

DO SELL-SIDE ANALYSTS PROVIDE MORE INFORMATION
FOLLOWING DEBT COVENANT VIOLATIONS?

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This dissertation is dedicated to my parents Yueming and Xuejun, and my husband Young.

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ABSTRACT

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This study examines whether financial analysts produce larger amounts of research output and whether their research is more valuable for investors following a debt covenant violation (DCV, hereafter). After a DCV, investor uncertainty about firm value and information asymmetry among stakeholders likely increases. It is therefore difficult for investors to assess firm prospects, resulting in increased demand for firm-specific information. Sell-side analysts, as sophisticated information intermediaries, are skilled at gathering and processing information; thus they are well-suited to provide more research output in response to increased investor demand. I predict and find that equity analysts provide a larger amount of research, proxied by recommendation revisions and earnings forecast revisions, after a DCV. I also document an incremental association between a DCV and analyst research production for firms with less financial flexibility, firms with low institutional ownership, and firms covered by more experienced analysts. In addition, I find evidence that analyst research becomes more valuable and that uncertainty-adjusted analyst forecast errors decrease following a DCV. These results suggest that a change in a firm's information environment associated with a DCV has significant influence on investors and equity analysts besides the economic consequences documented in prior literature.

1. INTRODUCTION

This study examines how research output provided by equity analysts changes after a debt covenant violation (DCV, hereafter). Specifically, I explore whether financial analysts produce larger amounts of research output, as measured by recommendation revisions and earnings forecast revisions, for firms after they breach debt covenants and whether these revisions are more informative for investors following a DCV.

After a DCV, a firm’s information environment typically changes. Uncertainty likely increases because information related to DCVs is often complex. For example, it is unclear how severe the violation is and thus how creditors will respond after they take control of the firm (Gao et al. (2017); Zhu and Gippel (2017); Nini et al. (2009); Chava and Roberts (2008)). This potentially leads to an increase in information asymmetry as shareholders have limited access to this complex information after a DCV. Specifically, equity investors typically do not participate in post-DCV renegotiations and encounter reduced firm disclosure (Vashishtha (2014); Nini et al. (2012); Baird and Rasmussen (2006)). Therefore, it is difficult for investors to assess firm prospects, resulting in increased demand for firm-specific information.

Analysts, as sophisticated information intermediaries, can fill investors’ demand for greater information. This is due to the fact that analysts have multiple sources of information, including macro-economy/industry data, non-public data, and political/personal connections, which help extract various types of information; they are also skilled at processing complex information (Cohen et al. (2010); Arif et al. (2019); Loh and Stulz (2018)). Therefore, my first hypothesis is that analysts provide larger amounts of research output following a DCV.

The effect of a DCV on analyst research output can vary with the level of investor demand for company information. For financially constrained firms, uncertainty potentially increases more significantly after a DCV, resulting in heightened investor

demand for information. This is because firms with financial constraints lack alternative outside capital to repay the violated agreement and thus lack significant negotiation power. Therefore, creditors could take their preferred actions more freely, increasing investor uncertainty about firm prospects (Campello et al. (2010); Roberts and Sufi (2009b)). For firms with low institutional ownership, investor demand is also likely higher. Prior literature shows that institutional investors have relatively better resources and abilities to satisfy their own information demand (Bushee et al. (2018); McCahery et al. (2016)). In addition, institutional investors typically ask for more firm disclosure, which increases firm transparency (Lin et al. (2018); Boone and White (2015)). In other words, firms' information environments are more opaque when institutional ownership is low, increasing ordinary investors' demand for analyst research. Finally, investors likely demand more information from experienced analysts, who are more skilled at generating their own private information, as well as processing complex information. This is due to the fact that experienced analysts are more likely to have long-standing relations with management and thus generate additional information through management access (Arif et al. (2019); Cheng et al. (2016); Green et al. (2014)).¹ Thus, investors are more likely to demand more information from experienced analysts post-DCV. Collectively, I predict that an incremental association exists between a DCV and analyst research output for financially constrained firms, firms with low institutional ownership, and firms followed by more experienced analysts.

In the presence of high uncertainty, despite the incentives to produce more research output, it may be harder for analysts to gather and process information. If true, signals conveyed through their research could become less precise. However, analysts' signals can still be more valuable as long as they deteriorate less than investors' *a priori* beliefs do (Pastor and Veronesi (2009)). To the extent that analysts are generally better skilled at gathering and processing information than ordinary investors, and

¹Private meetings with management are not necessarily against Reg FD. Specifically, participants who dedicate resources to collecting and processing information about the company have the opportunity to refine their private information, which is allowed under Reg FD.

that they work harder as uncertainty increases (Loh and Stulz (2018); Glode (2011)), I hypothesize that analyst research output is more valuable to investors post-DCV. In addition, prior literature (Loh and Stulz (2018); Vashishtha (2014)) finds that analysts' absolute forecast errors increase when uncertainty is high, normally resulting in less valuable analyst output. If, as I predict, analysts' research output is more valuable after a DCV, their forecast errors should at least be lower compared to the noise in investor-obtained information. Based on prior theoretical (Pastor and Veronesi (2009)) research, I hypothesize that uncertainty-adjusted analyst forecast errors decline after DCVs.

Alternatively, the amount and value of analyst research may not increase after a DCV for several reasons. First, shareholders may choose to rely on creditor monitoring after creditors take control. If this is the case, investors' information demand does not increase and analysts are likely not well incentivized to provide more research. Second, as it becomes more difficult and/or more costly for analysts to gather and analyze information after a DCV, analysts' signals may deteriorate significantly, reducing their informativeness to investors. Third, prior literature has well documented the herding behavior of analysts (Arya et al. (2005); Hong et al. (2000); Welch (2000); Trueman (1994)). If the increased amount of research after a DCV is primarily due to analyst herding, then not all analyst revisions contain useful information and are thus less valuable. Therefore, it is an empirical question how analyst research changes after DCVs.

To test my first hypothesis, I examine the relation between the amount of analyst research and disclosure of a DCV using the DCV data from 1996 to 2008 provided by Nini et al. (2012), available on the Amir Sufi's website. Following prior studies (Jennings (2019); Huang et al. (2014)), I use the number of recommendation revisions and earnings forecast revisions to proxy for research amount and examine whether this number is positively associated with DCV disclosure in SEC filings. Consistent with my first hypothesis, I find that analysts issue a greater number of recommendation/forecast revisions in the quarter after a DCV is disclosed. This suggests that

analysts respond to the change in a firm’s information environment after a DCV by increasing research production.

I test my second hypotheses by examining whether a higher level of investor demand for company information strengthens the association between a DCV and analyst research production. I predict that investor demand is higher for financially constrained firms, low institution-owned firms, and firms that are covered by more experienced analysts. Consistent with my second hypotheses, I find evidence that higher investor demand incrementally increases the amount of analyst research associated with a DCV. The evidence indicates that analysts incrementally produce more research output in response to the increased demand from investors after DCVs. These findings provide further support for my first hypothesis by showing a channel through which a DCV incrementally affects analyst research.

To test my third hypotheses, I first examine whether the informativeness of analyst research, measured by the absolute value of abnormal stock returns in the $[0,1]$ two-day window of analyst revisions, increases with DCV disclosure. I also examine whether relative forecast errors, which are scaled by uncertainty, decrease with DCV disclosure. Consistent with my third hypotheses, I find a positive association between the stock return response to analyst revisions and a DCV and a negative association between uncertainty-adjusted analyst forecast errors and a DCV. These findings, together with the increase in absolute forecast errors after a DCV documented by prior literature (Gao et al. (2017); Vashishtha (2014)), suggest that even though their own information worsens after a DCV, analysts are still able to incrementally inform investors.

One potential concern about my test design is that covenant-violating firms may tend to be followed by analysts who are more active revising their issuances and whose issuances/revisions are more influential. In other words, the likelihood of violating a covenant and having more active analysts may be jointly determined by some omitted variables. The discrete nature of a DCV allows me to use a discontinuity regression design that helps identify the effect of DCVs on analyst behavior. I follow

prior literature (Nini et al. (2012); Nini et al. (2009); Roberts and Sufi (2009a)) and employ “quasi-discontinuity” regressions in all my tests by including as right-hand side variables a DCV indicator variable along with linear and nonlinear functions of the underlying variables on which covenants are commonly written. With these functions included, the coefficient on the DCV indicator is identified as the effect of a DCV on a change in analyst research output under the assumption that analysts, in the absence of covenants, do not behave differently at the covenant threshold. No prior evidence suggests that this assumption is invalid. Also, it is least likely that covenants are placed at thresholds where analysts would have changed their research output.

This study offers two important contributions. First, I contribute to the debt contracting literature by exploring how investors and equity analysts respond to covenant violations. Prior literature has focused on economic consequences and firm behaviors after DCVs (Christensen et al. (2019); Vashishtha (2014); Nini et al. (2012); Nini et al. (2009); Roberts and Sufi (2009a); Chava and Roberts (2008)). My study extends this literature by examining analysts’ reactions after covenant violations, providing insight to how covenant violations impact a firm’s information environment.

Second, this paper adds to the growing literature that examines cross-market information flow. Prior studies (Ivashina and Sun (2011); Acharya and Johnson (2007)) primarily investigate how investors use information obtained in loan markets to facilitate their investment activities on the equity market. Some other studies (Gurun et al. (2016); Johnston et al. (2009)) examine how debt analysts contribute to the efficiency of the equity market. This paper is the first to examine how syndicated loan information affects equity analysts’ behaviors.

The paper proceeds as follows. Section 2 reviews prior literature and develops my hypotheses. Section 3 explains the research design. The data and sample are described in Section 4, and the empirical results are presented in Section 5. I conclude my study in Section 6.

2. PRIOR LITERATURE AND HYPOTHESIS DEVELOPMENT

Investor uncertainty about firm value and information asymmetry among stakeholders likely increases after a DCV. DCVs are relatively complex information events. By the time the DCV information is disclosed in SEC filings, creditor resolutions and violation outcomes are likely still unknown. Zhu and Gippel (2017) highlight that 80 percent of violating firms report uncertainty regarding violation outcomes. Shareholders are at an information supply disadvantage because they are updated about creditor intervention and/or renegotiation progress through SEC filings only on a quarterly basis, and firms' voluntary disclosure typically declines after DCVs (Vashishtha (2014)).¹ Nini et al. (2012) and Baird and Rasmussen (2006) document the widespread use of behind-the-scenes negotiations, which contain information that is even more difficult to access for shareholders.² Thus, shareholders are likely uncertain about how severe the violation is and what restriction is to be imposed on the firm (Gao et al. (2017); Nini et al. (2009); Roberts and Sufi (2009a); Chava and Roberts (2008)).

It can be difficult for investors to accurately interpret the information about the violation and creditor resolutions. A DCV commonly triggers a renegotiation process in which the right to accelerate payments lends creditors a high amount of bargaining power (Roberts and Sufi (2009b); Beneish and Eric (1993)). Investors likely view the creditor-friendly renegotiation outcomes as entirely bad news, such as increased interest rates, smaller credit lines, additional collateral, suppressed investment activities, increased new debt cost, and reduced net debt issuance (Butt (2019); Prilmeier

¹Michael Roberts' DCV dataset include formtypes of SEC filings other than 10-Q/K; less than 8% of DCVs are disclosed via non 10-Q/K formtypes, such as 8-K.

