared statistics to test the statistical significance of the differences in coefficients between subsamples. In Panel A, the Chi-squared statistics of the differences between the first (second) [third] two columns are 4.81 (21.88) [2.80]. In Panel B, the Chi-squared statistics of the differences between the first (second) [third] two columns are 2.94 (20.31) [2.02]. Thus, the differences in the coefficients on *COVID_exposure* between the subsamples with high and low litigation risk are generally significant, except the difference between the last two columns in Panel B. Further, the differences are economically significant. For example, when *PriorLawsuit* is used in Panel B, the marginal effect of *COVID_exposure* in the first column (0.3245) is 88 percent higher than that in the second column (0.1725). These results are consistent with our prediction 2 that the effect of exposure to the COVID pandemic on guidance withdrawal is more pronounced for firms with higher litigation risk.

4. Consequences of guidance withdrawals

4.1 Abnormal trading volume

We now turn to analyses of the consequences of guidance withdrawals. Our first set of tests relies on the trading volume reaction to evaluate the overall information content of withdrawal

[16] To illuminate the validity of our measures, we test their correlations with firm size. Consistent with smaller firms having lower litigation risk, *PriorLawsuit* is positively correlated with firm size. By definition, *Litigation* is also lower for smaller firms. Also, consistent with the results of Kim and Skinner (2012), *FPS* is negatively correlated with firm size.

decisions. Theoretical models predict that belief revisions around public announcements among investors generate trading (e.g., Bamber 1987; Kim and Verrecchia 1991; Kim and Verrecchia 1997). If the withdrawal announcements contain value-relevant information, we expect trading volume to increase in response to the withdrawal decision.

We measure abnormal trading volume as the mean daily trading volumes during the event window scaled by the mean trading volume in the benchmark period minus 1 (e.g., Beaver 1968; Chen et al. 2011). We use two alternative event windows: a two-day window from day *t* to day *t*+1 [0,1] and a three-day window from day *t* to day *t*+2 [0,2].[17] We also use four alternative windows for the benchmark period: (i) day *t*-15 to day *t*-1, (ii) day *t*-30 to day *t*-1, (iii) day *t*-60 to day *t*-1, and (iv) day *t*-90 to day *t*-1. The longer windows use a longer time series of data to infer the normal daily trading volume. Accordingly, the potential effects of other events during the benchmark period more likely average out.[18] However, the drastic change in macroeconomic conditions in the last part of the estimation period may have significantly changed the normal daily trading volume. As a result, the shorter windows may better capture the effect on trading volumes. In sum, these alternative windows complement each other.

We report the analyses of abnormal trading volumes in Table 5 Panel A. Specifically, we calculate the mean, standard deviation, bottom quartile, median, and top quartile of abnormal trading volumes. We also provide *t*-tests of the mean abnormal trading volumes. For these analyses, we exclude guidance withdrawals with confounding events announced in the same press releases. Thus, the sample size reduces to 249 observations. For all specifications, the mean abnormal trading volume is positive and significant at the 1 percent level. In terms of economic magnitude,

[17] One firm announced the withdrawal on a Saturday. We use the following two or three trading days after the announcement for this firm.
[18] Significant events during the benchmark period would increase the "normal" trading volume during the benchmark period, creating a bias against finding a trading-volume reaction in the event window.

the trading volume in the event window is 17 percent to 101 percent higher than that in the benchmark period. The magnitude of the effect is smaller when a shorter benchmark period is used, consistent with the shorter period better capturing the general impact of the pandemic on trading. These results are consistent with the withdrawal of management guidance delivering important economic information to investors.

4.2 Abnormal stock returns

Next we evaluate whether the news contained in the withdrawal decision is interpreted as positive or negative by testing the stock price reaction. If investors interpret guidance withdrawal as bad news, as shown in prior studies (Houston et al. 2010; Chen et al. 2011), they will react negatively to withdrawal announcements. However, investors may not necessarily react negatively if they recognize the difficulty in issuing credible and accurate forecasts under such high-uncertainty circumstances.

We use the same two alternative event windows as in the trading-volume tests. We use both raw stock returns and buy-and-hold abnormal returns calculated based on two different models: Fama-French three-factor model (three-factor) and Fama-French three-factor plus momentum factor model (four-factor).[19] The estimation period is the last quarter of 2019. We require each firm to have at least 30 observations in the estimation period. We also calculate the raw buy-and-hold stock returns.

We report the analyses of abnormal stock returns in Table 5 Panel B. As we similarly did for Panel A, we calculate the mean, standard deviation, bottom quartile, median, and top quartile

[19] Research shows asymmetric sensitivity of stock returns to market returns (e.g., Ang, Chen, and Xing, 2006). Therefore, in untabulated tests, we separate the market factor in the three-factor or four-factor model into two separate factors: positive market returns and negative market returns. Thus we calculate a positive market beta and a negative market beta for each firm. No conclusions are affected.

of abnormal stock returns. The sample further reduces to 248 observations due to missing values. For all the specifications reported, the stock return reactions are not significantly different from 0. Thus investors do not generally interpret the withdrawal announcements as bad or good news on average.

An implied assumption in these analyses is an efficient market. However, the efficiency of the stock market may be hurt by the pandemic. To address the possibility that insignificant results are due to noise traders or investor irrationality, we rerun the analyses in a subsample of days with smaller market movements and a subsample of large firms with market capitalization above median. Particularly, we exclude days with large market returns in the top and bottom quintiles. The remaining days with smaller market movements are calmer and less affected by market sentiment. Also, larger firms' valuations are less likely affected by noise traders. Untabulated results are similar in these two subsamples. That is, investors do not negatively react to the guidance withdrawal announcements.

4.3 Textual analyses

Research concludes that qualitative disclosures in management guidance contain important information to investors (e.g., Hutton, Miller, and Skinner 2003). Therefore we further analyze the role of textual characteristics in determining the abnormal stock returns. We construct several textural measures of the press releases or news reports for withdrawing firms. "*Tone*" is the number of positive words minus the number of negative words in the press release or news report, scaled by the number of words. "*# words*" is the total number of words in the press release or news report. "*Uncertainty related words*" is the percentage of uncertainty-related words in the press release or news report. The classification of negative, positive, and uncertain words is based on the Loughran and McDonald (2011) dictionary. After reading through the press releases and news reports, we find that the content can generally be decomposed into five categories: (1) cost control-related discussions, (2) health-related discussions, (3) liquidity-related discussions, (4) store closure-related discussions, and (5) supply chain-related discussions. Keywords used to classify these discussions and examples of these five categories are in Appendix B. We further construct five measures of the percentage of words in each category.

In Panel C of Table 5, we report the regression results for abnormal returns. The dependent variables are the buy-and-hold abnormal returns from day t to day t+1 and from day t to day t+2, respectively. Standard errors are clustered by date. We find that abnormal-stock returns are higher when firms have more health-related discussions. This is likely because firms with more health-related discussions are more proactive about COVID-related risks to customers and employees and thus could better avoid negative impacts of COVID-19 on firms' operations. However, the number of words and the other variables related to the content are not significantly associated with abnormal stock returns.[20]

4.4 Analyst reactions to guidance withdrawals

Sell-side equity analysts are important information intermediaries between investors and firms. To examine how analysts react to the firms that withdraw guidance, relative to the firms that do not withdraw, we use the following change regression Model (2) to test how analysts react to treated firms and control firms in different periods.

$$Analyst\ Behavior = \beta_0 + \beta_1\, Post + \beta_2\, Withdrawal \times Post + Firm\ Fixed\ Effects. \qquad (2)$$

[20] This is possibly because investors expected the content of the press releases in advance. For example, investors could infer a firm's financial liquidity based on the prior quarter's financial statements. Also, store closures could also be expected based on government regulations.

The dependent variable *Analyst Behavior* is either *Forecast Estimate* or *Forecast Dispersion*. *Forecast Estimate* is the consensus analyst EPS forecast, which is the mean of all outstanding EPS forecasts in IBES for a firm. *Forecast Dispersion* is the standard deviation of analyst forecasts. To calculate these two variables, we require each firm to be followed by at least two analysts.

We include two observations of each firm in our sample. For a withdrawing firm, we include a pre-period observation measured on the date of the last analyst forecast before the withdrawal announcement and a post-period observation measured on the date of the first analyst forecast after the withdrawal announcement. For a control firm, we include a pre-period observation measured on the date of the last analyst forecast issued before the end of March 2020 and a post-period observation measured on the date of the first analyst forecast issued after March 2020 but before the next management forecast issuance date. *Withdrawal* is an indicator set to 1 for withdrawing firms and 0 for control firms. *Post* is an indicator variable set to 1 for the post-period observations and 0 for the pre-period observations. Our focus is the interaction term *Withdrawal*× *Post*, whose coefficient captures the difference in analyst reactions to withdrawing firms in the pre-period and post-period, relative to control firms. Importantly, we include firm fixed effects to control for potential omitted time-invariant firm characteristics. The firm fixed effects subsume the main effect of *Withdrawal*. We cluster standard errors by firm to control for within-firm correlation of unobservable factors.

To address the possibility of differences in firm attributes between withdrawing firms and control firms, we reweight our sample by using entropy balancing (Hainmueller 2012; McMullin and Schonberger 2020).[21] Panel A of Table 6 reports the descriptive statistics before and after

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[21] Compared to propensity-score matching and other matching techniques, entropy balancing weights control group observations to reach covariate balancing instead of removing nonmatched observations, leaving the sample size less

entropy balancing. We require the first two moments to be balanced. As expected, we find that the mean and variance of all the variables become indifferent after entropy balancing.

Table 6, Panel B shows the results from estimating equation (2) using the entropy-balanced sample. As shown in Column (1), the coefficient for *Post* is negative and statistically significant at the 1 percent level, suggesting that firms generally experience decreases in analyst forecast estimates after the outbreak. This result also demonstrates the overall pessimistic outlook of the macroeconomy and extreme uncertainty during the pandemic. More importantly, we find that the coefficient on *Withdrawal*×*Post* is negative but insignificant, indicating that analysts do not hold more pessimistic views on the withdrawing firms, relative to control firms, following the guidance cessations. From this perspective, analysts do not interpret guidance withdrawals as bad news.

Column (2) displays results for the analyst forecast dispersion analysis. The coefficient for *Post* is positive and statistically significant at the 5 percent level, demonstrating increased difficulty in issuing forecasts for all firms after March 2020. In contrast to the insignificant difference in forecast estimates, we find that the coefficient for *Withdrawal*× *Post* is positive and statistically significant at the 5 percent level. This result is consistent with the expectation that guidance withdrawals lead to greater information uncertainty and thus higher forecast dispersion (Lang and Lundholm 1996; Barron, Kim, Lim, and Stevens 1998; Houston et al. 2010). But another possible explanation is that investors view the withdrawing decisions as a confirmation of underlying economic uncertainty by managers. While we cannot exclude this possibility, we provide an untabulated test to address this potential alternative explanation: we calculate the number of uncertainty-related words in firms' press releases or news reports for guidance withdrawal. We expect more uncertainty words to be a stronger signal of underlying economic

affected by the matching process. The goal is to match withdrawing firms, which is the treated group (*Withdrawal*=1), with non-withdrawing firms, which is the control group (*Withdrawal*=0).

uncertainty. Then, we rerun the analyst forecast dispersion test in the subsample with a low number of uncertainty-related words and continue to find similar results. Therefore, it is unlikely that the higher forecast dispersion is fully attributable to confirmation of underlying uncertainty.[22]

In Panel C, we reestimate the analyst forecast dispersion test after splitting the sample based on the median of *COVID_exposure*. We use entropy balancing to reweight each subsample (high exposure and low exposure). Similar to our previous analyses, we require the first two moments of the control variables in Model (1), except Δ*ROA*, *StockReturn*, and *Size*, to be balanced.[23] We expect the impact of the withdrawals to be stronger for firms with greater exposure to the pandemic. Consistent with our expectation, we find that the coefficient on *Withdrawal*× *Post* is positive and significant in the subsample with high exposure but insignificant in the subsample with low exposure.

5. Additional analyses

5.1 Alternative measures of COVID exposure

In Table 7, we reestimate Model (1) using two alternative measures of COVID exposure. Particularly, the first alternative measure (*COVID_news_sentiment*) is the sentiment of COVID-related news for a firm. In particular, we identify a news report as COVID-related news if the headline of the news contains at least one of the following words: COVID, coronavirus, corona virus, nCoV, SARSCoV, and pandemic. *COVID_news_sentiment* is then calculated as the mean composite sentiment score of all COVID-related news in RavenPack. We expect news to have a more negative tone if a firm is more severely affected by the pandemic. The second measure

[22] The result of the trading volume test could also be interpreted based on confirmation of underlying uncertainty. We also rerun the trading volume test in the subsample with low uncertainty words and find similar results.
[23] We cannot achieve covariate balance for Δ*ROA*, *StockReturn*, and *Size*. In untabulated tests, inferences are similar if we do not use entropy balancing for these tests.

(*Stringency index*) adopted from the Oxford COVID-19 Government Response Tracker is the strictness of lockdown-style policies in a firm's headquarters state (Hale et al. 2021). Stricter policies indicate greater impact of the pandemic. In both columns, results are consistent with our expectation. We find that the probability of guidance withdrawals is higher when the tone is more negative or when lockdown-style policies are stricter.

5.2 Industry fixed effects

Our primary analyses in Table 3 include several industry attributes. In Table 8, we replace these industry attributes with industry fixed effects. The two columns use a Logit regression and a linear regression, respectively. We continue to observe significant and positive coefficients on *COVID_exposure* and *ΔStockVolatility*, while coefficients on Δ*ROA* and *StockReturn* remain insignificant.

5.3 Guidance withdrawals and cessations before the pandemic

As an alternative control sample, we manually collect data on firms that withdrew their guidance in the two years *prior* to the pandemic (i.e., calendar years 2018 and 2019). However, we only find 11. While we cannot do meaningful regression analyses using this small control sample, we provide comparative statistics between firms that withdrew their guidance and those that had guidance withdrawals in the prior two years in Panel A of Table 9. The statistics for firms with withdrawals prior to the pandemic are calculated in the same way for control firms in our primary sample. Consistent with our expectation, we find that firms that withdrew their guidance during the pandemic have higher COVID exposure and are more likely to in cyclical industries than those that withdrew beforehand. These firms are not significantly different in Δ*ROA* and *StockReturn*, supporting the idea that the withdrawal decision is not due to bad economic news.

In addition, we also manually identify 54 observations that ceased their guidance in the prior year (i.e., 2019).[24] We report comparative statistics between firms that withdrew their guidance and firms that previously suspended their guidance in Panel B. Similar to Panel A, we find that firms with guidance withdrawals have higher COVID exposure and are more (less) likely to be in cyclical (high R&D) industries.

5.4 Entropy balancing

To further address the possibility of differences between withdrawing firms and control firms, we rerun our primary test after using entropy balancing to reweight our control sample. Specifically, we set the balancing constraints to the first two moments for the following control variables: *Size*, *Leverage*, *Cash*, *Multinational*, *InstOwnership*, *AnalystCoverage*, *Beta*, and *OperatingLeverage*. Thus, while we match the control firms and withdrawing firms based on these control variables, we maintain the variations in our variables of interest. In Panel A of Table 10, we compare the mean and variance statistics of the control variables between withdrawing firms and control firms after entropy balancing. The statistics become identical for most variables. In Panel B, we further use the reweighted sample to estimate the regression model without the control variables. The inferences remain robust.

[24] These firms have stopped their guidance from the prior year and thus no longer have guidance to withdraw in the current year. Therefore, we also cannot provide regression analyses using these firms.

5.5 Sequence of guidance withdrawals by industry

Our analyses above suggest that a firm's exposure to the pandemic significantly affects its withdrawal decision. Tse and Tucker (2010) find evidence of managers' herding in their voluntary disclosure decisions. Thus the pandemic may also affect guidance withdrawal decisions by changing peer firms' disclosure behavior. If herding exists, we expect an industry leader to have a greater impact on other firms' decisions than an average industry peer does. We find that in 13 industries in our sample, the first firm that made a withdrawal announcement is an industry leader. In Table 11, we run industry-day-level regression to test whether withdrawals by industry leaders in the past three days increase the probability of guidance withdrawals for other firms.[25] The dependent variable *#Withdrawal* is the number of withdrawals in an industry on a given day. In Panel A, *#Leader* is the number of industry leaders that announced withdrawals in the industry during the past three days, and *#Total* is the total number of firms that announced withdrawals in the industry during the past three days.[26] In Column (1), the coefficient on *#Leader* is positive and significant. In Column (2), we further control for *#Total*. Thus, the coefficient on *#Leader* indicated the differential effect of industry leaders relative to an average firm in the industry. However, the coefficient on *#Leader* becomes insignificant. Therefore we do not find that industry leaders have a greater effect than other firms in the industry.

In Panel B, we further use two indicators (*Leader* and *Total*) for the existence of guidance withdrawals by industry leaders or any firm in an industry during the past three days. The results

[25] We use three days to ensure it is a relatively short window and potentially incorporates the possibility that the announcement date is a non-working day.