²A typical example of behind-the-scenes negotiations is utilizing the threat of loan acceleration or the prospect of waiving the violation to discipline firm decisions (Baird and Rasmussen (2006))

(2017); Roberts and Sufi (2009a); Nini et al. (2009); Chava and Roberts (2008)). However, creditor intervention can benefit the violating firms in some cases, especially in the long run. For example, creditors enhance the violating firms' operating performance by restricting capital expenditures and by replacing poorly performing executives (Nini et al. (2012); Chava and Roberts (2008)). Of course, it is difficult for market participants to determine if and when creditor actions will ultimately benefit firms. Therefore, facing increased uncertainty and information asymmetry, equity investors have difficulty both accessing and interpreting information. Therefore, investors may need other market participants to assist in processing and analyzing such information.

Sell-side equity analysts, as sophisticated information intermediaries, are well-suited to provide information required by investors following a DCV. Analysts have a variety of sources to look for and aggregate information, even when management voluntary disclosure declines following DCVs.³ For example, analysts are able to gather and extract useful information from macro economy and industry information (Loh and Stulz (2018); Schmalz and Zhuk (2018); Jennings et al. (2017); Loh and Stulz (2011); Frankel et al. (2006)), from firm-specific information (Arif et al. (2019); Cheng et al. (2016)), from non-public information such as FDA records on drug and medical device applications (Klein et al. (2019)), from political connections (Christensen et al. (2017)), and from personal social networks (Cohen et al. (2010)). In addition, analysts have the expertise to analyze the information available and generate useful output (Loh and Stulz (2018)). Therefore, my first research hypothesis, stated in alternative form, is as follows:

H1: Following a DCV, equity analysts provide more recommendation revisions and earnings forecast revisions.

However, it is possible that investor demand for analyst research does not increase after a DCV. DCVs provide a unique context in which multiple parties, including shareholders, creditors, and managers, are involved. When creditors take control of a

³Vashishtha (2014) documents a decline in management forecasts following DCVs.

firm after a DCV, shareholders may be more likely to rely on creditor monitoring, as indicated by Vashishtha (2014). If this is true, analysts may fail to increase research production.

The association between a DCV and analyst research output can vary with the level of investor demand for company information. Investor demand for analyst research can incrementally increase for financially constrained firms. This is because investors are more uncertain about the impact of creditor intervention for these firms. For example, financially constrained firms lack significant negotiation power after DCVs as they lack the ability to either repay the violated agreement or to terminate the agreement with their existing creditors by obtaining financing from alternative sources; thus, creditors can take their preferred actions to a greater extent. In addition, prior studies (Campello et al. (2010); Roberts and Sufi (2009b)) suggest that a lack of external funds force firms to bypass attractive investment opportunities in the moments they need them most. Thus, financially constrained firms are associated with heightened uncertainty and thereby increased information asymmetry after a DCV, increasing the information demand of outside investors. Therefore, I examine the following hypothesis, in alternative form:

H2a: An incremental association exists between a DCV and analyst research production for firms with less financial flexibility.

Investor demand should also be higher for firms with low institutional ownership. Institutional investors have relatively better resources and abilities to satisfy their own information demand compared to individual investors. Prior literature suggests that institutional investors contribute more time to searching for firm information and often specialize in particular sectors (Barber and Odean (2007)), they generate additional private information through various interactions with management or the board (Bushee et al. (2018); McCahery et al. (2016); Barber and Odean (2007)), and they can afford to use proxy advisors, who are documented to be a reliable source of informed voting (Admati and Pfleiderer (2009)). Moreover, institutional investors elicit greater transparency by demanding more firm disclosure (Lin et al.

(2018); Boone and White (2015); Ajinkya et al. (2005)). With increased information transparency, ordinary investors likely need less assistance from analysts. Therefore, if institutional investors constitute a smaller proportion of a firm's investor base, demand for analyst information production should increase. Based on these arguments, I examine the following hypothesis, in alternative form:

H2b: An incremental association exists between a DCV and analyst research production for firms with low institutional ownership.

Investor demand is also likely higher when analysts are more experienced. Experienced analysts are more likely to generate private information through their long-term relations with management, which provides them with superior access to management. Prior literature (Arif et al. (2019); Cheng et al. (2016); Green et al. (2014); Soltes (2014)) suggests that subtle variants of management access, such as visits to company headquarters/factories, private analyst-manager meetings, and broker-hosted investor conferences, continue to provide analysts an information advantage after Reg FD. Furthermore, experienced analysts are better skilled at obtaining outside non-public information from non-management sources, such as FDA-generated records regarding healthcare firms (Klein et al. (2019)). In addition, analysts' general skills and industry/firm-specific knowledge improve over time, as do their forecasting abilities (Bradley et al. (2017); Bradley et al. (2017); Clement (1999)). Therefore, investors should rely more on experienced analysts when a firm violates a debt covenant. Given this argument, I state the following hypothesis, in alternative form:

H2c: An incremental association exists between a DCV and analyst research production for firms covered by more experienced analysts.

Alternatively, investor demand may not incrementally increase in the aforementioned circumstances. For example, financially constrained firms may use more firm disclosure to relax external financing constraints (Khurana et al. (2006)). If true, investors may not require additional information from sell-side analysts. Some studies find that ownership diffusion induces increased firm disclosure as shareholders require more monitoring in response to the increased agency costs (Kelton and Yang

(2008); Schadewitz and Blevins (1998)). Therefore, for firms with low institutional ownership, investor demand may not be incrementally higher due to increased firm disclosure.

I next explore how the informativeness of analyst revisions changes after DCVs. Pastor and Veronesi (2009) theoretically argue that an analyst signal becomes more valuable to investors insofar as its precision increases relative to the uncertainty associated with investors' *a priori* beliefs. This is because investors tend to put more weight on the new signal if it is relatively more precise than their own signals (Nagar et al. (2019); Barniv and Cao (2009); Kacperczyk and Seru (2007)). Analysts are generally better skilled at gathering and processing information than ordinary investors. They also work harder when the state of economy is hard to anticipate (Loh and Stulz (2018); Glode (2011)). In addition, analysts are under increased pressure to produce valuable output, as they have recently faced widespread skepticism over the incremental value their research adds to investment decisions (Spence et al. (2019)). A number of regulatory and technological reforms, such as NYSE Rule 472 and NYSD Rule 2711, and the resultant threats brought to them, have motivated sell-side analysts to ensure that their services are still valued by investors. Therefore, analysts should be incentivized to produce more valuable research after a DCV when uncertainty is high.

Prior literature (Loh and Stulz (2018); Vashishtha (2014)) shows that analysts' absolute forecast errors increase in times of uncertainty. Higher forecast errors are typically accompanied by less valuable analyst output; if, as I predict, analysts' research output is more influential on the capital market, there should be new analyst forecast properties that are influencing investors under high uncertainty. For example, analysts' forecast errors should at least be lower compared to the noise in investors' information after a DCV. Based on the same theoretical arguments (Pastor and Veronesi (2009)), I hypothesize that relative analyst forecast errors, which are uncertainty adjusted, decline after DCVs. Decreased relative forecast errors would further lend support to the mechanism through which the influence of analyst re-

search increases after a DCV. Given the aforementioned arguments, I examine the following hypotheses, in alternative form:

H3a: Following a DCV, analyst recommendation revisions and forecast revisions are more influential.

H3b: Following a DCV, relative analyst forecast errors decrease.

Ex ante, it is not clear whether research provided by analysts becomes more or less informative, or whether relative forecast errors change post-DCV. Like investors, analysts also confront heightened uncertainty and decreased firm disclosure after a DCV. Analyst signals may not be as precise nor incrementally informative to investors because it becomes much more difficult and/or more costly for analysts to obtain and process information. Further, prior literature has documented the herding behavior of analysts (Arya et al. (2005); Hong et al. (2000); Welch (2000); Trueman (1994)). If the increased amount of research after a DCV is primarily due to analyst herding, then not all analyst revisions contain useful information. Additionally, some findings in prior literature (Zhang (2006); Gu and Wang (2005); Amir et al. (2003)) cast doubt on analysts' value under uncertainty by showing decreased forecast accuracy and underreaction to new information. In summary, these considerations could prevent me from finding results consistent with my third hypotheses.

3. RESEARCH DESIGN

3.1 Hypothesis 1

To examine the effect of a DCV on analyst research output, I estimate the following two models:

$$\begin{aligned} AnalystOutput_{i,q} = & \alpha_0 + \alpha_1 Violation_{i,q-1} + Controls \\ & + \sum_q QTR + \sum_q Industry + \epsilon_{i,q} \end{aligned} \quad (3.1)$$

$$\begin{aligned} Pr (AnalystOutput_{i,q} > 0) = & \alpha_0 + \alpha_1 Violation_{i,q-1} + Controls \\ & + \sum_q QTR + \sum_q Industry + \epsilon_{i,q} \end{aligned} \quad (3.2)$$

where $Violation_{i,q-1}$ on the right-hand side is the main variable of interest. It is an indicator variable that is equal to one if there is a covenant violation for firm i in fiscal quarter $q-1$ and zero otherwise.¹ Quarter q is defined as the time period between the yearly or quarterly SEC filing (10-K or 10-Q) of fiscal quarter $q-1$ and that of fiscal quarter q . Figure 1 illustrates the timeline of the occurrence of a DCV and the SEC filings that disclose information of the DCV. SEC Regulation S-X (1988) requires that any breach of a covenant should be stated in the notes to the financial statements. SEC’s 2003 MD&A Interpretive Guidance has reinforced this requirement: “Companies that are, or are reasonably likely to be, in breach of such covenants must disclose material information about that breach and analyze the impact on the company if material.” It is reasonable to assume that the DCV information becomes publicly available after 10-K/Q filings.²

¹One potential concern is that cured DCVs are not required to be reported in 10-K or 10-Q, but some firms voluntarily report cured DCVs and are therefore included in Sufi data as violators. However, it is reasonable to argue that the inclusion of some cured DCVs biases against finding significant results.

²It is likely that information regarding covenant violations leaks out before SEC filings. However, this leakage would bias against finding significant results.

$AnalystOutput_{i,q}$ in the models denotes various measures that proxy for analyst research output. In Equation (3.1) I estimate the linear regression, with the number of yearly and quarterly analyst recommendation revisions ($RevRecm_{i,q}$) and earnings forecast revisions ($RevEstm_{i,q}$) issued by analysts who cover firm i during quarter q as the dependent variables, following Jennings (2019) and Huang et al. (2014). The two measures capture the aggregate analyst research production in quarter q . A positive association between these two proxies and $Violation_{i,q-1}$ would be consistent with analyst research output increasing after a DCV. In the meantime, as more analysts likely follow the firm after a DCV, the increase in total analyst research amount may be due to a larger number of analysts. I also use $RevRecm/AyFw_{i,q}$ and $RevEstm/AyFw_{i,q}$, by scaling $RevRecm_{i,q}$ and $RevEstm_{i,q}$ with the number of analysts following firm i in quarter q , to capture the average analyst production. If the relations between the scaled measures and $Violation_{i,q-1}$ remain significant and positive, it provides strong support to Hypothesis 1 that analysts produce larger amounts of research output after a DCV. In Equation (3.2) I estimate the logistic specification, using the likelihood of recommendation revision issuance $[Pr(RevRecm)_{i,q}]$ and the likelihood of earnings forecast revisions issuance $[Pr(RevEstm)_{i,q}]$ as the dependent variables.