[26] On one hand, it may take a few days for a firm to respond to peer firms' withdrawal decisions. On the other hand, using a long window would reduce the variations in these variables. After trading off these, we use a three-day window to measure *#Leader* and *#Total*. In untabulated tests, inferences are unaffected if we use two or four days as an alternative window.

resemble those reported in Panel A. Therefore our findings are inconsistent with herding in firms' guidance withdrawals.

6. Conclusion

Guidance withdrawals were rare in prior years. However, many publicly traded firms withdrew their guidance during the COVID-19 pandemic. We find that firms that have greater exposure to the pandemic and larger increases in economic uncertainty are more likely to announce guidance withdrawals. Also, the effect of exposure to the pandemic on guidance withdrawals is greater for firms with higher litigation risk. In contrast, we do not find that anticipated performance explains the withdrawal decisions. Further, our findings suggest that investors and analysts do not penalize firms' decisions to withdraw their guidance during the pandemic. In conclusion, our findings suggest that guidance withdrawals during the pandemic are due to firms' exposure to the pandemic and the resulting economic uncertainty rather than poor anticipated financial performance. We believe our study contributes to a better understanding of how the heightened economic uncertainty during the pandemic affects corporate disclosure behavior.

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Appendix A: Examples of Guidance Withdrawal Announcements

Example A: Cracker Barrel Old Country Store (8K Item 7.01)

On March 18, 2020, Cracker Barrel Old Country Store, Inc. (the "Company") announced that it is *withdrawing its previously issued fiscal 2020 outlook*, including fiscal 2020 earnings guidance, due to the uncertain impact of the coronavirus (COVID-19) pandemic.

The Company's top priority during this extraordinary time is the *health and safety* of its employees and guests, and the Company's teams are diligently working to mitigate the impacts of the COVID-19 pandemic and to adjust the Company's business accordingly. Given recent developments and significant ongoing uncertainty around the severity and duration of the pandemic, the Company is unable to reliably quantify the COVID-19 pandemic's current and future impact on its future financial results and cannot presently predict when it will be able to do so. The Company therefore believes it is appropriate to withdraw its fiscal 2020 outlook, previously issued on February 25, 2020, at this time, and investors should no longer rely upon this guidance. …

Example B: Nordstrom (Press release)

March 17, 2020

SEATTLE--(BUSINESS WIRE) -- Nordstrom, Inc. (NYSE: JWN) today announced business updates in response to the increased impact from novel coronavirus (COVID-19).

"*The health and safety* of our customers and employees remain our top priority as we continue to make decisions during this rapidly evolving situation. We're taking decisive actions across the business to help protect employees, customers and others in the communities we serve," said Erik Nordstrom, chief executive officer, Nordstrom, Inc.

To do its part to limit the spread of the virus, the Company will temporarily close its stores, including Nordstrom full-line, Nordstrom Rack, Trunk Club clubhouses and Jeffrey in the U.S. and Canada for two weeks, effective March 17, and provide pay and benefits for its store employees during this period. Nordstrom continues to serve customers through its online business, which made up one-third of sales in 2019. The Company remains open and ready to serve customers through its apps and online at Nordstrom.com, Nordstromrack.com, HauteLook.com and TrunkClub.com – including digital styling, online order pickup and curbside services at its full-line stores.

"During this unprecedented period of uncertainty, we have in place the appropriate business continuity plans, operational framework and team," said Erik Nordstrom. "This, in concert with ending 2019 with a solid financial position and healthy balance sheet, gives us the ability to weather this challenging moment in time."

The Company issued its fiscal 2020 guidance on March 3, 2020, which did not include the impact of COVID-19. Due to heightened uncertainty relating to the impacts of COVID-19 on the Company's business operations, including the duration and impact on overall customer demand, the Company is withdrawing its 2020 guidance.

Appendix A (Cont'd)

Example C: Whirlpool (News Report)

BENTON HARBOR, Mich., March 24, 2020 /PRNewswire/ -- With COVID-19 becoming a worldwide pandemic, Whirlpool Corporation (NYSE: WHR) ("Whirlpool" or "the Company") remains focused on ensuring the *safety* of its employees, as well as delivering the critical goods and services that customers across the world need to stay home and stay safe. …

As a result of this unprecedented uncertainty in our macro environment, the Company has decided to withdraw its previously announced guidance for 2020. …

Appendix B: Keywords Used to Classify Content of Press Releases and Examples of Press Release Discussions

Content	Keywords	Company	Example
Cost Control-related discussion	Cost control cost reduction furlough pay cut pay cuts salaries	TrueCar	We have begun implementing strict cost controls as we work to aggressively preserve the profitability of our business.
Health-related discussion	safe safety health wellbeing care protect	TTEC Holdings	TTEC's priority is the health and safety of its employees, clients' service, and support of communities where it operates during these rapidly changing and unprecedented times.
Liquidity-related discussion	cash liquidity flexibility credit facility credit facilities balance sheet financing facility financing facilities	Casey's General Stores	"Casey's maintains a strong balance sheet and ample liquidity to weather the near-term impacts and expects to emerge from the crisis in a position of strength," said Rebelez.
Store closure-related discussion	close cancel closure	Foot Locker	"The decision to close our stores was a difficult but necessary one," said Richard Johnson, Foot Locker Inc.'s chairman and chief executive officer.
Supply chain-related discussion	Supply chain supply supplier suppliers	Welbilt	Our supply chain has seen minimal disruption and has not caused significant production delays to date.

Appendix C: Variable Definitions

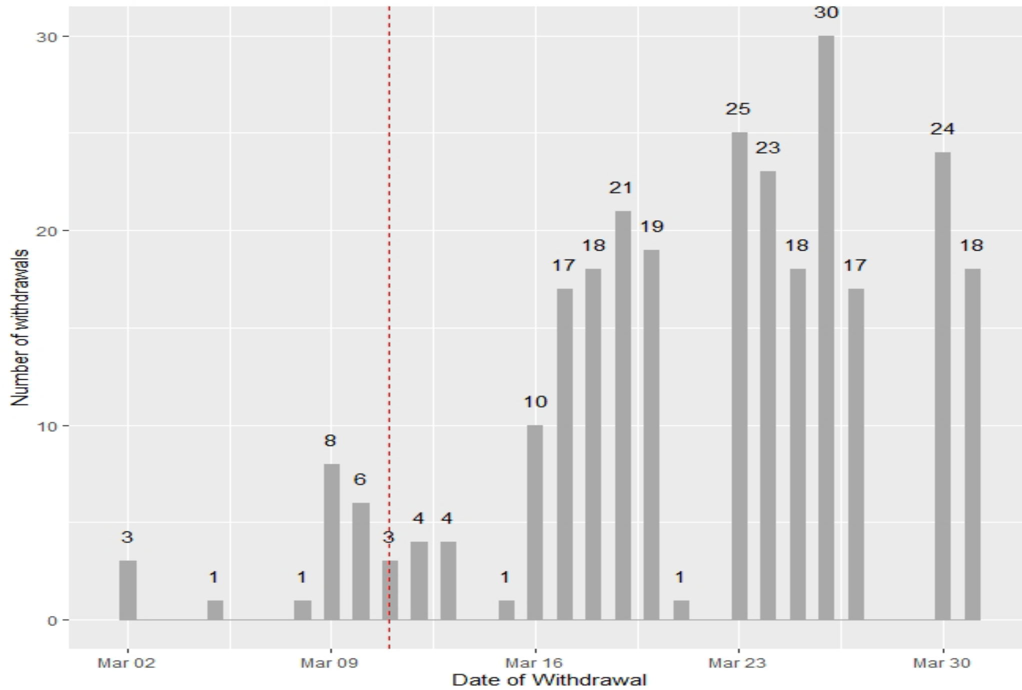
Variable	Definition	Data Source
Withdrawal	Indicator variable that equals 1 if a firm announces guidance withdrawal during March 2020 and 0 if a firm issues one financial guidance by March 1, 2020, for periods ending after March 31, 2020, and does not announce withdrawal from March 1, 2020, to June 30, 2020.	8-K, FactSet News, and IBES
Δ*ROA*	Change in return on assets (ROA) from the current quarter to the same quarter in the next year. ROA is calculated as income before extraordinary items (*ibq*) deflated by average total assets (*atq*). The current quarter is the fiscal quarter to which March 2020 belongs.	Compustat Quarterly
Size	The natural logarithm of market capitalization (*prccq*×*cshoq*) at the end of the last fiscal quarter. The last quarter is the fiscal quarter before the fiscal quarter to which March 2020 belongs.	Compustat Quarterly
Leverage	The ratio of total debt (*dlcq*+*dlttq*) to assets (*atq*) in the last fiscal quarter. The last quarter is the fiscal quarter before the fiscal quarter to which March 2020 belongs.	Compustat Quarterly
Cash	Cash and cash equivalents (*cheq*) scaled by total assets (*atq*) in the last fiscal quarter. The last quarter is the fiscal quarter before the fiscal quarter to which March 2020 belongs.	Compustat Quarterly
Multinational	Indicator variable that equals 1 if the firm has nonzero foreign pre-tax income (*pifo*) in the last year and 0 otherwise. The last year is the fiscal year before the current fiscal year to which March 2020 belongs.	Compustat Annual
Institutional Ownership	The percentage of institutional ownership (*shares*) at the end of March 2020.	Thomson Reuters 13F
Analyst Coverage	The number of analysts (*numest*) covering the firm before the withdrawal announcement for a withdrawing firm or before the end of March for a control firm.	IBES Summary
StockReturn	Abnormal stock returns from the beginning of January to the end of February using Fama-French three-factor risk model.	CRSP
Δ*StockVolatility*	Change in stock return volatility during the pandemic. Specifically, if a firm withdraws its guidance on date *t*, Δ*StockVolatility* is calculated as the standard deviation of daily abnormal returns from *t*-15 to *t*-1 scaled by that from *t*-30 to *t*-16. For a control firm without guidance withdrawal, Δ*StockVolatility* is calculated as the standard deviation of daily abnormal returns from March 16 to March 30 scaled by that from March 1 to March 15.	CRSP
Beta	Systematic market risk measured using the capital asset pricing model over the last year. The last year is the fiscal year before the current fiscal year to which March 2020 belongs.	CRSP

OperatingLeverage	Selling, general, and administrative expenses (*xsgaq*) divided by the total assets (*atq*) at the end of the last quarter.	Compustat Quarterly
COVID_exposure	The frequency of COVID-related words in the conference call transcript before the withdrawal announcement for a withdrawing firm or before the end of March for a control firm.	Hassan et al. (2020)
Cyclical	Indicator variable set to 1 for cyclical industries and 0 for other industries. Specifically, cyclical industries are all the industries, except those with the following two-digit SIC codes: 01, 02, 07, 09, 20, 21, 28, 49, 51, 54, 80, 81, 82.	Faccio and Xu (2015)
Laborintensity	Industry-level labor intensity, which is calculated as the total number of employees (*emp*) in an industry for the last year multiplied by 100 divided by the sum of total assets (*at*) of all firms in the industry for the last year. The last year is the fiscal year before the current fiscal year to which March 2020 belongs.	Compustat Annual
High R&D	Equals 1 if the industry mean R&D intensity is in the top quartile. R&D intensity is defined as the total R&D expenses (*xrd*) in an industry for the last year scaled by the total sales revenue (*sale*) in the industry for the last year. The last year is the fiscal year before the current fiscal year to which March 2020 belongs.	Compustat Annual
FPS	Indicator variable set to 1 for industries with high litigation risk and 0 for other industries. High litigation risk industries include the biotech (SIC codes 2833–2836 and 8731–8734), computer (3570–3577 and 7370–7374), electronics (3600–3674), and retail (5200–5961) industries.	Francis et al. (1994)
HighLitigation	Indicator variable set to 1 for firms with high litigation risk above sample median and 0 for other firms. Litigation risk is computed from model 3 by Kim and Skinner (2012) based on the data from the last fiscal year. The last year is the fiscal year before the current fiscal year to which March 2020 belongs.	Compustat and CRSP
LowLitigation	Indicator variable set to 1 for firms with low litigation risk below or equal to sample median and 0 for other firms. Litigation risk is computed from model 3 by Kim and Skinner (2012) based on the data from the last fiscal year. The last year is the fiscal year before the current fiscal year to which March 2020 belongs.	Compustat and CRSP
PriorLawsuit	Indicator variable set to 1 for firms with securities class action lawsuits in the past three years before March 2020 and 0 otherwise.	Stanford Securities Class Action Clearinghouse
Post	Indicator variable set to 1 for the post-period observations and 0 for the pre-period observations.	IBES
Forecast Estimate	The consensus analyst EPS forecast, which is the mean of outstanding EPS forecasts for a firm. We require that each firm is followed by at least two analysts.	IBES

Forecast Dispersion	The standard deviation of analyst EPS forecast. We require that each firm is followed by at least two analysts.	IBES
Tone	The number of positive words minus the number of negative words in the press release or news report, scaled by the number of negative words in the press release or news report.	8-K, FactSet News
Ln(#words)	The natural logarithm of the total number of words in the press release or news report.	8-K, FactSet News
Ln(Uncertainty related words+1)	The natural logarithm of one plus the percentage of uncertainty-related words in the press release or news report.	8-K, FactSet News
Ln(Health related words+1)	The natural logarithm of one plus the percentage of health-related words in the press release or news report.	8-K, FactSet News
Ln(Liquidity related words+1)	The natural logarithm of one plus the percentage of liquidity-related words in the press release or news report.	8-K, FactSet News
Ln(Store closure related words+1)	The natural logarithm of one plus the percentage of store closure-related words in the press release or news report.	8-K, FactSet News
Ln(Supply chain related words+1)	The natural logarithm of one plus the percentage of supply chain-related words in the press release or news report.	8-K, FactSet News
COVID_news_sentiment	The sentiment of COVID-related news from RavenPack news analytics. A news report is identified as covid_news if the headline of the news contains at least one of the following words: COVID, coronavirus, corona virus, ncov, sarscov, and pandemic. News reports are restricted to full-size articles with a relevance score of 75 or above and ENS (event-novelty score) of 100. The media sentiment is defined as [CSS (composite sentiment score) -50] /50 so that the media sentiment ranges from -1 to 1, with 0 being equivalent to neutral news. *COVID_news_sentiment* is the averaged CSS score of all COVID-related reports before the withdrawal announcement for a withdrawing firm or before the end of March for a control firm.	RavenPack
Stringencyindex	The strictness of lockdown-style policies that primarily restrict people's behavior in the firm's headquarters state. It is calculated using all ordinal containment and closure policy indicators, plus an indicator recording public information campaigns. For each company, the stringency index is based on data right before the withdrawal announcement for a withdrawing firm or before the end of March for a control firm.	Oxford COVID-19 Government Response Tracker
#Withdrawal	The number of withdrawals in an industry on a given day.	8-K, FactSet News
#Leader	The number of industry leaders that announced withdrawals in the industry during the past three days.	8-K, FactSet News
#Total	The total number of firms that announced withdrawals in the industry during the past three days.	8-K, FactSet News
Leader	An indicator for any industry leader that announced withdrawals in the industry during the past three days.	8-K, FactSet News

Total	An indicator for any firms that announced withdrawals in the industry during the past three days.	8-K, FactSet News

Figure 1: Number of Guidance Withdrawals by Date



Note: This figure shows the number of firms that withdrew their guidance on each day during March of 2020. The red line tags the date (March 11, 2020) when WHO announces the COVID-19 virus as a pandemic.

Table 1: Sample Distribution by Industry

FF-49 Industries	Industry Name	Frequency	Percentage	Cumulative Percentage
2	Food Products	1	0.37	0.37
3	Candy & Soda	1	0.37	0.74
4	Beer & Liquor	1	0.37	1.10
6	Recreation	1	0.37	1.47
7	Entertainment	4	1.47	2.94
8	Printing and Publishing	2	0.74	3.68
9	Consumer Goods	9	3.31	6.99
10	Apparel	13	4.78	11.76
11	Healthcare	5	1.84	13.60
12	Medical Equipment	7	2.57	16.18
13	Pharmaceutical Products	2	0.74	16.91
14	Chemicals	2	0.74	17.65
17	Construction Materials	1	0.37	18.01
18	Construction	2	0.74	18.75
21	Machinery	17	6.25	25.00
22	Electrical Equipment	3	1.10	26.10
23	Automobiles and Trucks	12	4.41	30.51
25	Shipbuilding, Railroad Equipment	2	0.74	31.25
27	Precious Metals	3	1.10	32.35
29	Coal	1	0.37	32.72
30	Petroleum and Natural Gas	6	2.21	34.93
32	Communication	7	2.57	37.50
33	Personal Services	4	1.47	38.97
34	Business Services	13	4.78	43.75
35	Computers	4	1.47	45.22
36	Computer Software	15	5.51	50.74
37	Electronic Equipment	8	2.94	53.68
38	Measuring and Control Equipment	2	0.74	54.41
39	Business Supplies	3	1.10	55.51
40	Shipping Containers	1	0.37	55.88
41	Transportation	10	3.68	59.56
42	Wholesale	6	2.21	61.76
43	Retail	32	11.76	73.53
44	Restaurants, Hotels, Motels	21	7.72	81.25
45	Banking	4	1.47	82.72
46	Insurance	1	0.37	83.09
47	Real Estate	4	1.47	84.56
48	Trading	41	15.07	99.63
49	Other	1	0.37	100.00
	Total	272		

Note: This table shows the distribution of guidance withdrawals by Fama-French 49 industries. The sample includes all the 272 firms that withdrew their guidance in March 2020.