I include several control variables that are expected to affect analyst research output, following prior literature (Jennings (2019); Huang et al. (2014); Vashishtha (2014); Palmon and Yezegel (2012)). Specifically, analysts are expected to provide more research for larger firms ($Size_{i,q-1}$), higher growth firms ($BM_{i,q-1}$), better performing firms ($ROA_{i,q-1}$, $Return_{i,q-1}$), higher risk firms ($Leverage_{i,q-1}$), firms with higher institutional ownership ($Inst_{i,q-1}$), and firms with more complex operations ($NumSegments_{i,q-1}$). Also included is the absolute value of the two-day cumulative abnormal returns surrounding earnings announcements and management forecasts ($Abs[EA/MF]_{i,q}$), which controls for the impact of the firm events. If the earnings announcement window and management forecast window overlap, I only count the abnormal return for one event. I include analyst following ($AyFw_{i,q}$) as a control in

Equation (3.2). It is more likely that revisions are issued when more analysts cover the firm. However, I don't control for analyst following in Equation (3.1) when the total number of revisions ($RevRecm_{i,q}$ or $RevEstm_{i,q}$) is the dependent variable, because the goal is examining whether analysts in aggregate produce larger amounts of research after a DCV. When the average number of revisions ($RevRecm/AyFw_{i,q}$ or $RevEstm/AyFw_{i,q}$) is the dependent variable, the effect of analyst following is already included and I don't control for analyst following either.

To disentangle the effect of a DCV from changes in analyst research that would have otherwise occurred, I employ "quasi-discontinuity" regressions by including high-order functions for performance metrics on which financial covenants are commonly written, following prior literature (Gao et al. (2017); Vashishtha (2014); Nini et al. (2012); Chava and Roberts (2008)). With the inclusion of these high-order controls, the impact of a DCV is identified by the discontinuity that occurs at the level of the violation, because presumably analysts would not change their research production discontinuously at the covenant threshold in the absence of a financial covenant. The "quasi-discontinuity" method is employed in all the major tests in this study. I follow Gao et al. (2017) and Vashishtha (2014) and use four covenant controls: current ratio ($CurrentRatio_{i,q-1}$), net worth ($NetWorth_{i,q-1}$), operating cash flow ($OCF_{i,q-1}$), and leverage ($Leverage_{i,q-1}$). All variable definitions are included in the appendix.

I also include calendar quarter fixed effects and industry fixed effects to control for macroeconomic factors and fundamental differences between industries, respectively. Standard errors are clustered at the firm level.³

3.2 Hypothesis 2

In the second hypotheses, I examine whether a higher level of investor demand for company information strengthens the association between a DCV and analyst research output. I hypothesize that investor demand is higher for financially con-

³I don't control for the effect of Regulation FD passage as time fixed effects have been included.

strained firms, low institution-owned firms, and firms that are covered by more experienced analysts. For financially constrained firms, investor demand for information is likely incrementally higher after a DCV as uncertainty potentially increases more significantly. A significant and positive coefficient on the interaction term *Violation * Financial_Constraints* in Equation (3.3) would be consistent with Hypothesis H2a and provide further support for the hypothesis that analysts produce more research output after DCVs.

$$\begin{aligned}
 AnalystOutput_{i,q} = & \alpha_0 + \alpha_1 Violation_{i,q-1} + \alpha_2 Financial_Constraints \\
 & + \alpha_3 Violation * Financial_Constraints + Controls \\
 & + \sum_q QTR + \sum_q Industry + \epsilon_{i,q}
 \end{aligned} \tag{3.3}$$

As in Farre-Mensa and Ljungqvist (2016) and Whited and Wu (2006), I use WW Index to measure financial constraints. *Financial_Constraints* is an indicator variable set to one if the WW Index ranks among the top tercile in the sample and zero for the bottom tercile. I additionally use two alternative measures, HP Index and availability of credit ratings, to proxy for financial constraints. I discuss in Section 5 that I obtain similar inferences from the two alternative measures. The control variables, fixed effects, and standard errors clustering are the same as in Equation (3.1).

To test Hypothesis H2b and H2c I also estimate Equation (3.3), with low institutional ownership (*Inst_Low*) and analyst experience (*Analyst_Exp*) replacing *Financial_Constraints*, respectively. *Inst_Low* is an indicator set to one if institutional ownership ranks among the lower half in the sample and zero for the upper half. *Analyst_Exp* is an indicator variable set to one for the half sample that ranks high in analyst experience and zero for the other half that ranks low. I use the number of years an analyst issued one or more annual earnings forecasts for a firm to proxy for analyst experience, following Jung et al. (2012)).

Institutional investors have better resources to form their own information portfolios and thus likely demand relatively less from analysts. A positive and significant coefficient on $Violation * Inst_Low$ would suggest that analysts provide incrementally more research output after DCVs for firms with low institutional ownership.

Because it is relatively more difficult and costly to produce research in an environment with high uncertainty and decreased management disclosure, more experienced analysts, who are better skilled at gathering and processing information, have the advantage to yield more output. Thus, investors likely demand more information from experienced analysts. A significant and positive coefficient on the interaction term $Violation * Analyst_Exp$ would support Hypothesis H2c and provide further support for the positive association between a DCV and analyst research output.

3.3 Hypothesis 3

My third hypotheses examine the effect of a DCV on the value, or the informativeness, of analyst research output and on the relative analyst forecast errors. To test H3a, I estimate the following specification:

$$Impact_{i,q} = \alpha_0 + \alpha_1 Violation_{i,q-1} + Controls + \sum_q QTR + \sum_q Industry + \epsilon_{i,q} \quad (3.4)$$

I measure the value of analyst research using the price impact, which captures how analyst signals affect investors' assessment of firm value, reflecting analysts' contribution to firms' information environment. I follow prior literature (Jennings (2019); Loh and Stulz (2018)) and use the absolute value of cumulative abnormal returns from the revision date to the following trading day, i.e. the [0,1] two-day window, to measure analyst research impacts. The abnormal return is calculated by using equally weighted market-adjusted return in the basic CAPM model. Day 0 is defined as the next trading day if the revision is issued on a non-trading day or after trading hours.

I examine the effect of a DCV both on the aggregate analyst output influence and on the individual analyst revision influence. For the aggregate influence, I sum the absolute value of abnormal returns of each two-day $([0,1])$ recommendation (earnings forecast) revision window within quarter q , i.e. $Abs[AR1]_{i,q}$ ($Abs[AR2]_{i,q}$). I include the abnormal return only once if multiple revisions are issued in the same window.⁴ Because I sum the revision informativeness in a quarter, the increase in analyst research influence may merely reflect a larger number of analysts following the firm after a DCV. To alleviate this concern, I use two alternative measures, $Abs[AR1]/AyFw_{i,q}$ ($Abs[AR2]/AyFw_{i,q}$), which are calculated as scaling the sum of abnormal returns by analyst following, to estimate the specification in Equation (3.4).

For the individual effect, I estimate the regression defined in Equation (3.4) at the revision level, each observation being one revision. This test examines the effect of a DCV on each individual revision's market influence. In a robustness test of the individual effect, I add analyst fixed effects in the specification. Because multiple revisions within one firm-quarter have the same firm characteristics, differences among revisions, such as being issued by different analysts, may not be sufficiently controlled. Thus, I include analyst fixed effects to control for the variance in analyst characteristics.

In summary, I use six measures as the dependent variables in Equation (3.4): $Abs[AR1]_{i,q}$ ($Abs[AR2]_{i,q}$) measures the sum of abnormal returns surrounding recommendation (earnings forecast) revisions for firm i in quarter q , $Abs[AR1]/AyFw_{i,q}$ ($Abs[AR2]/AyFw_{i,q}$) proxies for the average abnormal returns surrounding recommendation (earnings forecast) revisions for firm i in quarter q , and $Abs[AR3]_{i,j,q}$ ($Abs[AR4]_{i,j,q}$) measures the abnormal returns surrounding the j th recommendation (earnings forecast) revision issued for firm i in quarter q .

⁴To alleviate the concern about analyst herding, in which case analysts issue revisions following other analysts without providing much incremental information, I use an alternative measure that counts the abnormal return only once if revisions are issued within consecutive days. In Section 5, I discuss that the results are robust to using the alternative measure.

The same control variables as in Equation (3.1) are included: I expect analyst research to be more influential for larger firms ($Size_{i,q-1}$), higher growth firms ($BM_{i,q-1}$), better performing firms ($ROA_{i,q-1}$, $Return_{i,q-1}$), higher risk firms ($Leverage_{i,q-1}$), firms with higher institutional ownership ($Inst_{i,q-1}$), and firms with more complex operations ($NumSegments_{i,q-1}$). In addition, I include $Abs[/EA/MF]_{i,q}$ to control for the effect of firm events on stock market reaction. The high-order covenant controls are included as well. Additionally, I control for the effect of return volatility and trading volume on analyst research value. Frankel et al. (2006) indicate that analyst research informativeness increases in return volatility and trading volume. They use the portfolio ranks of these two values as instruments, assuming that whether a stock is in the low, medium, or high return volatility (trading volume) portfolio is not likely to be caused by endogeneity between analyst research informativeness and return volatility (trading volume), but the variation within the portfolio of high return volatility (trading volume) can be endogenously determined by analyst research informativeness. Following Frankel et al. (2006), I include the portfolio rank values of return volatility ($RetVol_{i,q}$) and trading volume ($TradingVol_{i,q}$) as control variables in Equation (3.4). In the test for the effect on the individual recommendation revision impact, I additionally control for the change in recommendation codes (e.g. the difference between "buy" (4) and "hold" (3)). Recommendation changes presumably affect the magnitude of revision influence positively.

Hypothesis H3b predicts that relative analyst forecast errors decline after DCVs. To test H3b, I also estimate Equation (3.4), replacing the dependent variable with the relative forecast error ($RFE_{i,q}$). I measure relative forecast error ($RFE_{i,q}$) by scaling absolute forecast errors with uncertainty. The uncertainty is proxied by the disagreement in analyst forecasts, measured as the variance in analyst forecasts in the quarter.⁵ Similar measurements have been used in prior literature (Jurado et al.

⁵I do not follow Loh and Stulz (2018) and use stock return volatility to measure uncertainty because return volatility measures a lot of factors other than uncertainty. For example return volatility also measures industry and firm risks (Campbell et al. (2001)). I want to identify the effect of uncertainties caused by DCVs and therefore exclude the impact of other possible factors.

(2015); Lahiri and Sheng (2010)), which suggests that larger disagreements among analysts correspond to greater information uncertainty. The absolute forecast error used in calculating $RFE_{i,q}$ is the average of the absolute errors of all forecasts made in the quarter, scaled by the stock price at the beginning of the quarter, following Dhaliwal et al. (2012).

I include the same control variables as in Equation (3.1) and add three additional controls following Dhaliwal et al. (2012). Earnings variance ($Earnings_Vari_{i,q-1}$) is included because more volatile earnings are more difficult to predict (Dichev and Tang (2009)). Indicator $Loss_{i,q-1}$ is included because earnings of firms using conservative accounting are more volatile when they have losses and thus are more difficult to forecast as well. The length of time between forecast date and earnings announcement date likely affects forecast accuracy, therefore I control for forecast horizon ($Forec_Hoz_{i,q}$).