Table 2: Sample Description

Panel A: Summary Statistics

	N	Mean	Std. Dev.	p25	Median	p75
Withdraw	721	0.37	0.48	0.00	0.00	1.00
COVID_exposure	721	0.33	0.55	0.00	0.00	0.46
ΔStockVolatility	721	0.04	0.07	0.01	0.03	0.06
ΔROA	721	0.02	0.10	0.00	0.01	0.02
StockReturn	721	0.00	0.01	0.00	0.00	0.00
Size	721	8.00	1.67	6.96	7.98	9.05
Leverage	721	0.38	0.24	0.22	0.37	0.51
OperatingLeverage	721	0.05	0.06	0.01	0.03	0.07
Cash	721	0.13	0.17	0.02	0.06	0.16
Multinational	721	0.62	0.49	0.00	1.00	1.00
Beta	721	1.07	0.52	0.70	1.07	1.39
InstOwnership	721	0.76	0.24	0.69	0.84	0.91
AnalystCoverage	721	10.14	7.42	5.00	8.00	14.00
Cyclical	721	0.80	0.40	1.00	1.00	1.00
LaborIntensity	721	0.26	0.35	0.05	0.18	0.25
High R&D	721	0.18	0.38	0.00	0.00	0.00

Panel B: Comparative Statistics

	(1) *Withdrawing firms*		(2) *Control firms*		*Tests of mean difference:* (1)-(2)	
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	*t-stat.*	*p-value*
COVID_exposure	0.49	0.65	0.23	0.46	6.36	<0.01
ΔStockVolatility	0.05	0.04	0.03	0.08	4.14	<0.01
ΔROA	0.02	0.12	0.02	0.09	0.57	0.57
StockReturn	0.00	0.01	0.00	0.01	-0.55	0.58
Size	7.89	1.67	8.07	1.66	-1.40	0.16
Leverage	0.45	0.27	0.34	0.21	5.89	<0.01
OperatingLeverage	0.06	0.06	0.05	0.06	2.29	0.02
Cash	0.11	0.13	0.14	0.19	-2.70	0.01
Multinational	0.66	0.48	0.60	0.49	1.60	0.11
Beta	1.08	0.49	1.06	0.53	0.40	0.69
InstOwnership	0.78	0.24	0.74	0.24	2.03	0.04
AnalystCoverage	10.70	7.81	9.81	7.18	1.56	0.12
Cyclical	0.93	0.26	0.73	0.44	6.54	<0.01
LaborIntensity	0.37	0.46	0.19	0.24	7.17	<0.01
High R&D	0.14	0.35	0.20	0.40	-2.07	0.04

Table 2 (Cont'd)
Panel C: Pearson Correlations

	Withdraw	*COVID_ exposure*	*ΔStock Volatility*	*ΔROA*	*Stock Return*	*Size*	*Leverage*	*Operating Leverage*	*Cash*
COVID_exposure	0.231***								
ΔStockVolatility	0.153***	0.014							
ΔROA	0.021	0.032	-0.084**						
StockReturn	-0.021	-0.090**	0.05	-0.107***					
Size	-0.052	-0.039	-0.039	-0.064*	-0.118***				
Leverage	0.214***	-0.009	0.104***	-0.044	0.007	-0.037			
OperatingLeverage	0.085**	0.147***	0.004	-0.037	0.095**	-0.150***	-0.121***		
Cash	-0.100***	-0.005	-0.047	-0.134***	0.142***	-0.080**	-0.189***	0.402***	
Multinational	0.060*	0.218***	-0.03	-0.009	0.109***	0.110***	-0.057	0.214***	0.209***
Beta	0.015	0.149***	-0.073**	0.131***	0.234***	-0.123***	-0.078**	0.130***	0.190***
InstOwnership	0.076**	0.012	-0.028	-0.104***	-0.012	0.272***	-0.039	0.026	0.012
AnalystCoverage	0.058	-0.031	-0.078**	0.063*	0.032	0.663***	0.019	0.02	0.053
Cyclical	0.237***	0.008	0.024	0.031	0.052	-0.102***	-0.037	0.041	-0.075**
LaborIntensity	0.258***	0.105***	0.090**	0.036	0.101***	-0.090**	0.214***	0.236***	-0.047
High R&D	-0.077**	0.003	-0.057	-0.021	0.018	0.000	-0.159***	0.271***	0.337***

	Multinational	*Beta*	*InstOwnership*	*AnalystCoverage*	*Cyclical*	*LaborIntensity*
Beta	0.256***					
InstOwnership	0.166***	0.087**				
AnalystCoverage	0.186***	0.165***	0.136***			
Cyclical	0.101***	0.171***	0.069*	0.042		
LaborIntensity	0.101***	-0.006	0.088**	0.116***	0.188***	
High R&D	0.226***	0.136***	0.058	0.081**	0.230***	-0.029

This table reports the description of the sample used to estimate Model (1). Panel A shows the descriptive statistics of variables used in Model (1), including the number of the observations, mean, standard deviations, bottom quartile, median, and top quartile. Panel B compares the mean and standard deviation statistics of variables between withdrawing firms and control firms. The last two columns report the t-statistics and *p*-values for tests of the differences. Panel C reports the Pearson correlations between variables. Variable definitions are in Appendix C. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.

Table 3: Determinants of Guidance Withdrawals

Panel A: Industry-Level Determinants

	(1)
Dep. Var.=	*Withdraw*
Cyclical	1.494***
	(3.634)
LaborIntensity	1.382***
	(2.594)
High R&D	-0.678**
	(-2.178)
Observations	721
Pseudo R-squared	0.095

Panel B Firm-Level Determinants

	(1)	(2)
Dep. Var.=	*Withdraw*	
COVID_exposure	0.926***	1.004***
	(3.387)	(4.460)
Δ*StockVolatility*	9.241***	8.267***
	(3.461)	(2.930)
Δ*ROA*	0.523	0.636
	(0.484)	(0.725)
StockReturn	-6.351	-12.335
	(-0.309)	(-0.616)
Size	-0.270***	-0.175**
	(-2.596)	(-2.144)
Leverage	1.944***	2.076***
	(4.658)	(4.337)
OperatingLeverage	3.950*	3.895**
	(1.785)	(1.963)
Cash	-1.602***	-0.622
	(-3.476)	(-0.897)
Multinational	0.153	0.081
	(0.412)	(0.242)
Beta	-0.290	-0.340
	(-0.989)	(-1.497)
InstOwnership	1.228***	1.007**
	(3.454)	(2.524)
AnalystCoverage	0.066**	0.051**
	(2.341)	(1.977)
Cyclical		1.762***
		(4.280)
LaborIntensity		0.547*
		(1.706)
High R&D		-0.625**
		(-2.038)
Observations	721	721
Pseudo R-squared	0.142	0.198

This table tests the determinants of guidance withdrawals. The dependent variable is an indicator variable *withdrawal* that equals 1 for the withdrawing firm and 0 for the control firms. In Panel A, we test three industry-level determinants. In Panel B, we further test the firm-level determinants. The variable of interest *COVID_exposure* is a measure of a firm's exposure to the COVID-19 pandemic from Hassan, Hollander, Van Lent, and Tahoun 2020. Standard errors are clustered by industry. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). Variable definitions are in Appendix C.