4. DATA AND SAMPLE

I use the DCV data provided by Nini et al. (2012), which are available on the Amir Sufi website. The authors construct the data set starting from all firm-quarter observations in Compustat. They then match the firm quarters to corresponding SEC filings (10-K and 10-Q) and extract information about covenant violations.¹ An indicator variable, *Violation*, denotes the occurrence of a violation by firm-quarter.

I obtain analyst data from I/B/E/S, accounting data from Compustat, stock return data from CRSP, institutional ownership data from S34 in Thomson Reuters, and management forecasts data from Zacks. The sample period is 1996 to 2008, which is mainly determined by the availability of DCV data. Sufi’s dataset includes DCV information of 262,673 firm-quarters. I delete observations with missing data to calculate common independent variables across tests, and I only include firm-quarters with at least one initial recommendation (earnings forecast) issuance. The observation number drops to 77,118 (106,731) for tests on the number of recommendation (earnings forecast) revisions in Table B.2. As I calculate the abnormal returns, I use the prior 90 trading days return data to obtain the coefficient on the market portfolio return, requiring at least 20 days of non-missing data. Thus, the number of observations drops to 52,131 (53,518) when I examine the effect of DCVs on abnormal returns around recommendation (earnings forecast) revisions.

Table B.1 reports descriptive statistics. The likelihood of the sample firms violating a covenant in a quarter is 5.7%. This suggests that covenant violations do not occur frequently, thus once a DCV occurs, it has significant impacts on a firm’s operating and information environment. The firms have an average total assets of approximately 197 million dollars and a mean book-to-market ratio of 0.659, which

¹<https://faculty.chicagobooth.edu/amir.sufi/chronology.html>. The supplemental data appendix for Nini et al. (2012) describes in detail how the dataset is constructed.

are similar to prior studies (Gao et al. (2017); Vashishtha (2014)). The mean leverage of 44.6% shows relatively high long-term debt proportion. The firms have, on average, two segments, showing reasonable complexity of firm operations. There are approximately 1.37 (2.05) recommendation (earnings forecast) revisions issued in one firm quarter, and, on average, 0.17 (0.19) recommendation (earnings forecast) revisions from each analyst following the firm per quarter.

5. EMPIRICAL RESULTS

5.1 DCV and the Amount of Analyst Research

In Table B.2 through B.4, I present the results examining whether the amount of analyst research output increases after a DCV occurs. Table B.2 shows the estimates in Equation (3.1) when the dependent variables are the total number of analyst recommendation revisions [Column (1)] and the number of earnings forecast revisions [Column (2)]. I find that the coefficients on the main variable of interest, *Violation*, are positive in both columns, statistically significant below the 0.01 level in Column (1) and below the 0.05 level in Column (2). This suggests that analysts produce larger amounts of research output after a DCV, providing support for the first hypothesis. In Column (1), the coefficient on *Violation* is 0.095, indicating that, on average, analysts provide 6.9% more recommendation revisions for a violating firm in the quarter after a DCV. In Column (2), the coefficient of 0.123 on *Violation* suggests that analysts provide approximately 6.0% more earnings forecast revisions for a violating firm after a DCV.

Table B.3 presents the results with *RevRecm/AyFw* and *RevEstm/AyFw* as the dependent variables. The coefficients on *Violation* remain positive and statistically significant (1 percent level in Column (1) and 5 percent level in Column (2)). The findings suggest that after scaling the number of revisions by the number of analysts following the firm during the quarter, per-analyst revisions increase after a DCV, providing further evidence consistent with Hypothesis 1.

I present the estimates in Equation (3.2) in Table B.4, which provides evidence on the relation between the occurrence of a DCV and the probability of analyst issuing a recommendation or forecast revision. I find positive and statistically significant, below the 0.01 level, coefficients on *Violation* for both columns, indicating that analysts

are more likely to issue both recommendation and earnings forecast revisions after a DCV. The coefficients show that analysts are 16.7% (13.7%) more likely to issue recommendation (earnings forecast) revisions after a DCV. I control for the number of analysts following in this specification. As expected, the coefficients on *AyFw* are positive and statistically significant (1 percent level) in both columns, suggesting that as more analysts cover the firm, revisions are more likely to be issued. The effect of a DCV on the likelihood of revision issuance is incremental to the increase in analysts after violations.

The three panels in Table B.2 through B.4 provide strong evidence that analysts provide larger amounts of research and that analysts are more likely to produce research output after a DCV. The analysis investigates the unconditional effects of a DCV on analyst research output; I then examine the cross-sectional predictions indicated in Hypothesis 2.

Table B.5 through B.7 present results from estimating augmented versions of Equation (3.1) and (3.2), which interact Violation with three indicator variables *Financial_Constraints*, *Inst_Low*, and *Analyst_Experience*. These cross-sectional analyses allow me to examine whether an incremental association exists between a DCV and analyst research production for firms with financial constraints, firms with low institutional ownership, and firms covered by more experienced analysts. For these three types of firms, investor demand for company information is likely incrementally higher after DCVs, potentially leading to an additional increase in analyst research output. I expect positive and statistically significant coefficients on the interaction terms.

Table B.5 provides evidence on the incremental association between a DCV and analyst research production for firms with financial constraints.¹ Column (1) and (2)

¹I proxy financial constraints using WW Index. I also use two alternative measures, availability of credit rating and HP index, for financial constraints. The untabulated results show qualitatively similar results. Unrated firms are those that do not have a credit rating from S&P, Moody's, Fitch, or Duff & Phelps, using data obtained from Compustat. HP index is constructed following Hadlock and Pierce (2010): $HP\ index = -0.737Size + 0.043Size^2 - 0.040Age$, where Size is the log of inflation-adjusted Compustat item AT.

show estimates when *RevRecm* and *RevEstm* are the dependent variables. The coefficients on the interaction *Violation*Financial_Constraints* are positive and statistically significant below the 0.01 level in Column (1) and below the 0.10 level in Column (2). The findings suggest that analysts research, in aggregate, incrementally increases for firms that are financially constrained, compared to non-financially constrained firms, after DCVs. Column (3) and (4) present estimates with *RevRecm/AyFw* and *RevEstm/AyFw* as the dependent variables. Positive and statistically significant coefficients on *Violation*Financial_Constraints* indicate that the average output of each analyst following a firm with financial constraints also additionally increases after a DCV. Column (1) through Column (4) provide evidence consistent with analysts producing incrementally more research, both in aggregate and on average, for financially constrained firms subsequent to a DCV. Column (5) and (6) present the results examining the additional likelihood of post-DCV revisions for financially constrained firms. I find positive and statistically significant coefficients on the interaction. A coefficient of 0.158 (0.338) suggests that analysts are 15.8% (33.8%) more likely to issue recommendation (earnings forecast) revisions for financially constrained firms, compared to non-financially constrained firms, after a DCV. It is interesting to note that in Table B.5's six columns, the coefficients on *Violation* mostly do not show statistical significance, indicating that analysts do not provide statistically different amounts of research before and after DCVs to firms not financially constrained. Collectively, the above results are consistent with investors of financially constrained firms having incrementally higher demand for company information, leading to greater analyst research production.

Table B.6 reports the analysis of whether the level of institutional ownership of a firm affects the relation between a DCV and analyst research output. *Inst_Low* is an indicator variable set to one if institutional ownership ranks the lower half in the sample and zero for the upper half. Column (1) through (4) present estimates in Equation (3.3), with *Inst_Low* replacing *Financial_Constraints*. I find a statistically significant (1 percent level) coefficient of 0.109 [0.388] on *Violation*Inst_Low* in

Column (1) [(2)], suggesting that analysts produce additionally 7.9% [19.0%] more recommendation [earnings forecast] revisions for a low institution-owned firm after a DCV, compared to a high institution-owned firm after a DCV. I present how average analyst production incrementally changes for firms with low institutional ownership in Column (3) and (4). Positive and statistically significant (1 percent level) coefficients on *Violation*Inst_Low* indicate that, on average, each analyst following a low institution-owned firm increases their revisions post DCV more than an analyst following a firm that has a larger proportion of institutional investors. In Column (5) and (6), a statistically significant (1 percent level) coefficient of 0.219 [0.191] on *Violation*Inst_Low* suggests that analysts are 21.9% [19.1%] more likely to increase their research production for a low institution-owned firm, than for a high institution-owned firm, after a DCV. The above findings are consistent with Hypothesis H2b that due to investors' higher information demand for firms with low institutional ownership after a DCV, analysts produce incrementally larger amounts of research.

Table B.7 presents the examination on whether analyst experience plays an incremental role in the relation between a DCV and analyst research output. In Column (1) and (2), the coefficients on the interaction term *Violation*Analyst_Experience* are both positive and statistically significant, with p-values below 0.01, implying that investors demand more information from experienced analysts after a DCV. The coefficients on *Violation*Analyst_Experience* are also positive and statistically significant [1 percent level in Column (3) and 10 percent level in Column (4)] when *RevRecm/AyFw* and *RevEstm/AyFw* are the dependent variables, indicating that the average output of a more experienced analyst incrementally increases after a DCV, compared to a less experienced analyst. Column (1) through Column (4) provide evidence consistent with more experienced analysts producing incrementally more research, both in aggregate and on average, after the firms they follow have a DCV. Column (5) and (6) reports estimates on the additional likelihood of revisions issued by more experienced analysts after a DCV. The coefficients on the interaction *Violation*Analyst_Experience* remain positive and statistically significant (below the 0.01

level), suggesting that more experienced analysts are incrementally more likely to revise recommendations and earnings forecasts than less experienced analysts, after a DCV. It is worth noting that the coefficients on *Analyst_Experience* and *Violation* are both positive and statistically significant in all six columns. The coefficients on *Analyst_Experience* in all columns are estimated to be significantly positive below the 0.01 level, showing that, in the absence of a DCV, experienced analysts issue more revisions than less-experienced analysts. In addition, the positive and significant coefficients on *Violation* indicate that analysts who are relatively less experienced also provide more research output after DCVs. Taken together, the evidence presented in Table B.7 suggests that analysts generally provide larger amounts of research in the quarter following DCVs and that more experienced analysts provide incrementally more output, compared to less experienced analysts.

In summary, the evidence presented in Table B.5 through B.7 strengthens the arguments for my first hypothesis by confirming that when investor demand incrementally increases after a DCV, analyst research production increases to a larger extent.

5.2 DCV and the Informativeness of Analyst Research

I further explore whether the influence of analyst research on the capital market changes after a DCV. Table B.8 through B.10 presents estimates in Equation (3.4). In Table B.8, I estimate the specification at a firm-quarter level, summing the cumulative abnormal returns for each firm-quarter observation. Column (1) and (2) show the results when $Abs[AR1]$ and $Abs[AR2]$ are the dependent variables, denoting the sum of abnormal returns surrounding recommendation and earnings forecast revisions for firm i in quarter q . The abnormal return is calculated using equally weighted market-adjusted return in the basic CAPM model.² A statistically significant (below the 0.01

²Alternatively, I use value-weighted market-adjust returns and Fama French three factor model in calculating abnormal returns. The untabulated results are statistically similar to those reported in Table B.8 through B.10.

level) coefficient of 0.009 (0.010) on *Violation* suggests that the absolute value of the two-day window abnormal returns of a recommendation (earnings forecast) revision is 9 (10) basis points higher, or 10% (11.2%) higher compared to mean abnormal returns after a DCV occurs. In addition, I use an alternative measure that counts the abnormal return only once if revisions are issued within consecutive days, attempting to alleviate the concern about analyst herding. My inferences remain unchanged to this alternate specification. Therefore, the aggregate influence of analyst revisions on the capital market is larger following a DCV.

Table B.9 reports the analysis using $Abs[AR1]/AyFw$ and $Abs[AR2]/AyFw$ as proxies for the average informativeness of an analyst following the firm. As I sum the quarterly revision informativeness in the above estimates in Table B.8, the increase in analyst research influence may be partially explained by a larger number of analysts following the firm after a DCV. Therefore, I also use two new measures, $Abs[AR1]/AyFw$ and $Abs[AR2]/AyFw$, calculated as dividing the sum of abnormal returns by the number of analysts following, to examine analyst research impacts after a DCV. Table B.9 shows that even after scaling by the number of analysts covering the firm, analyst output continues to be influential to investors after a DCV. A statistically significant (1 percent level) coefficient of 0.005 (0.002) on *Violation* suggests that the stock market impact of an average analysts' recommendation (earnings forecast) revision is 39.6% (19.0%) larger, relative to variable mean, after a DCV.

In Table B.10, I present the results of estimating Equation (3.4) on an individual revision level, with each observation being one revision. Different from the average informativeness per analyst in a quarter, I now examine specifically the effect of a DCV on each individual revision's informativeness. The coefficient, 0.006 [0.005], on *Violation* in Column (1) [Column (2)] is positive and statistically significant below the 0.01 level, suggesting that investor response to each individual recommendation [earnings forecast] revision is, on average, 12.3% [13.1%] stronger after a DCV. In other words, individual recommendation and earnings forecast revisions are more influential on the capital market after a DCV as well. The magnitude of the individual revision impact

is smaller than the aggregate impact reported in Table B.8, which is consistent with expectations. In a robustness test of the individual effect, I add analyst fixed effects to control for the variance in analyst characteristics. The untabulated results suggest that my inferences remain unchanged to this alternate specification. Taken together, I provide evidence that analyst revisions are more influential on the stock market, both in the aggregate and individually, after DCVs. This implies that analysts work harder in times of higher uncertainty and are able to generate research that is more informative.

Finally, I examine how relative analyst forecast errors change around DCVs. As the uncertainty and information asymmetry increase after DCVs, analyst forecast errors should increase. However, this does not necessarily mean that analysts' reports and revisions are less useful to investors. Kacperczyk and Seru (2007) stress that investors still tend to depend on experts, who they believe are better at searching and processing information, when their own information becomes noisier. In order to investigate how analyst signals change relative to investor signals after DCVs, I use a relative forecast error (*RFE*) measure, which is scaled by uncertainty. The uncertainty is proxied by the disagreement in analyst forecasts.

Table B.11 presents the results examining relative forecast errors after a DCV. The coefficient on *Violation* is estimated to be -0.165, which is statistically significant below the 0.05 level, suggesting that relative forecast errors (*RFE*), or forecast errors per unit of uncertainty, decline 9.9% compared to the variable mean after a DCV. This implies that even though heightened uncertainty after a DCV results in less accurate analyst signals, analysts can still inform investors, whose signals deteriorate even more. The evidence presented in Table B.11 indicates that financial analysts possess the abilities to gather, process, and interpret information, allowing them to provide informative output even facing higher uncertainty and information asymmetry.

Overall, the findings in this study provide credible evidence that analysts produce more research output after DCVs. They not only increase the amount of research, but also put forth greater efforts to collect and process information, thereby enhancing

the impact of their research on the capital market. The cross-sectional analyses are consistent with my arguments that heightened investor demand for company information strengthens the positive association between a DCV and analyst research production. The comparison between increased analyst forecast errors and decreased relative forecast errors illustrates from a novel angle how analysts are playing an important role in the economy. These findings together show us how a DCV reshapes the information environment of a firm, adding to our understanding of the economic and informational consequences of a DCV.

6. CONCLUSION

In this paper, I examine how information provided by sell-side analysts changes after DCVs. After a DCV, uncertainty and information asymmetry likely increase. As creditors take control of the firm, shareholders are uncertain about how severe the violation is and how creditors will respond. In the meantime, shareholders have limited access to firm information after a DCV, leading to increased information asymmetry. It is therefore difficult for shareholders to assess firm value and thus they have greater demand for company information. Analysts are skilled at gathering and processing information and thus can fill investors' demand for greater information after a DCV.

I investigate whether analysts generate larger amounts of information and whether this information is more valuable after a DCV. I first posit that analysts provide larger amounts of research following a DCV. Because investors' demand for information increases and analysts have the expertise to satisfy this demand, analysts should be incentivized to produce more research output. Consistently, my findings show that analysts provide a larger number of recommendation revisions and earnings forecast revisions after a DCV.

I further conjecture that an incremental association exists between a DCV and analyst research output for firms with financial constraints, firms with low institutional ownership, and firms followed by more experienced analysts. Investor demands incrementally increase for these three types of firms after DCVs, incentivizing analysts to generate incrementally more research output. Consistent with my conjecture, I find evidence that higher investor demand incrementally increases the amount of analyst research associated with a DCV. The evidence indicates that analysts incrementally produce more research output in response to the increased demand from investors after DCVs.

Finally, I investigate whether analyst research is more informative following a DCV. Theories suggest that an analyst's output is more valuable to investors as long as the precision of the analyst signal increases relative to the uncertainty associated with the investors' a priori beliefs. The evidence indicates that analyst revisions are more influential and that uncertainty-adjusted forecast errors decrease after a DCV.

This study extends the debt contracting literature that primarily studies economic consequences and firm behaviors after DCVs by exploring how investors and equity analysts respond to covenant violations. In addition, this paper is the first to examine how syndicated loan information affects equity analysts' behaviors, adding to the growing literature that examines cross-market information flow.

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APPENDICES

A. DEFINITIONS AND NOTATIONS

Table A.1.
Variable Definitions

Variable	Definition
$Violation_{i,q-l}$	An indicator variable set to one for firm i with a DCV in fiscal quarter $q-l$, zero otherwise.
$RevRecm_{i,q}$	The number of analyst recommendation revisions issued during quarter q for firm i . I define quarter q to be the time period between the yearly or quarterly SEC filing (10-K or 10-Q) of fiscal quarter $q-l$ and that of fiscal quarter q .
$RevRecm / AyFw_{i,q}$	$RevRecm$ (defined above) scaled by number of analysts following firm i in quarter q .
$RevEstm_{i,q}$	The number of analyst EPS forecasts revisions issued during quarter q for firm i .
$RevEstm / AyFw_{i,q}$	$RevEstm$ (defined above) scaled by number of analysts following firm i in quarter q .
$Abs[AR1]_{i,q}$	The sum of the absolute value of the cumulative market-adjusted returns (equally weighted index) of the two-day [0,1] window surrounding recommendation revisions issued during quarter q .
$Abs[AR1] / AyFw_{i,q}$	$Abs[AR1]$ (defined above) scaled by number of analysts following firm i in quarter q .
$Abs[AR2]$	The sum of the absolute value of the cumulative market-adjusted returns (equally weighted index) of the two-day [0,1] window surrounding earnings forecast revisions issued during quarter q .
$Abs[AR2] / AyFw_{i,q}$	$Abs[AR2]$ (defined above) scaled by number of analysts following firm i in quarter q .
$Abs[AR3]_{i,j,q}$	The absolute value of the cumulative market-adjusted returns (equally weighted index) of the two-day [0,1] window surrounding the j th recommendation revision issued during quarter q .
$Abs[AR4]_{i,j,q}$	The absolute value of the cumulative market-adjusted returns (equally weighted index) of the two-day [0,1] window surrounding the j th earnings forecast revision issued during quarter q .
$RFE_{i,q}$	Absolute forecast errors during quarter q scaled by the variance in analyst forecasts in the quarter.
$Size_{i,q-l}$	Natural log of (total assets + 1) of firm i in fiscal quarter $q-l$.
$BM_{i,q-l}$	The book value of equity divided by market value for firm i in fiscal quarter $q-l$.
$ROA_{i,q-l}$	Net income before extraordinary items for firm i in fiscal quarter $q-l$ scaled by total assets at fiscal quarter $q-5$.
$Return_{i,q-l}$	Stock return for firm i in fiscal quarter $q-l$.
$Leverage_{i,q-l}$	The book value of the total long-term debt divided by the total book value of assets at the end of fiscal quarter $q-l$.

$Inst_{i,q-1}$	The total shares owned by institutions divided by total shares outstanding for firm i in fiscal quarter $q-1$.
$Inst_Low_{i,q-1}$	Indicator set to one if institutional ownership ($Inst$) ranks the lower half in the sample and zero for the upper half.
$NumSegments_{i,q-1}$	Number of segments during fiscal quarter $q-1$.
$Abs[EA/MF]_{i,q}$	Absolute value of the cumulative market-adjusted returns (equally weighted index) surrounding earnings announcements and management forecasts issued by firm i during quarter q .
$AyFw_{i,q}$	Number of analysts following firm i in quarter q .
$RetVol_{i,q}$	Portfolio rank values in quarter q , which is obtained by ranking quarterly the sample firms according to return volatility and assign firms to three portfolios, with the lowest (highest) volatility portfolio rank of 0 (2).
$TradingVol_{i,q}$	Portfolio rank values in quarter q , which is obtained by ranking quarterly the sample firms according to trading volume and assign firms to three portfolios, with the lowest (highest) volatility portfolio rank of 0 (2).
$Chg_Recm_{i,j,q}$	Changes between recommendation codes “Strong buy” (5), “Buy” (4), “Hold” (3), “Underperform” (2), and “Sell” (1) in IBES
$Earnings_Var_{i,q}$	The natural logarithm of the time-series standard deviation of earnings per share (EPS). I use a rolling window of ten years before the current year and require at least three years of EPS to calculate the standard deviation.
$Loss_{i,q-1}$	Indicator set to one for firm i in fiscal quarter $q-1$ with a net loss (IBQ), and zero otherwise.
$Forec_Hoz_{i,q}$	The median forecast horizon (the number of days between earnings announcement date and forecast date) of analyst forecasts for each firm-quarter.
$Financial_Constraints_{i,q}$	Indicator set to one for firm-quarters in the top tercile in WW Index value and zero for firm-quarters in the bottom tercile. WW Index = $-0.091[(ibq + dpq)/atq] - 0.062[\text{indicator set to one if } dvc + dvpq \text{ is positive, and zero otherwise}] + 0.021[dlttq/atq] - 0.044[\log(atq)] + 0.102[\text{average industry sales growth, estimated separately for each three-digit SIC industry and each year}] - 0.035[\text{sales growth}]$, where variables in italics are Compustat data items.
$Analyst_Exp_{i,q}$	Indicator set to one for the half sample ranking high in analyst experience and zero for the half ranking low. Analyst experience is the number of years an analyst issued one or more annual earnings forecasts for firm i as of fiscal quarter q , using data starting from year 1980.
$CurrentRatio_{i,q-1}$	Current assets (ACTQ)/Current liabilities (LCTQ) at the end of the fiscal quarter $q-1$.
$NetWorth_{i,q-1}$	Stockholders' equity (SEQQ)/Total Assets (ATQ) at the end of the fiscal quarter $q-1$.
$OCF_{i,q-1}$	Operating Cash Flow/Total assets (ATQ) at the end of the fiscal quarter $q-1$.