Table 4: Moderating Role of Litigation Risk

Panel A: Cross-Sectional Tests without Industry Attributes

	(1)	(2)	(3)	(4)	(5)	(6)
	PriorLawsuit=1	*PriorLawsuit=0*	*FPS=1*	*FPS=0*	*High Litigation*	*Low Litigation*
Dep. Var.=			*Withdraw*			
COVID_exposure	2.032***	0.899***	1.970***	0.528*	1.393***	0.720***
	(3.763)	(3.304)	(7.272)	(1.917)	(4.300)	(3.402)
Difference	*1.133***		*1.442****		*0.673**	
Chi² statistics	*4.81*		*21.88*		*2.80*	
Δ*StockVolatility*	16.775**	9.467***	13.461**	8.386***	10.984***	8.759**
	(2.392)	(3.488)	(2.253)	(2.879)	(3.669)	(2.482)
Δ*ROA*	12.704*	0.098	16.962*	-0.488	-0.660	0.115
	(1.810)	(0.091)	(1.902)	(-0.494)	(-0.270)	(0.097)
StockReturn	34.554	-17.640	67.828	-40.772	-0.326	-1.437
	(0.768)	(-0.785)	(1.004)	(-1.524)	(-0.015)	(-0.055)
Size	-0.218	-0.306***	-0.477*	-0.220*	-0.239**	-0.256**
	(-0.877)	(-2.853)	(-1.884)	(-1.873)	(-2.079)	(-1.969)
Leverage	0.241	2.164***	1.029*	2.131***	2.453***	1.319**
	(0.194)	(4.622)	(1.838)	(3.966)	(3.995)	(2.176)
OperatingLeverage	8.112**	4.031*	-1.283	4.173*	3.749*	5.674**
	(2.275)	(1.747)	(-0.522)	(1.653)	(1.720)	(2.284)
Cash	-0.224	-2.327***	-1.693	0.933	-0.989	-2.689**
	(-0.132)	(-3.124)	(-1.243)	(0.656)	(-1.146)	(-2.573)
Multinational	-0.098	0.205	-1.199***	0.573	-0.045	0.506*
	(-0.138)	(0.548)	(-2.677)	(1.196)	(-0.163)	(1.656)
Beta	-1.028	-0.280	-0.571	-0.233	-0.294	-0.202
	(-1.580)	(-0.984)	(-1.223)	(-0.808)	(-1.052)	(-0.734)
InstOwnership	-2.247**	1.629***	0.983	1.153**	0.830	1.799***
	(-2.201)	(3.628)	(1.493)	(2.548)	(1.479)	(2.787)
AnalystCoverage	0.092**	0.063**	0.127***	0.062	0.047*	0.083***
	(2.070)	(2.160)	(2.669)	(1.518)	(1.780)	(3.336)
Observations	85	636	207	514	359	362
Pseudo R-squared	0.228	0.158	0.397	0.123	0.160	0.156

Table 4 (Cont'd)
Panel B: Cross-Sectional Tests with Industry Attributes

	(1)	(2)	(3)	(4)	(5)	(6)
	PriorLawsuit=1	*PriorLawsuit=0*	*FPS=1*	*FPS=0*	*High Litigation*	*Low Litigation*
Dep. Var.=			*Withdraw*			
COVID_exposure	2.171***	1.010***	2.078***	0.698***	1.486***	0.871***
	(3.439)	(4.201)	(9.769)	(2.713)	(4.675)	(2.761)
Difference	*1.161**		*1.380****		*0.615*	
Chi^2 statistics	*2.94*		*20.31*		*2.02*	
ΔStockVolatility	20.836**	8.246***	8.851*	8.288***	9.657***	8.639*
	(2.355)	(2.789)	(1.704)	(2.699)	(3.230)	(1.793)
ΔROA	14.886**	0.235	14.843**	-0.495	0.193	-0.373
	(2.283)	(0.261)	(2.149)	(-0.549)	(0.069)	(-0.259)
StockReturn	44.884	-24.002	58.038	-42.584*	5.364	-34.336
	(0.982)	(-1.052)	(0.813)	(-1.688)	(0.209)	(-1.091)
Size	-0.171	-0.201**	-0.350*	-0.186	-0.144	-0.174
	(-0.704)	(-2.172)	(-1.871)	(-1.641)	(-1.573)	(-1.296)
Leverage	0.241	2.347***	0.904	2.348***	2.654***	1.244*
	(0.188)	(4.123)	(1.476)	(3.942)	(4.322)	(1.863)
OperatingLeverage	11.599**	3.942*	-1.656	4.680**	4.076**	5.247
	(2.448)	(1.862)	(-0.433)	(2.215)	(2.040)	(1.572)
Cash	0.683	-1.444	0.142	0.637	0.088	-1.938**
	(0.345)	(-1.555)	(0.097)	(0.440)	(0.107)	(-1.973)
Multinational	-0.465	0.159	-1.211***	0.392	-0.145	0.523
	(-0.658)	(0.455)	(-2.604)	(0.892)	(-0.381)	(1.358)
Beta	-1.694**	-0.314	-0.192	-0.378	-0.369	-0.276
	(-2.047)	(-1.346)	(-0.411)	(-1.473)	(-1.175)	(-0.908)
InstOwnership	-2.642*	1.336***	0.736	1.028**	0.718	1.644***
	(-1.856)	(3.015)	(0.894)	(2.182)	(1.238)	(3.010)
AnalystCoverage	0.092**	0.046	0.091***	0.064	0.042	0.061**
	(2.126)	(1.636)	(2.908)	(1.635)	(1.295)	(2.393)
Cyclical	2.599***	1.817***	2.466***	1.573***	1.487***	2.275***
	(3.040)	(4.075)	(4.726)	(3.260)	(3.034)	(2.986)
LaborIntensity	-0.797	0.595*	0.853*	0.327	0.274	0.965*
	(-0.968)	(1.898)	(1.740)	(0.432)	(0.682)	(1.853)
High R&D	-1.264**	-0.603	-0.434	0.272	-0.435	-0.774***
	(-2.131)	(-1.630)	(-1.119)	(0.728)	(-1.033)	(-3.190)
Observations	85	636	207	514	359	362
Pseudo R-squared	0.329	0.214	0.446	0.168	0.197	0.240

This table reports the regression results of Model (1) in subsamples split based on litigation risk of the firms. Panel A does not include the three industry attributes. Panel B further includes these industry attributes. *PriorLawsuit* is an indicator equal to 1 if the firm files a lawsuit in the past three years window. *FPS* is an indicator equal to 1 for industries with high litigation risk (Francis, Philbrick, and Schipper 1994). *High Litigation* (*Low Litigation*) refers to firms whose litigation risk computed from the model 3 in Kim and Skinner (2012) is above (below or equal to) median. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Variable definitions are in Appendix C.

Table 5: Equity Market Reactions to Guidance Withdrawals

Panel A: Trading Volume

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Event Window	Benchmark Period	N	Mean	Std. Dev.	p25	Median	p75	*t*-statistics	*p*-values
[0,1]	[-15, -1]	249	0.18	0.64	-0.16	0.02	0.36	4.32	<0.01
[0,1]	[-30, -1]	249	0.38	0.88	-0.08	0.16	0.57	6.78	<0.01
[0,1]	[-60, -1]	249	0.77	1.27	0.13	0.47	1.03	9.49	<0.01
[0,1]	[-90, -1]	249	1.01	1.56	0.28	0.63	1.35	10.25	<0.01
[0,2]	[-15, -1]	249	0.17	0.60	-0.16	0.03	0.36	4.36	<0.01
[0,2]	[-30, -1]	249	0.37	0.83	-0.08	0.16	0.59	7.01	<0.01
[0,2]	[-60, -1]	249	0.75	1.18	0.12	0.41	1.02	10.06	<0.01
[0,2]	[-90, -1]	249	0.99	1.41	0.24	0.62	1.26	11.08	<0.01

Panel B: Stock Price Reaction

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Event Window	Model	N	Mean	Std. Dev.	p25	Median	p75	*t*-statistics	*p*-values
[0,1]	Raw Return	248	-0.99	16.35	-11.25	-2.68	7.37	-0.43	0.67
[0,1]	3-Factor	248	-0.59	15.07	-9.48	-1.95	6.44	-0.61	0.54
[0,1]	4-Factor	248	-0.36	15.41	-9.38	-2.16	6.63	-0.36	0.72
[0,2]	Raw return	248	-0.29	20.28	-12.62	-2.37	10.18	0.76	0.45
[0,2]	3-Factor	248	0.16	19.06	-11.18	-1.48	9.51	0.30	0.76
[0,2]	4-Factor	248	0.33	19.30	-10.77	-1.20	9.31	0.42	0.68