B. TABLES

Table B.1.
Descriptive Statistics

Variable	N	Mean	SD	P25	P50	P75
<i>Violation</i>	170,056	0.057	0.232	0	0	0
<i>Size</i>	170,056	5.296	1.964	3.837	5.135	6.597
<i>BM</i>	170,056	0.659	0.593	0.275	0.495	0.834
<i>ROA</i>	170,056	0.012	0.061	0.000	0.026	0.045
<i>Leverage</i>	170,056	0.446	0.218	0.262	0.449	0.623
<i>Inst</i>	170,056	0.412	0.300	0.137	0.381	0.662
<i>NumSegments</i>	170,056	1.941	1.462	1	1	3
<i>Return</i>	170,056	0.030	0.319	-0.151	0.002	0.163
<i>Abs[EA/MF]</i>	170,056	0.625	0.763	0.158	0.390	0.814
<i>AyFw</i>	170,056	4.616	6.193	0	2	7
<i>RetVol</i>	170,056	1.059	0.284	0.693	1.099	1.386
<i>TradingVolm</i>	170,056	1.059	0.284	0.693	1.099	1.386
<i>CurrentRatio</i>	170,056	3.111	3.136	1.375	2.142	3.510
<i>NetWorth</i>	170,056	0.557	0.224	0.393	0.559	0.742
<i>OCF</i>	170,056	0.001	0.078	-0.024	0.012	0.038
<i>Revrecm</i>	77,118	1.373	1.707	0	1	2
<i>RevRecm/AyFw</i>	77,118	0.174	0.234	0	0.125	0.250
<i>RevEstm</i>	106,731	2.046	4.466	0	1	2
<i>RevEstm/AyFw</i>	106,731	0.187	0.288	0	0.038	0.286
<i>Abs[AR1]</i>	52,131	0.090	0.133	0.020	0.048	0.107
<i>Abs[AR1]/AyFw</i>	52,131	0.013	0.026	0.002	0.005	0.013
<i>Abs[AR2]</i>	53,518	0.089	0.107	0.023	0.054	0.115
<i>Abs[AR2]/AyFw</i>	53,518	0.011	0.015	0.003	0.006	0.013
<i>Abs[AR3]</i>	105,309	0.049	0.071	0.011	0.027	0.057
<i>Abs[AR4]</i>	173,673	0.038	0.051	0.010	0.023	0.046
<i>Chg_Recm</i>	105,309	0.176	1.434	-1	1	1
<i>RFE</i>	66,866	1.672	2.480	0.258	0.666	1.751
<i>Loss</i>	66,866	1.535	2.596	0.473	0.810	1.480
<i>Earnings_Var</i>	66,866	0.249	0.433	0	0	0
<i>Forec_Hoz</i>	66,866	2.960	1.071	2.476	3.239	3.750

Table B.2.
Effect of covenant violations on analyst recommendation/forecast re-
visions: Panel A (OLS regression on absolute number of revisions)

Variables	(1) <i>RevRecm</i>	(2) <i>RevEstm</i>
<i>Violation</i>	0.095*** (0.029)	0.123** (0.052)
<i>Size</i>	0.397*** (0.013)	1.015*** (0.039)
<i>BM</i>	-0.247*** (0.021)	-0.815*** (0.062)
<i>ROA</i>	-0.254 (0.164)	-1.745*** (0.424)
<i>Leverage</i>	1.803 (1.173)	-9.722*** (3.055)
<i>Inst</i>	0.113** (0.057)	-0.018 (0.145)
<i>NumSegments</i>	-0.047*** (0.009)	-0.104*** (0.024)
<i>Return</i>	-0.298*** (0.024)	-0.461*** (0.037)
<i>Abs[EA/MF]</i>	0.240*** (0.012)	0.562*** (0.024)
<i>OCF^2</i>	0.830*** (0.263)	1.451*** (0.401)
<i>NetWorth^2</i>	0.126 (0.759)	13.147*** (2.257)
<i>CurrentRatio^2</i>	0.002 (0.001)	0.000 (0.003)
<i>Leverage^2</i>	-6.020*** (2.238)	19.547*** (5.993)
<i>OCF^3</i>	-1.456 (2.066)	-11.443*** (2.912)
<i>NetWorth^3</i>	-0.186 (0.799)	-12.168*** (2.259)
<i>CurrentRatio^3</i>	-0.000** (0.000)	-0.000 (0.000)
<i>Leverage^3</i>	3.942*** (1.423)	-10.243*** (3.512)
Calendar Q/Y fixed effect	Yes	Yes
Industry fixed effect	Yes	Yes
Observations	77,118	106,731
Adj R-squared	0.184	0.298

All continuous variables are winsorized at the 1 percentile and 99 percentile levels. Robust standard errors in parentheses. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.3.
Effect of covenant violations on analyst recommendation/forecast revisions: Panel B (OLS regression on number of revisions scaled by analyst following)

Variables	(1) <i>RevRecm/AyFw</i>	(2) <i>RevEstm/AyFw</i>
<i>Violation</i>	0.028*** (0.006)	0.009** (0.004)
<i>Size</i>	-0.014*** (0.001)	0.029*** (0.001)
<i>BM</i>	0.062*** (0.003)	-0.016*** (0.003)
<i>ROA</i>	0.043* (0.023)	-0.069*** (0.021)
<i>Leverage</i>	0.528*** (0.141)	-0.414*** (0.136)
<i>Inst</i>	-0.033*** (0.006)	0.043*** (0.006)
<i>NumSegments</i>	0.001 (0.001)	-0.003** (0.001)
<i>Return</i>	-0.011*** (0.004)	-0.020*** (0.003)
<i>Abs[EA/MF]</i>	0.009*** (0.001)	0.041*** (0.001)
<i>OCF</i> ²	0.036 (0.036)	0.024 (0.025)
<i>NetWorth</i> ²	-0.437*** (0.089)	0.502*** (0.099)
<i>CurrentRatio</i> ²	-0.000** (0.000)	-0.000 (0.000)
<i>Leverage</i> ²	-1.173*** (0.254)	0.886*** (0.263)
<i>OCF</i> ³	0.069 (0.328)	-0.150 (0.205)
<i>NetWorth</i> ³	0.424*** (0.094)	-0.463*** (0.101)
<i>CurrentRatio</i> ³	0.000** (0.000)	0.000 (0.000)
<i>Leverage</i> ³	0.707*** (0.157)	-0.451*** (0.156)
Calendar Q/Y fixed effect	Yes	Yes
Industry fixed effect	Yes	Yes
Observations	77,118	106,731
Adj R-squared	0.056	0.171

All continuous variables are winsorized at the 1 percentile and 99 percentile levels. Robust standard errors in parentheses. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.4.
Effect of covenant violations on analyst recommendation/forecast revisions: Panel C (logistic regression on probability of revisions)

Variables	(1) <i>Pr(RevRecm)</i>	(2) <i>Pr(RevEstm)</i>
<i>Violation</i>	0.147*** (0.048)	0.102*** (0.038)
<i>Size</i>	0.033*** (0.011)	0.128*** (0.013)
<i>BM</i>	0.272*** (0.025)	-0.031 (0.025)
<i>ROA</i>	0.000 (0.196)	-0.574*** (0.207)
<i>Leverage</i>	2.218* (1.222)	-0.804 (1.172)
<i>Inst</i>	0.386*** (0.047)	0.380*** (0.050)
<i>NumSegments</i>	-0.001 (0.007)	0.001 (0.008)
<i>Return</i>	-0.216*** (0.031)	-0.108*** (0.028)
<i>Abs[EA/MF]</i>	0.119*** (0.011)	0.272*** (0.011)
<i>AyFw</i>	0.107*** (0.003)	0.179*** (0.004)
<i>OCF^2</i>	-0.420 (0.308)	-0.357 (0.329)
<i>NetWorth^2</i>	-1.062 (0.735)	0.872 (0.818)
<i>CurrentRatio^2</i>	-0.002* (0.001)	-0.001 (0.001)
<i>Leverage^2</i>	-4.112* (2.310)	2.307 (2.141)
<i>OCF^3</i>	8.184*** (2.895)	1.914 (2.426)
<i>NetWorth^3</i>	1.403* (0.800)	-0.660 (0.865)
<i>CurrentRatio^3</i>	0.000 (0.000)	0.000 (0.000)
<i>Leverage^3</i>	2.298 (1.446)	-1.196 (1.219)
Calendar Q/Y fixed effect	Yes	Yes
Industry fixed effect	Yes	Yes
Observations	77,118	106,731

All continuous variables are winsorized at the 1 percentile and 99 percentile levels. Robust standard errors in parentheses. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.5.
Effect of covenant violations on analyst revisions - Cross-sectional
Analysis: Panel A (Financially Constrained Firms)

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>RevRecm</i>	<i>RevEstm</i>	<i>RevRecm/ AyFw</i>	<i>RevEstm/ AyFw</i>	<i>Pr(RevRecm)</i>	<i>Pr(RevEstm)</i>
<i>Financial_Constraints</i>	0.309*** (0.056)	0.277*** (0.090)	0.007 (0.005)	0.007* (0.004)	-0.019 (0.031)	0.118*** (0.041)
<i>Violation</i>	0.105* (0.058)	-0.250* (0.132)	0.021* (0.012)	-0.009 (0.009)	0.105 (0.131)	0.003 (0.088)
<i>Violation*Financial_Constraints</i>	0.457*** (0.075)	0.576*** (0.134)	0.027* (0.015)	0.022** (0.009)	0.158*** (0.060)	0.338*** (0.093)
<i>Size</i>	0.448*** (0.018)	1.109*** (0.050)	-0.012*** (0.001)	0.030*** (0.002)	0.320*** (0.010)	0.582*** (0.016)
<i>BM</i>	-0.301*** (0.031)	-0.884*** (0.095)	0.056*** (0.004)	-0.013*** (0.005)	-0.035 (0.024)	-0.518*** (0.039)
<i>ROA</i>	-0.002 (0.223)	-2.111*** (0.598)	0.025 (0.030)	-0.054** (0.027)	-0.337* (0.204)	-1.026*** (0.307)
<i>Leverage</i>	2.436 (1.781)	-10.835** (4.330)	0.450** (0.179)	-0.479*** (0.181)	1.461 (1.270)	-2.640 (1.832)
<i>Inst</i>	0.142* (0.076)	-0.050 (0.207)	-0.037*** (0.009)	0.045*** (0.009)	0.467*** (0.051)	0.531*** (0.072)
<i>NumSegments</i>	-0.047*** (0.011)	-0.096*** (0.031)	0.001 (0.001)	-0.001 (0.001)	-0.033*** (0.008)	-0.038*** (0.011)
<i>Return</i>	-0.274*** (0.036)	-0.568*** (0.059)	-0.014*** (0.005)	-0.023*** (0.004)	-0.299*** (0.030)	-0.300*** (0.040)
<i>Abs[EA/MF]</i>	0.305*** (0.021)	0.675*** (0.041)	0.010*** (0.002)	0.042*** (0.002)	0.170*** (0.012)	0.353*** (0.018)
<i>OCF^2</i>	1.271*** (0.407)	2.241*** (0.603)	0.027 (0.047)	0.047 (0.033)	-0.202 (0.298)	0.061 (0.394)
<i>NetWorth^2</i>	-0.877 (1.052)	14.076*** (2.843)	-0.367*** (0.112)	0.546*** (0.119)	0.460 (0.795)	2.830** (1.180)
<i>CurrentRatio^2</i>	0.003 (0.002)	0.005 (0.004)	-0.000 (0.000)	0.000 (0.000)	-0.001 (0.001)	0.005** (0.002)
<i>Leverage^2</i>	-6.689** (3.344)	21.048*** (8.118)	-1.148*** (0.302)	0.989*** (0.339)	-3.178 (2.425)	5.047 (3.208)
<i>OCF^3</i>	-1.808 (3.027)	-18.947*** (4.837)	0.127 (0.349)	-0.337 (0.277)	6.336** (2.891)	-1.606 (3.216)
<i>NetWorth^3</i>	0.945 (1.147)	-13.242*** (2.996)	0.326*** (0.117)	-0.524*** (0.126)	-0.021 (0.849)	-2.633** (1.282)
<i>CurrentRatio^3</i>	-0.000* (0.000)	-0.000* (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000*** (0.000)
<i>Leverage^3</i>	3.769* (2.094)	-10.850** (4.751)	0.732*** (0.172)	-0.489** (0.202)	1.827 (1.521)	-2.739 (1.805)
Calendar Q/Y fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,714	59,597	46,714	59,597	46,714	59,597
Adj R-squared	0.206	0.324	0.058	0.194		