Panel C: Textual Attributes and Abnormal Returns

	(1)	(2)	(3)	(4)	(5)	(6)
	Raw Return	3-Factor	4-Factor	Raw Return	3-Factor	4-Factor
Dep. Var.=	Buy-and-Hold Returns (0,1)			Buy-and-Hold Returns (0,2)		
Tone	0.012	0.008	0.006	0.011	0.008	0.001
	(1.039)	(0.726)	(0.547)	(0.662)	(0.529)	(0.080)
Ln (#words)	0.020	0.012	0.017	0.008	0.003	0.013
	(0.891)	(0.684)	(0.949)	(0.256)	(0.116)	(0.511)
Ln (Uncertainty related words+1)	0.474	-1.145	-0.648	0.297	-1.160	-0.802
	(0.292)	(-0.845)	(-0.481)	(0.118)	(-0.578)	(-0.444)
Ln (Cost control related words+1)	-3.403	-5.743	-6.030*	-8.321	-10.608	-11.285
	(-1.307)	(-1.679)	(-1.814)	(-1.516)	(-1.571)	(-1.672)
Ln (Health related words+1)	0.587***	0.473***	0.500***	0.544***	0.411**	0.413**
	(4.210)	(3.344)	(3.835)	(3.116)	(2.798)	(2.301)
Ln (Liquidity related words+1)	0.370	0.265	0.262	0.499	0.399	0.414
	(1.449)	(0.956)	(0.974)	(1.215)	(0.957)	(1.009)
Ln (Store closure related words+1)	1.513	1.996	1.037	2.359	3.834	2.465
	(0.858)	(0.992)	(0.662)	(1.117)	(1.498)	(1.487)
Ln (Supply chain related words+1)	-0.636	-1.818*	-1.557	-0.251	-1.909*	-1.768
	(-0.467)	(-1.995)	(-1.694)	(-0.167)	(-1.775)	(-1.686)
Observations	248	248	248	248	248	248
Adj. R-squared	0.031	0.024	0.015	0.011	0.017	0.007

This table shows the stock market reactions to guidance withdrawals. Panel A shows the trading-volume reaction to announcements of guidance withdrawals. Abnormal trading volume is the average daily trading volume in the event window scaled by the average daily trading volume in the benchmark period. Date *t* is the date of the withdrawal announcement. The first (last) four rows use day *t* to day *t*+1 (*t*+2) as the event window, and the sample includes the 249 observations that announced guidance withdrawals during March 2020. Four benchmark periods are used respectively: day *t*-15 to day *t*-1, day *t*-30 to day *t*-1, day *t*-60 to day *t*-1, and day *t*-90 to day *t*-1. Columns (3) to (8) report the number of observations and the mean, standard deviation, bottom quartile, median, and top quartile of abnormal trading volumes, respectively. The last two columns report the *t*-tests of the mean abnormal trading volumes and the corresponding *p*-values.

Panel B shows the stock-price reaction to announcements of guidance withdrawals. We report the raw buy-and-hold return and two measures of buy-and-hold abnormal returns (in basis points) in the event windows. The two different models used to calculate abnormal returns are the Fama-French three-factor model (3-Factor) and Fama-French three-factor plus momentum factor model (4-Factor). Date *t* is the date of the withdrawal announcement. The first two rows use day *t* to day *t*+1 as the event window, and the sample includes the 248 observations that announced guidance withdrawals during March 2020.The next two rows use day *t* to day *t*+2 as the event window. Columns (3) to (8) report the number of observations and the mean, standard deviation, bottom quartile, median, and top quartile of stock returns. The last two columns report the *t*-tests of the mean stock returns and the corresponding *p*-values. The estimation period is the last quarter of 2019, and we require at least 30 observations.

Panel C reports the association between textual characteristics and stock returns. Date *t* is the date of the withdrawal announcement. The dependent variable in the first three columns is the buy-and-hold stock returns from day *t* to day *t*+1 (in basis points). The dependent variable in the last three columns is the buy-and-hold stock returns from day *t* to day *t*+2 (in basis points). In the first and fourth columns, the buy-and-hold stock returns are calculated using raw returns. In the second and fifth columns, the buy-and-hold stock returns are calculated using Fama-French three-factor model (3-Factor). In the third and sixth columns, the buy-and-hold stock returns are calculated using the Fama-French three-factor plus momentum factor model (4-Factor). Standard errors are clustered by date. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level (two-tailed), respectively. Variable definitions are in Appendix C.

Table 6: Analyst Reactions to Withdrawal Announcements

Panel A: Statistics before and after Entropy Balancing

	Before Entropy Balancing				**After Entropy Balancing**			
	Withdrawing firms		*Control firms*		*Withdrawing firms*		*Control firms*	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
COVID_exposure	0.49	0.43	0.22	0.21	0.49	0.43	0.49	0.43
ΔStockVolatility	0.05	0.00	0.03	0.01	0.05	0.00	0.05	0.00
ΔROA	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.01
StockReturn	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Size	7.89	2.79	8.07	2.77	7.89	2.79	7.89	2.79
Leverage	0.45	0.07	0.34	0.05	0.45	0.07	0.45	0.07
OperatingLeverage	0.06	0.00	0.05	0.00	0.06	0.00	0.06	0.00
Cash	0.11	0.02	0.14	0.03	0.11	0.02	0.11	0.02
Multinational	0.66	0.23	0.60	0.24	0.66	0.23	0.66	0.23
Beta	1.08	0.24	1.06	0.29	1.08	0.24	1.08	0.24
InstOwnership	0.78	0.06	0.74	0.06	0.78	0.06	0.78	0.06
AnalystCoverage	10.70	61.02	9.81	51.50	10.70	61.02	10.70	61.02
Cyclical	0.93	0.07	0.73	0.20	0.93	0.07	0.93	0.07
LaborIntensity	0.37	0.21	0.19	0.06	0.37	0.21	0.37	0.21
High R&D	0.14	0.12	0.20	0.16	0.14	0.12	0.14	0.12

Table 6 (Cont'd)
Panel B: Analyst Forecasts Reaction

	(1)	(2)
Dep. Var.=	*Forecast Estimate*	*Forecast Dispersion*
Withdrawal× Post	-0.356	0.452**
	(-1.634)	(2.371)
Post	-0.459***	0.305**
	(-2.848)	(2.496)
Observations	1,328	1,328
Firm FE	Yes	Yes
Adj. R-squared	0.995	0.949

Panel C: Partition the Sample Based on Level of COVID Exposure

	(1)	(2)
	High Exposure	Low Exposure
Dep. Var.=	*Forecast Dispersion*	
Withdrawal× Post	0.750***	-0.152
	(3.320)	(-0.262)
Post	0.173***	0.613
	(2.668)	(1.077)
Observations	654	674
Firm FE	Yes	Yes
Adj. R-squared	0.704	0.849

This table shows tests of analyst reaction to guidance withdrawals. Panel A compares the mean and variance statistics of variables between withdrawing firms and control firms. The first four columns use the sample before entropy balancing. The last four columns use the sample after entropy balancing. Panel B presents the regression results of analyst reactions to withdrawal announcements. *Forecast estimate* is the mean estimated value of outstanding analyst EPS forecasts. *Forecast dispersion* is the standard deviation of outstanding analyst EPS forecasts. *Withdrawal* equals 1 if a firm withdraws guidance during March and 0 otherwise. *Post* is an indicator variable set to 1 for the post-period observation. We include firm fixed effects in the regression model. Standard errors are clustered by industry. Panel C presents the regression results of analyst reactions to withdrawal announcements after further splitting the sample based on firms' exposure to the COVID-19 pandemic. We include firm fixed effects in the regression model. Standard errors are clustered by firm. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Variable definitions are in Appendix C.

Table 7: Alternative Measures of Firm-Level Exposure to the Pandemic

	(1)	(2)
Dep. Var.=	*Withdraw*	
COVID_news_sentiment	-9.208***	
	(-5.029)	
Stringencyindex		0.020**
		(2.563)
Δ*StockVolatility*	8.090***	7.964***
	(3.043)	(2.862)
Δ*ROA*	0.493	0.584
	(0.559)	(0.635)
StockReturn	-23.920	-27.601
	(-1.220)	(-1.367)
Size	-0.152*	-0.154*
	(-1.841)	(-1.892)
Leverage	2.007***	1.942***
	(4.164)	(3.982)
OperatingLeverage	4.475**	4.169**
	(2.243)	(1.975)
Cash	-0.785	-0.725
	(-1.188)	(-1.038)
Multinational	0.321	0.289
	(0.991)	(0.897)
Beta	-0.166	-0.179
	(-0.698)	(-0.744)
InstOwnership	0.829**	0.772**
	(2.388)	(2.037)
AnalystCoverage	0.039	0.041
	(1.465)	(1.514)
Cyclical	1.547***	1.533***
	(3.914)	(3.972)
LaborIntensity	0.708*	0.787**
	(1.773)	(1.974)
High R&D	-0.703*	-0.669*
	(-1.806)	(-1.650)
Observations	721	721
Pseudo R-squared	0.170	0.170

This table reports the regression results of using alternative specifications of firm-level COVID exposure. In Column (1), *COVID_news_sentiment* is the sentiment of COVID-related news from RavenPack database for a firm. In Column (2), *Stringencyindex* is the strictness of lockdown-style policies in a firm's headquarters state from Oxford COVID-19 Government Response Tracker. Standard errors are clustered by industry. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Variable definitions are in Appendix C.

Table 8: Using Industry Fixed Effects

	(1)	(2)
Dep. Var.=	*Withdraw*	
COVID_exposure	0.716***	0.111***
	(2.897)	(2.682)
Δ*StockVolatility*	8.511**	0.525**
	(2.285)	(2.215)
Δ*ROA*	0.568	0.032
	(0.428)	(0.154)
StockReturn	-16.783	-3.459
	(-0.630)	(-0.804)
Size	-0.212**	-0.033**
	(-2.549)	(-2.620)
Leverage	1.584**	0.220***
	(2.208)	(2.937)
OperatingLeverage	2.502	0.290
	(1.133)	(0.855)
Cash	-0.685	-0.081
	(-0.919)	(-0.688)
Multinational	0.516	0.054
	(1.340)	(1.111)
Beta	-0.055	0.003
	(-0.176)	(0.051)
InstOwnership	0.709	0.099
	(1.438)	(1.344)
AnalystCoverage	0.061**	0.009**
	(2.436)	(2.350)
Observations	639	721
Industry FE	Yes	Yes
Pseudo/Adj. R-squared	0.246	0.285

This table reports the regression results of Model (1) after replacing the industry attributes with industry fixed effects. A Logit regression and a linear regression are used in the two columns, respectively. The dependent variable is an indicator variable *withdrawal* that equals 1 for the withdrawing firm and 0 for the control firms. The variable of interest *COVID_exposure* is a measure of a firm's exposure to the COVID-19 pandemic from Hassan, Hollander, van Lent, and Tahoun (2021). Standard errors are clustered by industry. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). Variable definitions are in Appendix C.

Table 9: Guidance Withdrawals and Cessation Prior to the Pandemic

Panel A: Firms with Withdrawals before the Pandemic vs. during the Pandemic

	(1) *Withdrawals Before Pandemic*		(2) *Withdrawals During Pandemic*		*Tests of mean difference* (1)-(2)	
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	*t-stat.*	*p-value*
COVID_exposure	0.24	0.61	0.49	0.65	-1.19	0.24
ΔStockVolatility	0.06	0.03	0.05	0.04	0.52	0.60
ΔROA	0.02	0.03	0.02	0.12	-0.11	0.91
StockReturn	0.00	0.00	0.00	0.01	0.26	0.80
Size	7.06	2.22	7.89	1.67	-1.52	0.13
Leverage	0.46	0.25	0.06	0.06	0.16	0.87
OperatingLeverage	0.04	0.03	0.45	0.27	-1.06	0.29
Cash	0.09	0.07	0.11	0.13	-0.32	0.75
Multinational	0.50	0.53	0.66	0.48	-1.01	0.31
Beta	0.98	0.36	1.08	0.49	-0.64	0.52
InstOwnership	0.64	0.31	0.78	0.24	-1.84	0.07
AnalystCoverage	7.90	7.22	10.70	7.81	-1.12	0.26
Cyclical	0.70	0.48	0.93	0.26	-2.63	0.01
LaborIntensity	0.19	0.20	0.37	0.46	-1.25	0.21
High R&D	0.70	0.48	0.14	0.35	4.92	<0.01

Panel B: Guidance Cessations before the Pandemic vs. Guidance Withdrawals during the Pandemic

	(1) *Cessation firms*		(2) *Withdrawing firms*		*Tests of mean difference* (1)-(2)	
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	*t-stat.*	*p-value*
COVID_exposure	0.30	0.58	0.49	0.65	-2.09	0.04
ΔStockVolatility	0.04	0.05	0.05	0.04	-1.21	0.23
ΔROA	0.03	0.09	0.02	0.12	0.66	0.51
StockReturn	0.00	0.01	0.00	0.01	-0.16	0.88
Size	6.63	2.29	7.89	1.67	-4.79	<0.01
OperatingLeverage	0.06	0.07	0.06	0.06	0.11	0.91
Leverage	0.29	0.31	0.45	0.27	-3.96	<0.01
Cash	0.20	0.22	0.11	0.13	4.45	<0.01
Multinational	0.46	0.50	0.66	0.48	-2.7	0.01
Beta	0.95	0.45	1.08	0.49	-1.84	0.07
InstOwnership	0.59	0.32	0.78	0.24	-5.04	<0.01
AnalystCoverage	5.77	4.87	10.70	7.81	-4.54	<0.01
Cyclical	0.77	0.43	0.93	0.26	-3.69	<0.01
LaborIntensity	0.29	0.71	0.37	0.46	-1.18	0.24
High R&D	0.48	0.50	0.14	0.35	6.12	<0.01

This table compares withdrawing firms with alternative sets of control firms. Panel A compares the mean and standard deviation statistics between firms with guidance withdrawals during the two years before the pandemic and firms with guidance withdrawals in March 2020 during the pandemic. Statistics are calculated using data from the first quarter of 2020. The first two columns use firms with guidance withdrawals during the two years before the pandemic. The second two columns use firms with guidance withdrawals during the pandemic. The last two columns report the t-statistics and *p*-values for tests of the differences. Panel B compares the mean and standard deviation statistics between firms with guidance cessations in the year before the pandemic and firms with guidance withdrawals in March 2020 during the pandemic. Statistics are calculated using data from the first quarter of 2020. The first two columns use firms with guidance cessations in the year before the pandemic. The second two columns use firms with guidance withdrawals during the pandemic. The last two columns report the t-statistics and *p*-values for tests of the differences. Variable definitions are in Appendix C.

Table 10: Entropy Balancing

Panel A: Comparative Statistics of Control Variables after Entropy Balancing

	Withdrawing firms		*Control firms*	
	Mean	Variance	Mean	Variance
Size	7.89	2.79	7.89	2.79
Leverage	0.45	0.07	0.45	0.07
Cash	0.11	0.02	0.11	0.02
Multinational	0.66	0.23	0.66	0.23
InstOwnership	0.78	0.06	0.78	0.06
AnalystCoverage	10.70	61.02	10.70	61.02
Beta	1.08	0.24	1.08	0.24
OperatingLeverage	0.06	0.00	0.06	0.00

Panel B: Regression Results

	(1)
Dep. Var.=	*Withdraw*
Covid_exposure	1.070***
	(3.861)
Δ*StockVolatility*	7.463***
	(2.661)
Δ*ROA*	0.653
	(0.629)
StockReturn	1.544
	(0.074)
Cyclical	1.451***
	(3.915)
LaborIntensity	0.609*
	(1.829)
High R&D	-0.689**
	(-2.323)
Observations	721
Pseudo R-squared	0.124

This table reruns our primary tests using entropy balancing to reweigh the control sample. We set the balancing constraints to the first two moments for the following control variables: *Size*, *Leverage*, *Cash*, *Multinational*, *InstOwnership*, *AnalystCoverage*, *Beta*, and *OperatingLeverage*. Panel A compares the mean and variance statistics of control variables between withdrawing firms and control firms after entropy balancing. Panel B tests the determinants of guidance withdrawals. The dependent variable is an indicator variable *withdrawal* that equals 1 for the withdrawing firm and 0 for the control firms. The variable of interest *COVID_exposure* is a measure of a firm's exposure to the COVID-19 pandemic from Hassan, Hollander, van Lent, and Tahoun 2021. Standard errors are clustered by industry. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). Variable definitions are in Appendix C.

Table 11: Sequence of Guidance Withdrawals by Industry

Panel A: Number of Withdrawals by Industry Members

	(1)	(2)
Dep. Var.=	*#Withdrawals*	*#Withdrawals*
#Leader	0.277***	-0.103
	(3.155)	(-1.379)
#Total		0.266***
		(6.725)
Observations	173	173
Date FE	Yes	Yes
Adj. R-squared	0.061	0.186

Panel B: Indicator of Withdrawals by Industry Members

	(1)	(2)
Dep. Var.=	*#Withdrawals*	*#Withdrawals*
Leader	0.593*	0.354
	(2.037)	(1.188)
Total		0.451**
		(2.524)
Observations	173	173
Date FE	Yes	Yes
Adj. R-squared	0.010	0.033

This table shows tests of whether withdrawals by industry leaders in the past three days increases the probability of guidance withdrawals for other firms. The dependent variable *#Withdrawal* is the number of withdrawals in an industry on a given day. In Panel A, *#Leader* is the number of industry leaders that announced withdrawals in the industry during the past three days, and *#Total* is the total number of firms that announced withdrawals in the industry during the past three days. In Panel B, *Leader* is an indicator for any industry leader that announced withdrawals in the industry during the past three days, and *Total* is an indicator for any firms that announced withdrawals in the industry during the past three days. Date fixed effects are included. Standard errors are clustered by industry. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). Variable definitions are in Appendix C.