All continuous variables are winsorized at the 1 percentile and 99 percentile levels. Robust standard errors in parentheses. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.6.
Effect of covenant violations on analyst revisions - Cross-sectional
Analysis: Panel B (Lower Institutional Ownership)

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>RevRecm</i>	<i>RevEstm</i>	<i>RevRecm/ AyFw</i>	<i>RevEstm/ AyFw</i>	<i>Pr(RevRecm)</i>	<i>Pr(RevEstm)</i>
<i>Inst_Low</i>	-0.030 (0.025)	0.153*** (0.054)	0.015*** (0.003)	0.013*** (0.004)	-0.037 (0.033)	0.007 (0.032)
<i>Violation</i>	0.064 (0.041)	0.037 (0.072)	0.020*** (0.007)	0.011* (0.006)	0.098 (0.064)	0.106** (0.052)
<i>Violation* Inst_Low</i>	0.109*** (0.039)	0.388*** (0.081)	0.055*** (0.011)	0.018*** (0.007)	0.219*** (0.073)	0.191*** (0.070)
<i>Size</i>	0.402*** (0.012)	1.032*** (0.036)	-0.014*** (0.001)	0.033*** (0.002)	0.321*** (0.010)	0.550*** (0.012)
<i>BM</i>	-0.251*** (0.021)	-0.826*** (0.061)	0.063*** (0.003)	-0.018*** (0.004)	-0.037 (0.024)	-0.502*** (0.028)
<i>ROA</i>	-0.213 (0.164)	-1.630*** (0.420)	0.037 (0.023)	-0.066*** (0.024)	-0.332 (0.204)	-1.085*** (0.224)
<i>Leverage</i>	1.841 (1.173)	-9.598*** (3.053)	0.519*** (0.141)	-0.584*** (0.171)	1.399 (1.272)	-0.046*** (0.008)
<i>NumSegments</i>	-0.048*** (0.009)	-0.105*** (0.024)	0.001* (0.001)	-0.004*** (0.001)	-0.033*** (0.008)	-0.254*** (0.027)
<i>Return</i>	-0.301*** (0.024)	-0.466*** (0.037)	-0.011*** (0.004)	-0.020*** (0.003)	-0.300*** (0.030)	0.354*** (0.012)
<i>Abs[EA/MF]</i>	0.240*** (0.012)	0.563*** (0.024)	0.008*** (0.001)	0.047*** (0.002)	0.169*** (0.012)	-2.043 (1.315)
<i>OCF^2</i>	0.817*** (0.263)	1.397*** (0.400)	0.038 (0.036)	0.039 (0.028)	-0.192 (0.298)	0.019 (0.305)
<i>NetWorth^2</i>	0.002* (0.001)	0.000 (0.003)	-0.000*** (0.000)	-0.000 (0.000)	0.500 (0.793)	2.959*** (0.920)
<i>CurrentRatio^2</i>	0.154 (0.758)	13.222*** (2.258)	-0.437*** (0.089)	0.677*** (0.124)	-0.001 (0.001)	0.002 (0.001)
<i>Leverage^2</i>	-6.070*** (2.237)	19.408*** (5.989)	-1.162*** (0.254)	1.235*** (0.336)	-3.034 (2.422)	3.786 (2.383)
<i>OCF^3</i>	-1.487 (2.064)	-11.338*** (2.899)	0.086 (0.328)	-0.321 (0.234)	6.268** (2.890)	-0.857 (2.363)
<i>NetWorth^3</i>	-0.000** (0.000)	-0.000 (0.000)	0.000** (0.000)	0.000 (0.000)	-0.061 (0.849)	-2.626*** (0.967)
<i>CurrentRatio^3</i>	-0.206 (0.799)	-12.200*** (2.258)	0.424*** (0.094)	-0.629*** (0.127)	-0.000 (0.000)	-0.000** (0.000)
<i>Leverage^3</i>	3.963*** (1.422)	-10.199*** (3.511)	0.703*** (0.157)	-0.627*** (0.201)	1.732 (1.517)	-1.921 (1.355)
Calendar Q/Y fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,118	106,731	77,118	106,731	77,118	106,731
Adj R-squared	0.184	0.299	0.055	0.182		

All continuous variables are winsorized at the 1 percentile and 99 percentile levels. Robust standard errors in parentheses. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.7.
Effect of covenant violations on analyst revisions - Cross-sectional
Analysis: Panel C (Experienced Analysts)

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>RevRecm</i>	<i>RevEstm</i>	<i>RevRecm/ AyFw</i>	<i>RevEstm/ AyFw</i>	<i>Pr(RevRecm)</i>	<i>Pr(RevEstm)</i>
<i>Analyst_Experience</i>	0.265*** (0.015)	0.217*** (0.035)	0.047*** (0.002)	0.015*** (0.002)	0.833*** (0.019)	0.078*** (0.018)
<i>Violation</i>	0.080** (0.034)	0.195*** (0.061)	0.018** (0.007)	0.017*** (0.006)	0.147*** (0.057)	0.152*** (0.055)
<i>Violation*Analyst_Experience</i>	0.398*** (0.046)	0.234*** (0.076)	0.093*** (0.010)	0.012* (0.007)	1.106*** (0.085)	0.200*** (0.057)
<i>Size</i>	0.386*** (0.013)	1.005*** (0.039)	-0.015*** (0.001)	0.032*** (0.002)	0.299*** (0.010)	0.548*** (0.012)
<i>BM</i>	-0.269*** (0.022)	-0.833*** (0.062)	0.058*** (0.003)	-0.019*** (0.004)	-0.112*** (0.025)	-0.505*** (0.028)
<i>ROA</i>	-0.257 (0.163)	-1.730*** (0.423)	0.042* (0.023)	-0.067*** (0.024)	-0.333 (0.205)	-1.082*** (0.224)
<i>Leverage</i>	1.699 (1.164)	-9.876*** (3.050)	0.509*** (0.139)	-0.596*** (0.171)	1.202 (1.251)	-2.091 (1.311)
<i>Inst</i>	0.084 (0.056)	-0.039 (0.145)	-0.039*** (0.006)	0.047*** (0.008)	0.382*** (0.051)	0.552*** (0.053)
<i>NumSegments</i>	-0.048*** (0.009)	-0.104*** (0.024)	0.001 (0.001)	-0.004*** (0.001)	-0.035*** (0.008)	-0.046*** (0.008)
<i>Return</i>	-0.304*** (0.024)	-0.465*** (0.037)	-0.012*** (0.004)	-0.020*** (0.003)	-0.326*** (0.030)	-0.255*** (0.027)
<i>Abs[EA/MF]</i>	0.246*** (0.012)	0.566*** (0.024)	0.010*** (0.001)	0.047*** (0.002)	0.195*** (0.012)	0.355*** (0.012)
<i>OCF^2</i>	0.884*** (0.264)	1.494*** (0.400)	0.046 (0.036)	0.043 (0.028)	-0.037 (0.297)	0.031 (0.305)
<i>NetWorth^2</i>	0.117 (0.757)	13.161*** (2.255)	-0.438*** (0.089)	0.679*** (0.124)	0.484 (0.796)	2.926*** (0.918)
<i>CurrentRatio^2</i>	0.002* (0.001)	0.000 (0.003)	-0.000** (0.000)	-0.000 (0.000)	-0.000 (0.001)	0.002 (0.001)
<i>Leverage^2</i>	-5.917*** (2.225)	19.814*** (5.981)	-1.153*** (0.251)	1.253*** (0.336)	-3.007 (2.404)	3.834 (2.379)
<i>OCF^3</i>	-1.471 (2.065)	-11.739*** (2.892)	0.070 (0.329)	-0.355 (0.232)	6.233** (2.946)	-0.973 (2.362)
<i>NetWorth^3</i>	-0.199 (0.795)	-12.193*** (2.256)	0.422*** (0.094)	-0.633*** (0.127)	-0.099 (0.845)	-2.612*** (0.965)
<i>CurrentRatio^3</i>	-0.000** (0.000)	-0.000 (0.000)	0.000* (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000** (0.000)
<i>Leverage^3</i>	3.919*** (1.416)	-10.386*** (3.504)	0.701*** (0.156)	-0.635*** (0.201)	1.862 (1.512)	-1.942 (1.354)
Calendar Q/Y fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,118	106,731	77,118	106,731	77,118	106,731
Adj R-squared	0.190	0.300	0.065	0.181		

All continuous variables are winsorized at the 1 percentile and 99 percentile levels. Robust standard errors in parentheses. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.8.
Effect of covenant violations on two-day window abnormal returns of
analyst revisions: Panel A (Aggregate Effect)

Variables	(1) <i>Abs[AR1]</i>	(2) <i>Abs[AR2]</i>
<i>Violation</i>	0.009*** (0.003)	0.010*** (0.003)
<i>Size</i>	0.007*** (0.001)	0.006*** (0.001)
<i>BM</i>	0.005** (0.002)	0.009*** (0.003)
<i>ROA</i>	-0.101*** (0.018)	-0.087*** (0.016)
<i>Leverage</i>	0.422*** (0.083)	0.000 (0.086)
<i>Inst</i>	0.005 (0.004)	0.005 (0.003)
<i>NumSegments</i>	-0.003*** (0.001)	-0.003*** (0.000)
<i>Return</i>	-0.024*** (0.003)	-0.012*** (0.002)
<i>Abs[EA/MF]</i>	0.036*** (0.001)	0.030*** (0.001)
<i>RetVol</i>	0.055*** (0.003)	0.038*** (0.002)
<i>TradingVolm</i>	0.035*** (0.003)	0.044*** (0.003)
<i>OCF^2</i>	0.062 (0.039)	0.027 (0.031)
<i>NetWorth^2</i>	-0.269*** (0.062)	0.048 (0.053)
<i>CurrentRatio^2</i>	0.000*** (0.000)	-0.000 (0.000)
<i>Leverage^2</i>	-1.030*** (0.156)	-0.079 (0.156)
<i>OCF^3</i>	-0.588** (0.254)	-0.346* (0.206)
<i>NetWorth^3</i>	0.254*** (0.063)	-0.042 (0.057)
<i>CurrentRatio^3</i>	-0.000*** (0.000)	0.000 (0.000)
<i>Leverage^3</i>	0.661*** (0.093)	0.111 (0.092)
Calendar Q/Y fixed effect	Yes	Yes
Industry fixed effect	Yes	Yes
Observations	52,131	53,518
Adj R-squared	0.154	0.179

All continuous variables are winsorized at the 1 percentile and 99 percentile levels. Robust standard errors in parentheses. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.9.
Effect of covenant violations on two-day window abnormal returns of
analyst revisions: Panel B (Analyst Average Effect)

Variables	(1) <i>Abs[AR1]/AyFw</i>	(2) <i>Abs[AR2]/AyFw</i>
<i>Violation</i>	0.005*** (0.001)	0.002*** (0.001)
<i>Size</i>	-0.003*** (0.000)	-0.002*** (0.000)
<i>BM</i>	0.002*** (0.001)	0.000 (0.000)
<i>ROA</i>	-0.020*** (0.004)	-0.010*** (0.003)
<i>Leverage</i>	0.056*** (0.016)	-0.013 (0.010)
<i>Inst</i>	-0.008*** (0.001)	-0.005*** (0.000)
<i>NumSegments</i>	0.000** (0.000)	0.000 (0.000)
<i>Return</i>	-0.001 (0.001)	0.001*** (0.000)
<i>Abs[EA/MF]</i>	0.003*** (0.000)	0.003*** (0.000)
<i>RetVol</i>	0.006*** (0.001)	0.004*** (0.000)
<i>TradingVolm</i>	0.001 (0.001)	0.001** (0.000)
<i>OCF^2</i>	0.023*** (0.008)	0.007 (0.004)
<i>NetWorth^2</i>	-0.050*** (0.018)	0.000 (0.006)
<i>CurrentRatio^2</i>	-0.000* (0.000)	-0.000*** (0.000)
<i>Leverage^2</i>	-0.141*** (0.035)	0.010 (0.018)
<i>OCF^3</i>	-0.174*** (0.044)	-0.059** (0.027)
<i>NetWorth^3</i>	0.046*** (0.016)	-0.002 (0.007)
<i>CurrentRatio^3</i>	0.000 (0.000)	0.000*** (0.000)
<i>Leverage^3</i>	0.092*** (0.020)	0.002 (0.011)
Calendar Q/Y fixed effect	Yes	Yes
Industry fixed effect	Yes	Yes
Observations	52,131	53,518
Adj R-squared	0.131	0.149

All continuous variables are winsorized at the 1 percentile and 99 percentile levels. Robust standard errors in parentheses. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.10.
Effect of covenant violations on two-day window abnormal returns of
analyst revisions: Panel C (Individual Revision Effect)

Variables	(1) <i>Abs[AR3]</i>	(2) <i>Abs[AR4]</i>
<i>Violation</i>	0.006*** (0.002)	0.005*** (0.002)
<i>Size</i>	-0.005*** (0.000)	-0.003*** (0.000)
<i>BM</i>	0.005*** (0.001)	-0.003* (0.001)
<i>ROA</i>	-0.069*** (0.010)	-0.053*** (0.008)
<i>Leverage</i>	0.118*** (0.037)	0.036 (0.031)
<i>Inst</i>	-0.003** (0.001)	-0.007*** (0.001)
<i>NumSegments</i>	-0.000 (0.000)	-0.000 (0.000)
<i>Return</i>	-0.004*** (0.001)	-0.005*** (0.001)
<i>Abs[EA/MF]</i>	0.013*** (0.001)	0.010*** (0.001)
<i>RetVol</i>	0.007*** (0.001)	0.007*** (0.001)
<i>TradingVolm</i>	0.006*** (0.001)	0.003*** (0.001)
<i>AyFw</i>	0.000* (0.000)	0.000** (0.000)
<i>Chg_Recm</i>	-0.000*** (0.000)	
<i>OCF^2</i>	0.018 (0.015)	0.057** (0.026)
<i>NetWorth^2</i>	-0.086*** (0.025)	-0.048** (0.019)
<i>CurrentRatio^2</i>	0.000 (0.000)	-0.000 (0.000)
<i>Leverage^2</i>	-0.310*** (0.068)	-0.127** (0.057)
<i>OCF^3</i>	-0.188 (0.164)	0.007 (0.200)
<i>NetWorth^3</i>	0.081*** (0.026)	0.044** (0.020)
<i>CurrentRatio^3</i>	-0.000 (0.000)	0.000 (0.000)
<i>Leverage^3</i>	0.221*** (0.040)	0.097*** (0.036)
Calendar Q/Y fixed effect	Yes	Yes
Industry fixed effect	Yes	Yes
Observations	105,309	173,673
Adj R-squared	0.124	0.160

All continuous variables are winsorized at the 1 percentile and 99 percentile levels. Robust standard errors in parentheses. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

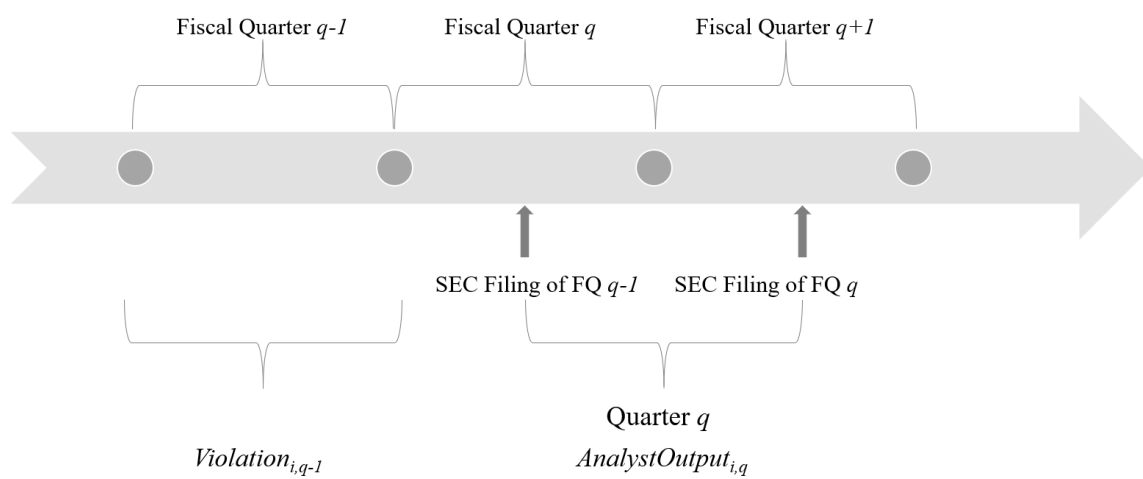
Table B.11.
Effect of covenant violations on relative analyst forecast errors

Variables	(1) <i>RFE</i>
<i>Violation</i>	-0.165** (0.074)
<i>Size</i>	-0.228*** (0.012)
<i>BM</i>	0.633*** (0.046)
<i>ROA</i>	-1.906*** (0.418)
<i>Leverage</i>	8.146*** (1.639)
<i>Inst</i>	-0.680*** (0.070)
<i>NumSegments</i>	-0.006 (0.009)
<i>Return</i>	-0.261*** (0.042)
<i>Abs[EA/MF]</i>	-0.092*** (0.014)
<i>Earnings_Var</i>	-0.010* (0.006)
<i>Loss</i>	-0.130*** (0.036)
<i>Forec_Hoz</i>	-0.037** (0.017)
<i>OCF^2</i>	0.234* (0.126)
<i>NetWorth^2</i>	-5.183*** (1.095)
<i>CurrentRatio^2</i>	0.002 (0.002)
<i>Leverage^2</i>	-14.528*** (2.877)
<i>OCF^3</i>	-5.465*** (1.934)
<i>NetWorth^3</i>	5.289*** (1.178)
<i>CurrentRatio^3</i>	-0.000 (0.000)
<i>Leverage^3</i>	7.751*** (1.573)
Calendar Q/Y fixed effect	Yes
Industry fixed effect	Yes
Observations	66,866
Adj R-squared	0.057

All continuous variables are winsorized at the 1 percentile and 99 percentile levels. Robust standard errors in parentheses. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

C. FIGURES

Fig. C.1. Timeline



VITA

VITA
RIXING LOU, CPA

ACADEMIC POSITION

Assistant Professor, Accounting (starting August 2020)
California State University, Monterey Bay - Seaside, CA

EDUCATION

Ph.D., Accounting (August 2020, defended June 2020)
Purdue University, Krannert School of Management – West Lafayette, IN
M.A., Accounting (May 2011)
University of Michigan, Ross School of Business – Ann Arbor, MI
B.A., Accounting (May 2009)
Nanjing University, School of Business – Nanjing, China

RESEARCH INTERESTS

Financial Reporting and Disclosure, Financial Analysts, Corporate Governance
Crowdsourcing, Machine Learning, and other Data-Driven approaches applied to Accounting

RESEARCH WORK

Dissertation/Job Market Paper

“Do Sell-Side Analysts Provide More Information Following Debt Covenant Violations?”

CONFERENCE PARTICIPATION (* - PRESENTATION)

AAA Annual Meeting (August 2019)
AAA Western Region Meeting (April 2019)
Midwest Accounting Research Conference (2016, 2017, 2018, 2019)
Purdue Theory Conference (2016, 2017, 2018, 2019)
KDSA Research Symposium, Purdue University (2016*, 2019*)
BKD Research Workshop, Purdue University (2017*, 2019*)

TEACHING EXPERIENCE

Instructor, Advanced Management Accounting, Purdue University (Spring 2020)

Recitation Instructor, Introduction to Management Accounting, Purdue University (Fall 2018)

- Krannert Certificate for Distinguished Recitation Teaching

Teaching Assistant, Introduction to Financial Accounting, Purdue University (2016, 2017, 2019)

AWARDS AND HONORS

Runner-up Award at KDSA Research Symposium (2019)

Krannert Certificate for Distinguished Recitation Teaching (2018)

Crowe Horwath Doctoral Scholarship (2017-2018)

Frederick N. Andrews Fellowship (2015-2017)

Dean Scholarship, Ross School of Business, University of Michigan (2010-2011)

PROFESSIONAL EXPERIENCE AND COMMUNITY SERVICES

Audit Associate	2014-2015
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Silberstein Ungar, PLLC - Bingham Farms, MI

Accountant	2012-2013
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TransNav Technologies – New Baltimore, MI

Consulting Intern	2009-2010
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Bain & Company - Shanghai, China

Volunteer at Basketball Stadium	2008
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2008 Beijing Summer Olympics

LICENSE AND MEMBERSHIPS

Certified Public Accountant, State of Illinois (active)	2014-present
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American Accounting Association and FARS Member	2015-present
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